#StateOfMind: The relationship between social media use, gender, and family life, with mental health and well-being. Longitudinal evidence from young people in the UK and South Korea

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I, Memta R Jagtiani, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

Background: Social media use has complex associations with mental health and well-being, particularly among children, adolescents and young adults. I analysed how gender and family factors may modify associations between social media use (SMU)/phone-based interpersonal communication (PIC), self-esteem and depression over time among 10-21-year-olds in the UK and 14-18-year-olds in South Korea.

Methods: I used two longitudinal datasets, the UK Household Longitudinal Study (UKHLS) and the Korean Children and Youth Panel Survey (KCYPS) to examine whether self-esteem (UKHLS and KYCPS) and depression (KCYPS) changed over time with SMU/PIC, using linear mixed-effects modelling. A key aspect of my work investigated whether gender and family factors such as parent-child relationship quality (UKHLS) and parenting styles (KCYPS) confound or modify these associations.

Results: Using the UKHLS, female non-users had higher baseline self-esteem than light users ($\beta = 0.34$; 95% CI: [0.03, 0.64]) but moderate ($\beta = -0.21$; 95% CI: [-0.47, 0.04]) and heavy users ($\beta = -0.30$; 95% CI: [-0.62, 0.02]) had lower baseline self-esteem than light users. This association was absent in males. Family structure moderated the association between the duration of social networking site use and self-esteem at baseline in females ($p=0.022$).

Using the KCYPS, gender did not moderate the associations between computer SMU/PIC, self-esteem and depression ($p>0.05$). Higher frequency of computer SMU was associated with lower self-esteem ($\beta = -0.48$; 95% CI: [-0.71, -0.25]) and higher log-transformed depression (Model 3: $\beta = 0.02$; 95% CI: [0.01, 0.04]) at baseline. Higher frequency of PIC was associated with higher self-esteem at baseline ($\beta = 0.38$ 95% CI: [0.09, 0.66]). Positive parenting moderated the associations between computer SMU/PIC and self-esteem at baseline ($p=0.045$ and $p=0.018$, respectively).

Conclusions: The relationships between SMU/PIC, self-esteem and depression may vary according to sociodemographic factors. A nuanced understanding of social media usage patterns could inform policies and interventions, which should consider gender-, family- and country-specific variations.

Impact Statement

My PhD thesis examined the associations between social media use and self-esteem/depression in young people (children, adolescents and young adults) using data from the UK Household Longitudinal Study (UKHLS) and the Korean Children and Youth Panel Survey (KCYPS). My thesis also explored whether gender and family factors modify these associations. The research undertaken has important implications both within and outside of academia.

My research advances the understanding of the mechanisms through which social media impacts the mental health and well-being of young people. It also underscores the role that parents can play in supporting their children's use of social media, as the findings of my research revealed that positive parenting practices had a significant impact on the relationships between computer social media use, phone-based interpersonal communication and self-esteem among young people in South Korea. In June 2023, I had the honour of being invited as a Guest Lecturer by the Anna Freud Centre to deliver teaching on my research to students pursuing the Postgraduate Diploma in Child and Young Persons Psychological Wellbeing Practice at University College London. My research findings can inform university curricula by providing insights into how sociological factors such as parenting styles modify the associations between social media use and mental health and well-being in young people.

Additionally, I have contributed to the academic discourse by publishing related research in a peer-reviewed journal, Cyberpsychology, Behavior, and Social Networking, in December 2019. Moreover, I had the opportunity to disseminate my PhD research findings at esteemed conferences such as the Society for Longitudinal and Lifecourse Studies and the British Society for Population Studies in September 2021.

My commitment to advancing knowledge in this field continues, as I am currently in the process of preparing manuscripts based on my PhD research for submission to prominent journals. This proactive engagement not only amplifies the reach and influence of my research but also contributes to the broader understanding of the critical issues at the intersection of social media, mental health and well-being.

The practical implications of my research extend beyond academia in several ways. My research has the potential to inform public and non-profit organisations and raise awareness of the complexities around social media's influence on mental health and well-being, including the role of gender. My research revealed that among young people in the UK, chatting and interacting with friends on social networking sites was negatively associated with self-esteem in females but not in males. However, when evaluating social media use more holistically among young people in South Korea, no gender differences were observed.

Additionally, my research findings can aid in the development of policies and interventions aimed at regulating social media use to maximise its benefits while minimising its harms. In September 2018, as part of the Scroll Free September campaign initiated by the Royal Society for Public Health, I authored a blog article on the interconnectedness of social media use, family life (e.g., family meals) and well-being. The campaign encourages individuals to take a break from social media, and with the support of resources such as my blog, prompts them to reflect on their usage patterns, for example, what they missed about social media and what they genuinely enjoyed.

Social media companies could also benefit from this research by thinking of ways to enhance the design of social media that entails protecting users' welfare, for example by removing addictive features that drive up usage. This could shift the focus away from engagement-based revenue and toward more sustainable business models that prioritise users' welfare.

Finally, my research examining data from different countries (UK and South Korea) could also have an international impact in the future such as through collaborations with academic and non-academic specialists and engagement with public policymakers and social media companies.

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As I complete my PhD journey, I am filled with a deep sense of gratitude for the people who have supported me every step of the way. Their unwavering guidance and encouragement have been vital in getting me to where I am today.

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Finally, I would like to express deep gratitude to the Almighty for blessing me with the strength, patience and wisdom to complete this endeavour. Thank you.

I am humbled by the opportunity to contribute to the fields of (i) Social Media, Mental Health and Well-Being, (ii) Epidemiology and Public Health and (iii) Data Science. I hope that my work will make a meaningful difference in the lives of people in today's world. Thank you all for being a part of my life and for helping me achieve my dreams.

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List of Abbreviations

AAP	American Academy of Pediatrics
AddHealth	National Longitudinal Study of Adolescent Health
BFAS	Bergen Facebook Addiction Scale
BHPS	British Household Panel Survey
BSMAS	Bergen Social Media Addiction Scale
CES-D-10	10-item Centre for Epidemiological Studies Depression Scale
CESD-R	Centre for Epidemiological Studies Depression Scale – Revised
CFPS	China Family Panel Studies
CI	Confidence Interval
CS	Cross-sectional
CSMU	Computer social media use
DMHDS	Dunedin Multidisciplinary Health and Development Study
DSM-5	Diagnostic and Statistical Manual of Mental Disorders – Fifth edition
EMBS	Ethnic Minority Boost Sample
EMC	Electronic media communication
ES	Emotional support
ESPAD	European School Survey Project on Alcohol and Other Drugs
ESTUDES	Spanish Survey on Drug Use in the School Population
FOMO	Fear of missing out
GAIN-SS	Global Appraisal of Individual Needs – Short Screener
GfK	Growth from Knowledge panel
GHQ-12	12-item General Health Questionnaire
GLM	Generalised linear model
GPS	General Population Sample
GSS	General Social Survey
H	Hypothesis
HBSC	Health Behaviour in School-aged Children
IV	Instrumental Variables
K-10	Kessler Psychological Distress Scale
KCC	Korea Communications Commission
KCYPS	Korean Children and Youth Panel Survey
KPYS	Korean Youth Panel Survey
KYRBS	Korean Youth Risk Behavior Web-based Survey
LIFECOURSE	Longitudinal Investigation For Epidemiologic Causes and OUtcomes RiSing in Early Childhood and Adolescence
LISS	Longitudinal Internet Studies for the Social Sciences
LSYPE	Longitudinal Study of Young People in England
LT	Longitudinal
MAR	Missing at random
MASC	Multidimensional Anxiety Scale for Children

MCS	Millennium Cohort Study
MESH	Medical Subject Headings
MHI-5	5-item Mental Health Inventory
MI	Multiple imputation
MICE	Multiple imputation using chained equations
MSOM	Making Sense of Media
MtF	Monitoring the Future
NYPI	National Youth Policy Institute
ONS	Office for National Statistics
OSC	Original Symptom Checklist
OSDUHS	Ontario Student Drug Use and Health Survey
PATH	Population Assessment of Tobacco and Health
PHQ-4	4-item Patient Health Questionnaire
PMM	Predictive mean matching
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
PROMIS	Patient-Reported Outcomes Measurement Information System
PSHE	Personal, Social, Health and Economic
PSMU	Problematic social media use
PIC	Phone-based interpersonal communication
PSU	Primary sampling unit
ref	Reference category
RQ	Research Question
RRT	Relational Regulation Theory
RSES-R	Rosenberg Self-Esteem Scale – Revised
SD	Standard deviation
SDQ	Strengths and Difficulties Questionnaire
SEP	Socioeconomic position
SMDS	Social Media Disorder Scale
SME	Social media engagement
SM-ES	Social media emotional support
SMFQ	Moods and Feelings Questionnaire – Short version
SMU	Social media use
SNS	Social networking site
TCS	Taiwan Communication Survey
UK	United Kingdom
UKHLS	United Kingdom Household Longitudinal Study
UN	United Nations
USA	United States of America
WHO	World Health Organisation
YAPS	Youth Activity Participation Study
YRBSS	Youth Risk Behavior Surveillance System

Chapter 1: Background

This chapter describes the issues around mental health and well-being in young people (children, adolescents and young adults) and highlights the trends of social media use across countries. Next, it outlines the design of social media and presents theories linking social media use to mental health and well-being outcomes. Finally, I refer to Bronfenbrenner's ecological framework, which forms the foundation of my PhD, when discussing the role of gender and family factors in potentially modifying this relationship.

Engaging in social media sites is among the most popular internet activities. Meta Platforms own four of the biggest social media platforms: Facebook, Messenger, WhatsApp and Instagram, each with over one billion global monthly users as of January 2023 (1). Over the last decade, however, there has been a global rise in concerns about the possible adverse effects of social media use on health outcomes such as mental health and well-being, especially among children and adolescents, leading in some instances to calls for restrictions on its use (2).

Any indication of positive or negative effects of social media use on mental health and well-being warrants attention from mental health, public health and psychological perspectives. This introductory background section aims to set the scene for my PhD by:

1. Describing the issues around mental health and well-being in young people (children, adolescents and young adults).
2. Highlighting the definition of social media and its trends across countries.
3. Outlining the design of social media and evidence linking social media use to mental health and well-being (including potential key mechanisms).
4. Discussing the role of gender and family in the relationships between social media use and mental health and well-being with reference to Bronfenbrenner's ecological framework (3).

1.1 Mental health and well-being

Poor mental health or low well-being in childhood and adolescence is a major public health concern as this is a period when mental health issues develop (4). Evidence highlights that about half of lifetime cases of mental illness in the United States of America (USA) begin by age 14 and about three-quarters of these cases onset before the age of 24, based on the latest (fifth) edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (5). As Jean Twenge, Professor of Psychology at San Diego State University, states in her book *iGen* (6) *"iGen'ers look so happy online, making goofy faces on Snapchat and smiling in their pictures on Instagram. But dig deeper, and reality is not so comforting. iGen is on the verge of the most severe mental health crisis for young people in decades. On the surface, though, everything is fine."* (p. 94).

Adolescence is a particularly critical period for socialisation with friends; this developmental phase involves developing greater independence and establishing connections beyond the family circle (7). Although adolescents could potentially derive benefits from social media use through enhancing existing and new connections online, at the same time, social media has been described by Patton and colleagues (4) as being able to *"equally amplify vulnerabilities from intense emotions"* (p. 2429).

Health-related behaviours and mental health and well-being track from childhood and adolescence through to adulthood (8). Moreover, young people have reported higher levels of emotional distress in recent decades, particularly in the form of symptoms related to anxiety and feelings of sadness, with females being particularly affected (9). Among young people, there is also evidence to suggest that mental health and well-being outcomes worsen with increasing age, especially for adolescent females more so than adolescent males, and there might be differences in the association between social media interaction and well-being by gender and age among young people (10). As such, it is paramount to explore through longitudinal studies the associations between social media use and mental health and well-being among children, adolescents and young adults, including the consideration of gender and family factors which could modify this relationship. Such an understanding could have future benefits for population health.

Mental health can be grouped into two continuums: psychological well-being and psychopathology (11). Campbell and Osborn (2021) conducted network analyses on adolescents in Kenya to examine a network of psychological well-being (measured by positive affect scales) and psychopathology (measured by negative affect scales) measures and found that they were two distinct concepts among adolescents (11). In the sections below, I will further elaborate on a measure of each of the two distinct concepts that I will study in the empirical chapters of my PhD (Chapters 5, 6 and 7).

1.1.1 Self-esteem (psychological well-being)

Rosenberg (12) defines self-esteem as evaluations of the self or the degree of satisfaction with the self. It represents one's overall perceived sense of self-worth (13). He argues that there are two underlying motives of the self – firstly, the **self-esteem motive** which is the *"wish to think well of oneself"*, and secondly, the **self-consistency motive** which is the *"wish to protect the self-concept against change"* (p. 53-54). Individuals with low self-esteem often experience heightened anxiety when they attempt to uphold a façade of themselves that does not accurately reflect who they truly are (13). Low self-esteem in young people has been established with adverse outcomes. For instance, low global self-esteem (indicated as generalised feelings of self-worth) in pre-adolescence (aged 9 to 13 years) was associated with adolescent (aged 15 years) reports of problem eating, suicidal ideation and multiple health-compromising behaviours in the Dunedin Multidisciplinary Health and Development Study (DMHDS) in New Zealand (14). In another prospective study that also used data from the DMHDS, adolescents who had low levels of self-esteem experienced inferior mental and physical well-being, diminished economic opportunities and a higher likelihood of engaging in criminal activities during their adult years, in contrast to adolescents who had high self-esteem (15).

Self-esteem is an important indicator of subjective well-being (16-18), which refers to how individuals perceive their quality of life and can encompass cognitive evaluations (i.e., life satisfaction) and emotional responses (i.e., positive affect) (19). Indicators of subjective well-being can offer a valuable alternative to more objective, medical-oriented metrics (20). Researchers have argued that social media is particularly important to study in relation to user self-esteem. This is attributed to the user's potential to compare themselves and their lives to the content posted by others within their network (21), which is predominantly characterised by positive and idealised portrayals (22).

1.1.2 Depression (psychopathology)

According to the National Institute of Mental Health, the lead federal agency for research on mental disorders in the USA (23), depression is a mood disorder that affects how one thinks, feels and copes with daily activities, for example eating and sleeping. Depression is also synonymous with major depressive disorder or clinical depression and symptoms must persist for at least two weeks for an individual to be diagnosed with depression. Examples of symptoms include experiencing a persistent low mood and a loss of interest or pleasure in hobbies and everyday activities that are beyond typical negative emotions that an individual would experience (24). Clinical depression often first begins as depressive symptomatology in adolescence and is prone to track through adulthood (25). Causes of depression are known to be wide-ranging, encompassing biological, social, familial and emotional factors (26). According to a systematic review and meta-analysis conducted in 2020, 34% of adolescents aged 10 to 19 years are at risk of developing clinical depression globally (27). Pertaining to social media use, a systematic review conducted in 2018 found that all four domains of social media: time spent, activity, investment and addiction were correlated with depression (28).

1.2 Social media use

In this section, I will outline the definition of social media, describe the prevalence and trends in social media use and discuss the different ways that social media use can be measured.

1.2.1 Definition of social media

Definitions of social media in the literature vary widely across different disciplines and there is currently no mutually agreed-upon definition (29). However, for my PhD, I will be using the definition laid out by Carr and Hayes (29) because they have reviewed extant definitions and came to a *"deductive, descriptive, and robust [definition]: as applicable to today's social media as to the social media of 2035, whatever form they take"* (p. 49). These authors formally define social media as:

> *"Internet-based, disentrained, and persistent channels of mass-personal communication facilitating perceptions of interactions among users, deriving value primarily from user-generated content."* (p. 49)

A simpler, rephrased explication of the above is:

> *"Social media are Internet-based channels that allow users to opportunistically interact and selectively self-present, either in real-time or asynchronously, with both broad and narrow audiences who derive value from user-generated content and the perception of interaction with others."* (p. 50)

This definition can be broken down into various parts as follows:

Internet-based. This definition acknowledges that social media need not be Web-based and so can include stand-alone applications such as Snapchat that do not require the web to function.

Disentrained, persistent channels. Social media are persistently available whether a user is active or not. This facilitates disentrained communication which means that users can participate when they can commit to participating, as opposed to face-to-face interaction that requires a commitment to participate at the same time. For example, Facebook operates continually; anyone can log on at their preferred time to use the application.

Perceived interactivity. Users need only perceive an interactive element to consider a medium as social, even if there is no direct interaction with other users. For example, I can watch a vlog uploaded on social media and feel a sense of connection towards the person or construct being explored in the vlog without engaging directly with the vlogger.

User-generated value. The benefit or enjoyment of using social media may be derived from the interactions of other users rather than directly from the content provider. For example, I can gain more utility and value from users' comments about a product being promoted on social media sites, thereby providing me with useful information on product quality over and above the intended marketing message.

Mass-personal communication. Messages can flow between users, between audiences, from the user to the audience or from the audience to the user on social media, creating mass and/or interpersonal communication. For example, a user on

Instagram may post a photo of her showing solidarity with the Black Lives Matter Movement, thereby broadcasting her message to her followers (mass audience). Later, followers could share this post on their channel with their own set of followers, thereby allowing a message to flow between audiences.

Table 1.1 below outlines examples of what can and cannot be considered a social medium.

Table 1.1: Examples of social media and non-social media platforms

Social medium	Not a social medium
Social network sites (e.g., Facebook)	Wikipedia
Chatboards and discussion fora	Skype
Social/casual games (e.g., Farmville)	Netflix
Instagram	E-mail
	SMS

Source: Adapted from Carr and Hayes (2015)

According to Carr and Hayes' definition of social media, other examples such as activity-sharing applications (e.g., Strava) can be considered as social media. In addition, it is paramount to distinguish social media from social network sites (SNSs). SNSs such as Facebook or KakaoTalk (SNS used in Korea) are a subset of social media but not all social media are inherently SNSs (29).

1.2.2 Prevalence and trends in social media use

Social media use is prevalent worldwide. In the USA, 84% of young adults aged 18 to 29 reported that they use social media, based on nationally representative data from the Pew Research Center in 2021 (30). Most 18- to 29-year-olds reported that they use Instagram or Snapchat, and about half reported that they use TikTok, with those at the younger end of this cohort – ages 18 to 24 – being especially likely to have reported using Instagram (76%), Snapchat (75%) or TikTok (55%) (30). In South Korea, 93.8% of teenagers aged 15 to 19 years and 95.9% of young adults aged 20 to 29 years reported that they use KaKaoTalk, a free mobile messaging app developed in South Korea, based on data from Statista in 2021 (31). In England, 62% of children aged 3 to 17 years and 94% of children aged 16 to 17 years had their profile on at least one social media application or site based on data from Ofcom in 2021 (32). In China, WeChat, a Chinese social media and multipurpose application, had over one billion monthly active users as of 2022 (33). These worldwide figures highlight the ubiquity of social media use.

Alongside the increasing prevalence of social media use, an increasing number of people are also aware of the pressures associated with social media. For example, recent UK evidence from the tenth edition of The Prince's Trust Youth Index released in 2019 revealed that 57% of individuals between the ages of 16 and 25 years indicated that social media places excessive pressure on them to excel, and 46% reported that comparing themselves to others on social media made them feel insufficient (34). Users might also experience a "fear of missing out" (FoMO) if they perceive their friends to be leading more interesting and rewarding lives, fuelling the need to constantly be online (35).

Social media can not only provoke users to question their self-worth but also their safety. For example, evidence from the Mental Health of Children and Young People Survey in 2022 found that in England, young women aged 17 to 24 years were almost twice as likely to report having been bullied online than young men (19.5% compared to 11.3%) (36). Young women were also less likely to agree that they felt safe using social media than young men (48.6% agreeing compared to 65.9%) (36). A plausible explanation for cyberbullying could be linked to online disinhibition effects, which refer to users being less cautious and burdened by their verbal and behavioural actions online due to the absence of face-to-face communication (37). This is a serious problem as cyberbullying has been shown to lead to depression, anxiety and suicide in victims (38).

1.2.3 Measurement of social media

Social media use can be measured in various ways, for example, the duration and frequency of use, active and passive use, investment in social media and social media addiction.

Duration and frequency: Most of the research on social media has investigated social media use in terms of how much time (e.g., hours of use in a day) an individual spends on social media sites (39-41) or how frequently (e.g., three times a week) they engage with social media (42-44), the former denoting *duration* (a quantifiable measure of time) and the latter denoting *frequency* (an unquantifiable measure of time). This will be further discussed in my review of the literature (Chapter 2; Section 2.3.4).

Active and passive use: Active social media use involves chatting, posting personal content (e.g., photos and status updates) to an audience and/or liking or commenting on posts from friends/followers, whilst passive social media use refers to browsing and/or reading content from others (45). Active use can signify one's self-concept expressed through posts or comments used to engage with others whereas passive use requires minimal effort through consuming information alone and is less related to one's self-concept (46).

Investment in social media refers to how important social media applications are to the user, for example, perceiving it as an integral part of daily life and feeling disconnected when not on social media (47).

Social media addiction can be defined by the biopsychosocial model (48), which I describe in the next section. Social media addiction can be measured by the Bergen Social Media Addiction Scale (BSMAS) (49), a modified version of the Bergen Facebook Addiction Scale (BFAS) (50).

1.3 Social media, mental health and well-being

This section aims to first describe in detail how social media sites and applications are designed and how human psychology is manipulated to drive up the usage of social media. I then discuss how social media use potentially impacts mental health and well-being through various mechanisms.

1.3.1 Design of social media

The Attention Economy

Attention Economics was first theorised by psychologist and economist Herbert A. Simon. The Attention Economy asserts that human attention is a scarce commodity, and it is used as an extractable resource (51). Revenue is a function of continuous consumer attention, which is measured in clicks and time spent. The 2020 Internet Minute, coined by Lori Lewis who runs a social media management, marketing and monetisation firm, highlights that screen time is not a unitary activity. It could encompass, for example, the type of screen used, the way the screen is used, the length of time on the screen and the type of activity engaged in while using the screen (52). Similarly, these various aspects of internet use can be found within social media use, a subset of internet use.

One of the challenges in the digital era we live in today is the design of various internet-enabled devices and applications that have emerged over the past two decades. Much of the digital content that users interact with is created according to the concept of persuasive design (53), which aims to maximise how much time and attention the user devotes to an application to the exclusion of other online or offline activities. For example, sleep has been identified as the biggest competition for the continued success of technology giants such as Netflix (54). Our attention as a commodity is not new. The difficulty to stop using social media stems from the fact that these platforms are engineered to maintain our attention (53). With continued use, the behavioural scientists responsible for these technologies gather data on our behavioural patterns, enhancing their ability to sustain our engagement. Unfortunately, many technology developers do not target the rational and logical parts of the brain's operating system. Evolutionarily speaking, our brains are designed to reward us when we get information as hunter-gatherers because that information could save our lives (55). In the digital age, there is no cap on the amount of information we receive, thereby making it easier for us to gorge on information and obtain dopamine hits.

In effect, social media applications such as Facebook closely resemble the design of slot machines for gambling (56). They differ in the type of rewards used to reinforce the behaviour – money in the case of slot machines and social information in the case of social media applications – but the principle of intermittent reinforcement that drives continued attention and engagement is fundamental to both. Indeed, the term digital addiction is commonly used to refer to the difficulties that individuals experience in managing the use of their digital devices. The DSM-5 listed Internet Gaming Disorder as a condition for further study (57). Although the criteria included in the DSM-5 are specific to Internet Gaming Disorder rather than to digital addiction or pathological social media use, the latter two do share common symptoms, which can be explained by the biopsychosocial model (48) of behavioural addictions in general (58). Symptoms include **mood modification** (prolonged use of social media resulting in distinct alterations in emotional state), **salience** (fixation on social media), **tolerance** (increasing duration of social media use), **withdrawal symptoms** (undesirable emotions and psychological difficulties such as restlessness and anxiousness when access to social media is limited), **conflict** (interpersonal issues resulting from social media use) and **relapse** (resuming prolonged usage after a period of refraining from social media). This commonality was further corroborated by a study of nationally representative German adolescents aged 12 to 17 years in 2020. This study found that problematic social media use, based on the German version of the Social Media Disorder Scale (SMDS), was significantly associated with Internet Gaming Disorder in multivariate analyses (59).

It is important to note the distinction between heavy social media use and pathological social media use. The latter entails multiple addiction-like symptoms (e.g., mood modification, salience, tolerance, conflict, relapse, etc.) (60). As such, individuals could be heavy users of social media, but only those that experience negative addiction-like symptoms are considered pathological users.

The Hook Model

The Hook Model was coined by behaviour design expert Nir Eyal in his book *Hooked: How to Build Habit-Forming Products* (61) to describe the strategy used in social media applications to engage users into a behaviour habit. It follows a four-step process: Trigger, Action, Variable Reward and Investment.

A trigger refers to internal or external cues that make us engage in a particular action on social media. An example of an internal trigger could be the need to check the number of likes received on a social media post and an example of an external trigger could be a notification ringtone.

The action then follows the trigger(s) received and it depends on our motivation and ability to carry it out. Action will be easier if there are fewer “friction points” or obstructions in doing so.

Receiving a variable (random) reward piques our curiosity and sustains our attention as opposed to a standard reward because the variability creates a sense of engagement and focus. This is also known as intermittent reinforcement, which describes the process by which a subject receives a reward only at random intervals. This process has been likened to Classical/Pavlovian conditioning, which was first studied by Ivan Pavlov in 1897. It refers to a learning procedure in which a biologically potent stimulus (e.g., food) is paired with a previously neutral stimulus (e.g., a bell) (62). This results in the neutral stimulus eliciting a response (e.g., salivation) similar to that of the potent stimulus. Some examples of variable rewards on social media include receiving "likes", social information from newsfeeds and friend requests.

The variable reward then creates investment, for example, time spent on a social media application. A common phenomenon observed is the overconsumption of posts on newsfeeds due to the lack of stopping cues. This is coined as the *"Bottomless Bowl"* by Tristan Harris, an American technology ethicist, referring to a study that found that people eat 73% more soup out of self-refilling bowls than out of regular ones, without realising that they have consumed extra (63).

1.3.2 Theories linking social media use to mental health and well-being

The current trends in social media have had unintended consequences in several domains, including mental and physical health, social relationships, productivity, safety and security, and societal cohesion. Many of the concerns interact with each other, however, the focus of my PhD will be on the potential impact of social media use on mental health and well-being outcomes.

Several hypotheses in the literature shed light on the impact of social media use on mental health and well-being, suggesting that factors such as heavy social media use (compared to light or moderate use) may have positive or negative effects. For example, Valkenburg and Peter (64) set out two opposing mechanisms of online communication on adolescents' well-being: the stimulation effect and the displacement effect. There are also other theories and behaviours, discussed below, that potentially explain associations between social media use and mental health and well-being outcomes. These hypotheses, theories and behaviours shed light on both positive and negative aspects of social media use and in turn challenge the narratives of social media as an inherently risky tool.

Stimulation Effect

The stimulation effect states that social media use can positively influence mental health and well-being by enhancing existing friendships and their quality (64). This effect tends to dominate in active users (e.g., commenting, sharing, reacting) (65) compared to passive users (e.g., clicking, watching, viewing) (66) due to the tendency for active users to enhance their social capital (discussed below) and social connectedness (65).

The stimulation effect is linked to the concept of social support, which is defined as the perception and reality that one is cared for, has access to help from others and experiences a sense of belonging within a supportive social circle (67). Social media can offer a safe platform for young people to discuss sensitive health issues such as sexually transmitted diseases (68), which they may not otherwise discuss with friends or parents due to the stigmas surrounding these issues. This bridges the users' social capital by providing support online (69). Having online social support can therefore improve well-being and potentially buffer against mental health challenges such as anxiety and depression among young people (70).

Nonetheless, identifying social media as a source of social support may not be an adequate substitute for face-to-face support in improving mental health and well-being outcomes. A study of nationally representative young adults (aged 18-30 years) conducted in the USA in 2018 (71) found that receiving emotional support in person related to a slightly reduced likelihood of developing depression, whereas receiving emotional support through social media was linked to slightly higher odds of experiencing depression. The absence of interpersonal cues and interpersonal connections online could explain the negative impact of receiving emotional support through social media, as face-to-face emotional support often relies on these factors to be effective (72).

Displacement Effect

On the other hand, the displacement effect posits that heavy social media users are more susceptible than non-users, occasional users, or moderate users of social media to poorer mental health or lower levels of well-being (64). The reason for this is that spending time online leads to less time being available for other activities which could be more beneficial to mental health and well-being, such as socialising with friends in person, physical exercise and sleep in young people (43, 64). Apart from time displacement, there could also be a displacement of strong social ties with weak social ties online, which may not be particularly helpful for psychosocial well-being (73, 74).

Pertaining to family connectedness, an intensive longitudinal experience sampling study conducted in 2015-17 in North Carolina found limited evidence to suggest that time spent using digital technology displaced time spent interacting with parents offline, nor did it result in more negative or less positive parent-adolescent offline interactions in adolescents aged 9 to 15 years at baseline (75). These results suggest that spending time on digital technology does not necessarily reduce the quantity or quality of parent-adolescent offline interactions. This could mean that parent-adolescent offline interaction may not be subjected to time displacement nor its negative effects on mental health and well-being.

Social Capital

Social capital refers to social resources, both actual and virtual, that are available to individuals through their social networks, which can be utilised to accomplish their goals (76), for example feeling socially supported. There are two types of social capital: bonding social capital and bridging social capital.

Bonding social capital refers to strong relationships between individuals that allow for emotional support, trust and companionship (77). An example of a social media application that fosters bonding social capital is Snapchat (78). Bridging social capital refers to weak, distant relationships between individuals that make opportunities available for information sharing and knowledge transfer (77). Examples of social media applications that foster bridging social capital are LinkedIn (79) and Twitter (78).

Research on social capital shows that social media use increases both bonding and bridging social capital (80, 81) and that strong social ties are valuable for both bonding and bridging social capital (78). The positive influences of social media use on social capital are dependent on how and with whom we communicate and what affordances (properties of technology that allow for specific actions) the platforms provide (82).

Social Comparison

Social Comparison Theory was first explored by psychologist Leon Festinger in 1954. It is defined as the process through which people come to know themselves by evaluating their attitudes, abilities and beliefs in comparison with others (83). We determine our social and personal worth based on how we stack up against others, as a result, we make self and other evaluations across a variety of domains – emotion, attractiveness, intelligence and success.

Social comparison and peer feedback could be mechanisms that explain potential associations between social media use and outcomes such as self-esteem and depression. Those who are more likely to socially compare themselves with others would more likely expose themselves to positively biased self-presentations and rewarding experiences of others (83). Examples include reading about positive life events of friends (e.g., getting a job, buying a house, etc.) through status updates or looking at images of their peers participating in socially attractive activities (e.g., attending parties, going on vacations, etc.). These social media users might therefore conclude that others are doing better than themselves, which is a central aspect of the fear of missing out (FoMO) (35).

Furthermore, social media use not only leads to an increased frequency of social comparisons but also results in more frequent feedback from peers (35). When users present information on their social media profiles, they receive feedback from their peers, such as comments on photos or "likes" of specific posts or comments. This feedback not only arrives quickly, but young people also receive it from a much larger number of individuals than they would in face-to-face interactions. Research shows that adolescents actively seek this feedback. In a study conducted by Valkenburg, Schouten and Peter (2005), children and adolescents aged 9 to 18 years from the Netherlands reported that one of their primary reasons for using the internet to explore their identities was to gain knowledge about themselves through feedback from others (84). As social comparison and peer feedback are critical factors in adolescents' self-evaluations (85), it is theoretically plausible that the increased frequency with which these occur online could contribute to the possible associations between social media use and mental health and well-being.

Social media users who experience negative and upward social comparison may be more vulnerable to poorer well-being, which occurs when users compare themselves on social media to those they perceive to be superior (86), potentially evoking envy and making them feel worse about themselves afterwards. Reer, Tang and Quandt (2019) conducted a web survey of nationally representative young adults in Germany (survey year unknown) and found that social comparison was a significant mediator of the association between psychosocial well-being and FoMO (42). The study measured social comparison using the shortened (6-item) version of the Iowa-Netherlands Comparison Orientation Measure. Example items are “I often compare how I am doing socially (e.g., social skills, popularity) with other people” and “I often try to find out what others think who face similar problems as I face”. Those high in loneliness, depression and anxiety (the measures of psychosocial well-being in the study) could socially compare with others more frequently to reduce self-uncertainty (87). They could then develop the fear of missing out if they perceive others to be more involved in rewarding experiences (negative upward social comparison), leading to a downward spiral in their mental health and well-being as their discontent increases (42).

On the other hand, upward social comparison can also lead to positive effects. The Identification-Contrast Model (Table 1.2), developed by Buunk and Ybema (88), outlines that social comparison (in general) can be seen positively or negatively depending on whether individuals identify or contrast themselves with other people. Identifying with another person can help shift the focus away from oneself and the concept of having a separate self.

Table 1.2: The Identification-Contrast Model

	Contrasting (ways in which we are different from another person)	**Assimilative** (ways in which we are similar to another person)
Upward comparison (comparing to those perceived as better off)	Envy, reduced self-esteem	Inspiration, motivation to become better
Downward comparison (comparing to those perceived as worse off)	Pride, increased self-esteem, vain	Compassion, gratitude

Based on this model, there is some evidence to suggest that social comparison on social media does not necessarily impact negatively on well-being via contrasting upward social comparison and feelings of envy. Based on a study conducted in 2016 on German-speaking Instagram users aged 18 to 52 years, Meier and Schafer (2018) explored benign envy, an upward form of social comparison that leads to inspiration and motivation to become more similar to the portrayed person (89). They found that Instagram users who experienced assimilative upward comparisons, defined as a *"shift (in) the individual's focus toward becoming similar to the comparison target"* (p. 411) felt more inspired and consequently happier as a result. However, caution must be taken in generalising these findings as the sample size of this study was relatively small (n = 385), and research in this area is still new.

Phubbing

Phubbing, a portmanteau of the root words 'phone' with 'snubbing', refers to the act of ignoring one's companion(s) in favour of using a phone or other mobile device (90). Conversations with phubbing are perceived as less meaningful and satisfying due to the lack of eye contact and attentiveness. Eye contact is an important non-verbal and social cue (91), as such, our brains experience a lack of eye contact as exclusion and pain, and some may choose not to pay full attention in return. Phubbing is so normalised in today's generation that being alone together has become a phenomenon in and of itself. Sherry Turkle's book *Alone Together: Why We Expect More from Technology and Less from Each Other* (92) brings this issue to the forefront. The book highlights that our phones are used to escape from the messiness that relationships bring. This leads to potentially lost opportunities for real intimacy and genuine connection and, as a result, being alone together. Nonetheless, it is important to acknowledge that using phones in person could also bridge social connections, for example by sharing photos or scrolling through social media together.

Buffer Effect

Socially supportive relationships may also mediate relationships between social media use and mental health and well-being via the buffer effect, which posits that social connections can have a positive influence on mental health and well-being both directly (independent of other factors) and indirectly (through helping people cope with life stressors such as the loss of a child, divorce, or job loss) (93). The indirect positive influence of social connections on health outcomes could occur through various forms of support or social belonging that can potentially mitigate the detrimental effects of life's stressors, thereby serving as a buffer (94).

The buffer effect could be relevant as the potential negative impacts of social media use on mental health and well-being (e.g., negative upward social comparisons) could be mitigated by the presence of supportive relationships offline. Theoretical work on this hypothesis has shown social relationships to be a buffer against the stressors that exacerbate poor mental health and low well-being (95). In cross-national research conducted in 2013-14 among adolescents and young adults, the negative effects of cybercrime on well-being were most felt by younger adults who only had weak social ties offline (96). In another study using data from the 2018 Health Behaviour in School-aged Children (HBSC) study, social support reduced the risk of cyber-victimisation in adolescents aged 11, 13 and 15 years in Italy (97). The buffer effect could inform the ongoing debate about the impact of social media on mental health and well-being. The buffer effect suggests that helping social media users to develop effective coping strategies to deal with potential online harms (either by themselves or with support from family and friends) may be more practical than simply telling users to refrain from using social media. By focusing on building resilience and coping skills, social media users can be empowered to make informed choices about their online interactions and maintain a healthy balance between their digital and offline lives.

In addition, the buffer effect can be supported by an understanding of stress. Stress is the perception that we do not have enough resources (e.g., time, money, energy, and other people) to accomplish our responsibilities (98). Hans Selye defined two types of stress: Type 1 – acute stress, which is specific and temporary, and Type 2 – chronic stress, which is accumulated stress over time (99).

The Stress-Vulnerability Theory was founded by Zubin and Spring in 1977, which discusses the relationship between stress and genetic predispositions toward mental illness (100). Individuals with a genetic predisposition to certain mental illnesses, such as depression and anxiety disorders, are more likely to experience symptoms when exposed to high levels of stress.

Stress resilience is defined as the increased capacity over time to manage stress better, both physically and mentally, and to bounce back from stress without being overwhelmed by it (101). As detailed by the Digital Wellness Collective (102), one can either raise their stress threshold or lower stress to prevent themselves from succumbing to mental health difficulties. Examples of raising one's stress threshold could incorporate taking an afternoon nap, writing in a gratitude journal, taking a walk in nature, or meditating. Examples of lowering stress could include taking stock of one's resources and increasing the perception of our available resources (e.g., people you can call on for help) (102). As such, those with better capabilities to cope with stress will be better able to mitigate the potential negative effects of social media use and/or be able to use social media as a resource to lower stress in times of difficulty, thereby promoting positive mental health and well-being.

The buffer effect can also be explained by the mindsets of social media users. Carol Dweck was the first to explore the importance of having the right mindset to maximise our potential and capitalise on our strengths in her book *Mindset: The New Psychology of Success* (103). She found that children with a fixed mindset believe that their intelligence cannot be altered; therefore, they were less motivated to try on a test which then led to lower academic achievement. In contrast, children with a growth mindset believe that they could get smarter if they tried hard enough; therefore motivating them and increasing their academic achievement.

The Digital Wellness Collective, a small and medium enterprise in the USA has further extended these mindset typologies specific to social media use into the tool mindset and the addiction mindset (102). The social media tool mindset identifies whether individuals use social media as a meaningful tool to accomplish their goals (102). They may derive benefits from social media use regardless of whether they are using it actively or passively. For example, users might have an ambient awareness of feeling connected to others while passively browsing social media. Conversely, the social media addiction mindset identifies social media as a harmful and difficult-to-manage aspect of life (102). When viewed as a time-consuming and attention-grabbing activity, social media can have a detrimental impact on one's mental health and well-being, irrespective of the nature of use (active or passive). For example, when parents perceive their children's social media use as a waste of time, these children might feel less socially supported by their social media use than if their parents were more positive about it. As such, these mindsets could affect whether social media is used positively or negatively, regardless of the nature of its use.

1.3.3 Cyclical associations between social media use and mental health and well-being

As stated by Kelly, Zilanawala, Booker, et al. (2018), any longitudinal investigations exploring associations between social media use and mental health and well-being outcomes need to acknowledge the possibility of a bidirectional/cyclical relationship, for example, poor mental health may correlate with greater social media use, and higher levels of social media use may in turn correlate with poorer mental health (104). For example, in a longitudinal study conducted in 2016-17 on adults aged 16 to 74 years in the Netherlands (105), SNS use was no longer an independent predictor of mental health problems after prior levels of mental health had been accounted for, indicating the possibility that increased SNS use may *"occur as a symptom of underlying problems"* (p. 207).

1.4 Conceptual framework

In this section, I will discuss a conceptual framework that can help to elucidate the complexities involved in the relationships between social media use and mental health and well-being in young people. Through this framework, I will also highlight how the role of the family may influence this relationship.

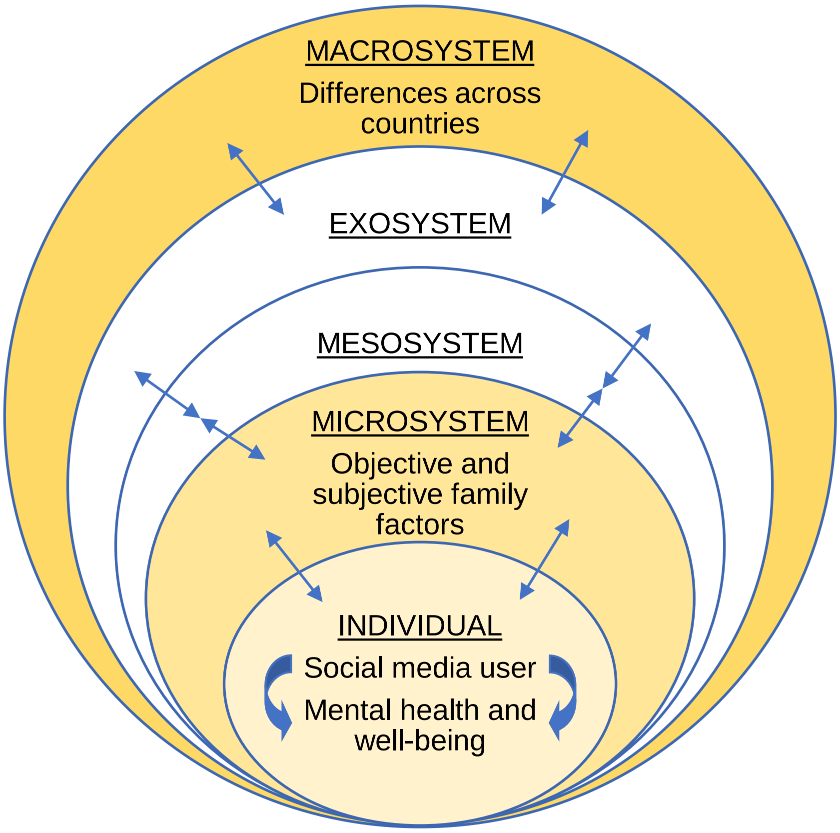
1.4.1 Bronfenbrenner's ecological framework

I refer to Bronfenbrenner's ecological framework which forms the foundation of my PhD research. Bronfenbrenner's Ecological Systems Theory explains how the intrinsic characteristics of children and their environments intertwine and influence their growth and development (3). Children are nested within various ecosystems. For example, the microsystem, which plays an immediate and explicit role in a child's life, could include the family, neighbourhood, religious community, school and peers (3). This framework is useful as it connects to my main research interests: the impact of gender and family factors on the associations between social media use and mental health and well-being in young people. According to this ecological framework, the impact of social media use on mental health and well-being can be influenced not only by individual factors (e.g., gender, age), but also by interpersonal factors (e.g., relationships with parents) and contextual factors (e.g., cultural norms).

Additionally, this framework shaped the Korean Children and Youth Panel Survey (KCYPS) and its question items (106), which I utilise in my PhD. Bronfenbrenner's Ecological Systems Theory emphasises that human development stems from the dynamic interplay between the individual and their surrounding environments. Consequently, the quality of an individual's interactions within their environmental systems significantly shapes their developmental trajectory (3). Guided by this ecological framework, the KCYPS was constructed with the purpose of investigating the holistic growth of adolescents and the influence of their environments (106). As such, it was a sensible choice of dataset for my PhD research. This will be discussed further in Chapter 4.

As an illustration, the shaded concentric circles in Figure 1.1 refer to the ecosystems that I focus on in my PhD.

Figure 1.1: Conceptual framework (adapted Ecological Systems Model)



Adapted from: Bronfenbrenner (1979), Ecological Systems Model

Considering the significant role that social media plays in the lives of young people, it is crucial to investigate the connections between young people's social media use and other important environments, such as the family.

Social media could be a mechanism by which families could be more or less connected within the family microsystem. It could be a source for strengthening family bonds or a source that weakens face-to-face family connections.

In a paper that I published with my supervisory team (107), using data collected from the UK Household Longitudinal Study (UKHLS) in 2011-13 to 2012-14, evening shared family meal frequency significantly moderated the association between the duration of SNS use and subjective well-being in young people (aged 16 to 21 years) that were living with their parents. Among those reporting no evening shared family meals in the last seven days, heavy SNS users (4+ hours/weekday) had lower well-being scores on average than non-users. This cross-sectional finding could be explained by a bidirectional/cyclical association between SNS use and well-being, where the lack of face-to-face communication within families, which may be associated with family disagreements or conflict, could lead to extensive use of social networking sites, which in turn may increase users' susceptibility to online risks.

Another key finding from this study was the similar well-being levels among all SNS users (i.e., regardless of time spent) who shared at least one evening family meal. This could be supported by an intensive longitudinal experience sampling study conducted in 2015-17 in North Carolina, USA which found limited evidence to suggest that time spent using digital technology displaced time spent interacting with parents offline nor did it result in more negative or less positive parent-adolescent offline interactions in adolescents aged 9 to 15 years at baseline (75). This could mean that family mealtimes may not be subjected to time displacement nor its negative effects on mental health and well-being, resulting in similar levels of well-being regardless of time spent on SNSs.

1.5 The role of gender

Over the past few decades, there has been an increase in self-reported emotional distress in young people, with symptoms of anxiety and depressed mood being particularly prevalent in females (9). One theory that could explain this is Objectification Theory, which proposes that women are more likely to be objectified, leading to self-objectification and body surveillance because women are acculturated to internalise an observer's perspective as their own (108). This could result in negative psychological consequences. Social media, with its emphasis on appearance and self-presentation, can contribute to objectification experiences of women more so than men and in turn increase their risk of experiencing poorer mental health and/or well-being.

1.6 The role of age

Bronfenbrenner's Ecological Systems Theory suggests that the impact of social media use on mental health and well-being can be influenced by various individual factors (e.g., age) (3). As noted by the literature, the associations between social media use and mental health and well-being may differ by developmental stage (3). Young people at different stages of development may have different social contexts and support structures, which can interact with social media use to produce varying effects on mental health and well-being. Socioemotional Selectivity Theory may help to explain possible differential effects of social media use on mental health and well-being by age. This theory suggests that motivations and goals in social interactions change over time; as individuals age, their social preferences shift from information-seeking to emotional satisfaction (3). It implies that older individuals, such as young adults, may use social media more selectively to maintain and enhance close relationships, which could have positive effects on their mental health and well-being. In contrast, younger individuals, such as adolescents, may be more susceptible to the negative impacts of social media use due to their increased focus on information-seeking and social comparison.

According to Social Comparison Theory, social media platforms may facilitate social comparisons (83). Adolescents, who are in a period of identity formation and are more likely to compare themselves with their peers, may be more vulnerable to experiencing negative social comparisons, more so than younger children or young adults. This may in turn lead to more negative self-evaluations, lower self-esteem, and increased depressive symptoms among adolescents. Younger children may not have developed the faculties for social comparison, whilst young adults may be better able to discern the various forms of social comparison (e.g., contrasting versus assimilative upward social comparison). This can be supported by Cognitive Development Theory, which focuses on the cognitive capabilities and developmental stages of individuals (3). Children and adolescents may be more vulnerable to the negative effects of social media use (in general, over and above negative social comparison) due to their limited cognitive abilities for critical thinking, self-regulation, and the understanding of online contexts (e.g., recognising the potential for misinformation and implications of privacy settings). Young adults, on the other hand, may have developed better cognitive skills, allowing them to navigate social media with greater discernment and self-control.

1.7 The role of family

According to Bronfenbrenner's Ecological Systems Theory (3), the immediate family is instrumental in the socio-emotional development of the child. During adolescence, self-concept is formed, and sociality develops largely through interactions with peers rather than the family (109), not least of which their interactions and relationships with peers on social media. Therefore, adolescents with negative peer interactions on social media, for example by experiencing negative upward social comparison or being "ghosted" by peers online, may internalise such experiences and lack confidence in interpersonal relationships, resulting in lower self-esteem than adolescents who have experienced positive interactions with peers on social media. When considering self-esteem and social development from online interactions with peers during adolescence, it is also important to consider aspects of the family during adolescence, such as family structure and parental child-rearing attitudes, and assess the associations of both the family and friend spheres on self-esteem. This is supported by research from the Millennium Cohort Study (MCS) conducted in 2004-12 on children in the UK (ages 3, 5, 7 and 11), which highlighted the importance of investigating interrelated features of a child's proximal family environment alongside examining patterns in children's behaviour across childhood (110).

Bronfenbrenner's Ecological Systems Theory, as discussed in Section 1.4.1, emphasises the multiple environmental systems that individuals interact with, including the family, school, community and broader society (3). In the context of social media use, mental health and well-being, family structure and parental child-rearing attitudes can be seen as one part of the larger ecological system that can shape individual experiences and outcomes. Family factors, such as family composition and parent-child relationship quality, can potentially modify the impact of social media use on mental health and/or well-being by creating a protective or risk-inducing environment.

1.7.1 Family structure

Family structure (e.g., family composition, such as whether adolescents live in households in which two biological parents are present) can be understood by Murray Bowen's Family Systems Theory (111), which views the family as an interconnected system where changes in one member can affect the entire family unit. In relation to the associations between social media use and mental health and well-being, family structure can influence the family dynamics and communication patterns around social media use. It is plausible that the associations between social media use and mental health and well-being in young people could be confounded or moderated according to whether their family structure (e.g., composition) has been stable or transient (e.g., moving from a two-parent to a one-parent household). A stable family structure may mitigate negative mental health effects associated with excessive or problematic social media use.

1.7.2 Parent-child relationship quality and parenting styles

Adolescents have three types of relationships – parent-child, sibling and peer relationships – that are particularly important to their mental health and well-being (113). Part of the focus of my thesis is on whether parent-child relationship quality and parenting styles confound or modify any observed associations between social media use and mental health and well-being.

Parent-child relationships can be understood by Relational Regulation Theory (RRT) (114), which states that individuals regulate emotions, thoughts and actions through social interactions. There are two types of social support: instrumental and emotional (115), both of which are associated with different behavioural and emotional outcomes. For example, emotional support has been associated with a reflective stage of information processing, including processing a stressor (e.g., I have someone who will talk me through how I feel and reappraise the situation after the initial fear has passed). Instrumental support has been associated with a reflexive stage of information processing that includes solving or managing the stressor (e.g., I have the resources to solve this problem right now) (116). Young people may benefit from emotional and instrumental support from parents and this could potentially buffer against some of the challenges of navigating social media.

Conversely, alienation from one's parents could make it difficult for young people to manage the pressures of social media. Based on longitudinal data from the British Household Panel Survey (BHPS) conducted from 1994-95 to 2008-09, parent-child relationship quality (talking to and quarrelling with mother and father) was found to be more strongly associated with young people's life satisfaction than parents' life satisfaction (117). Therefore, the absence of such supportive relationships could leave young people more vulnerable to online risks.

Parental child-rearing attitudes refer to parents' behaviours, language and nonverbal communication exhibited as they rear their children, to promote their growth and development (118). Parental child-rearing attitudes can be understood by John Bowlby's Attachment Theory (119), which suggests that the quality of parent-child attachment can influence an individual's socioemotional development. In the context of social media use, mental health and well-being, parenting styles that promote secure attachment may contribute to healthier social media use and better mental health and well-being outcomes for young people. In a study conducted in 2015 using the Korean Children and Youth Panel Survey (KCYPS), affectionate and monitoring parenting styles were found to be associated with lower depression scores, whilst the over-control parenting style was associated with higher depression scores in adolescents aged 14 to 16 years (120). It is possible that parenting styles could moderate the associations between social media use and mental health and well-being outcomes.

As illustrated in Figure 1.4, my PhD focuses on exploring how individual elements (e.g., gender) and elements in the microsystem (e.g., family factors) interact and influence the relationships between social media use and mental health and well-being outcomes among young people.

1.8 Conclusion

In this chapter, I first described the issues around mental health and well-being in young people and highlighted the trends in social media use across countries. I then outlined the design of social media and presented theories linking social media use to mental health and well-being outcomes. With reference to Bronfenbrenner's ecological framework, I further discussed the role of individual factors and the microsystem in potentially modifying this relationship, a key focus of my PhD.

Chapter 2: Systematic Literature Review

This chapter sets out my systematic literature review which will inform the subsequent empirical chapters of my thesis. It examines and summarises global evidence for the relationships between various aspects of social media use and key mental health and well-being outcomes in young people, including previous work that has explored aspects of gender and family factors. Finally, this chapter summarises the gaps in evidence that I intend to address in my PhD.

2.1 Aims and objectives

Many systematic reviews and meta-analyses have been conducted on the associations between social media use and indicators of mental health and well-being (28, 124-126). However, many of them used convenience samples and the Experience Sampling Method (ESM); very few are based on secondary data analysis of existing nationally representative panel or longitudinal survey data. In one study, researchers used ESM (127, 128) to collect data on behaviours, emotions or cognitions related to mobile social media use over a period of multiple, randomly chosen points in time (129). Participants were asked to respond with minimal delay; thus providing nearly real-time accounts of their media consumption behaviours. Consequently, information obtained through ESM studies relies less on users' recollections compared to retrospective self-reports (129).

Although time-diary studies are considered the most reliable method, data obtained through experience sampling techniques for social media are not commonly utilised in longitudinal or panel studies because of the substantial costs and time involved. Nonetheless, investigations comparing survey responses and experience sampling data from the same individuals reveal that survey estimates align with experience sampling results, particularly for activities that happen frequently (130). As such, my systematic literature review focused on cross-sectional and longitudinal studies that use nationally representative survey data to examine the relationships between social media use and mental health and well-being. Whilst longitudinal studies have the benefit of disentangling the temporal order of the relationships in question, cross-sectional data were not ruled out from my literature review as they could become longitudinal in the future (e.g., cross-sectional as baseline data) and these studies could also provide additional theoretical insight to supplement my understanding. In addition, my systematic literature review accounted for studies that analysed aspects of gender and family factors that could underlie the associations between social media use and indicators of mental health and well-being.

2.1.1 Aim

The systematic literature review aimed to examine and summarise global evidence for the influence of various aspects of social media use on key mental health and well-being outcomes among young people, including previous work that has explored aspects of gender and family life such as family structure (e.g., family composition: whether living with two parents or a single parent) and quality of relationships with parents (e.g., talking to and quarrelling with parents).

2.1.2 Specific objectives

The specific objectives of this literature review were as follows:

1. Describe and summarise peer-reviewed studies on the associations between social media use and mental health and well-being outcomes among young people (children, adolescents and young adults).
2. Select studies that have utilised national and/or cross-national datasets and that have conducted comparative work to scope for potential datasets for the empirical chapters of my PhD.
3. Describe and summarise the literature regarding gender, family structure and young people’s relationships with their parents as potential moderators or mediators of the associations between social media use and mental health and well-being.
4. Consolidate and critically analyse key findings from my literature review.
5. Identify potential gaps in the research field that could be addressed in my PhD research.

2.2 Literature search method

I conducted a systematic literature search on the academic databases (i) Web of Science and (ii) PsycINFO from February 2019 to April 2019 in the initial phase to locate relevant studies. These databases were chosen based on their relevance to my research. In the second phase, I re-ran the literature search in May 2021 and scoured for new articles published between 2019 and 2021. In the third phase, I re-ran the literature search in January 2023 and located new articles published between 2021 and 2023. This process facilitated me in keeping up to date with my systematic literature review.

2.2.1 Eligibility criteria

I formulated several criteria for articles to be considered in this review, these are set out in Table 2.1 below. For the main exposure, my focus was on social media use as a tool for social networking; hence, studies covering blogs, online forums and the use of social media for educational purposes were not included. For the main outcomes, my focus was on mental health and well-being; hence, other health outcomes outside this scope such as substance use and eating disorders were not included. The criteria were relaxed slightly for papers that studied family factors due to the limited number of these papers.

Table 2.1: Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Quantitative studies	Qualitative studies
Children, adolescents and young adults	Studies conducted before 2000
Explanatory variables: indicators of social media use[1]	Use of social media in education, marketing and business
Outcome variables: indicators of mental health and well-being[2]	Outcomes such as substance use, eating disorders, body image problems, personality attributes, cyberbullying and problematic internet use/internet addiction[3]
Family factor(s) as exposure, moderator, mediator, or outcome variables	Other aspects of internet use[3] such as online forums, blogs and gaming
Research studies published in peer-reviewed journals with full text available in English	Reviews and meta-analyses
Studies that used nationally or provincially (e.g., Ontario, Canada and Western Australia) representative cross-sectional or longitudinal survey data	Duplicates, inaccessible studies and studies that used convenience samples
	Privacy and ethical issues around social media use

2.2.2 Search strategy

Search terms were identified to include the key terms to comprehensively identify studies matching the inclusion criteria. Comprehensive search terms, including synonyms, were created with truncations, Medical Subject Headings (MESH) and Boolean operators ‘OR’ and ‘AND’. MESH was only available in PsycINFO and it was used to maximise potentially relevant articles in the search results. Tables 2.2 and 2.3 below show the exposure and outcome search strategies, respectively.

[1] Except for two studies: one study that examined mental health indicators as explanatory variables and time spent on SNSs as the outcome variable and one study that examined parenting styles as explanatory variables and excessive internet use as the outcome variable.
[2] Except for one study that examined parent-child relationship quality as the outcome variable.
[3] Unless the paper explored family variables.

Table 2.2: Exposure search strategy

MESH (for search in PsycINFO only)	Key Search Terms (for search in PsycINFO and Web of Science)
Social media (explode)	"Social media"
Social networks (explode)	"Social network*"
Online community (includes virtual community)	"Virtual communit*" OR "Online communit*"
Internet addiction (explode)	"Internet addict*"
Online social networks (explode)	"Online adj3 network*"
	"Online forum*"
	"Web 2.0"
	Facebook OR Instagram OR WhatsApp OR Snapchat OR TikTok OR Twitter OR KakaoTalk OR Minihomp*

Table 2.3: Outcome search strategy

MESH (for search in PsycINFO only)	Key Search Terms (for search in PsycINFO and Web of Science)
Major depression (explode) OR depression (emotion)	Depress*
Anxiety OR computer anxiety OR social anxiety	Anxi* OR Computer Anxi* OR Social Anxi*
Self-esteem	Self-esteem
Happiness	Happ*
Life satisfaction (explode)	"Life satisf*"
Well being	"Well being" OR well*
Quality of life	"Quality adj3 life"
	Gender OR "female*" OR "male*" OR "girl*" OR "boy*"
Family relations (explode) OR family structure OR family	"Family adj3 suppor*", "family adj3 conflic*", "family adj3 structure", "family adj3 belong*", "family tie*",
Parenting styles (explode) OR parenting	"Parent*", "parent-child"
	Worr* (worry)

2.2.3 Data extraction

All papers were collated using Endnote 20 reference management software. After duplicates were removed, I screened the remaining articles to assess the eligibility criteria. In a three-stage process, papers were screened first on the title, then on the abstract and lastly on the full text. Key information relevant to the research question was systematically extracted and tabulated to aid the comparison and synthesis of studies. Consideration was also given to the role of the family (e.g., family structure and quality of relationships with parents) in terms of potential confounders, mediators, or moderators in the associations between social media use and mental health and well-being.

2.3 Results of the literature search

2.3.1 Study selection

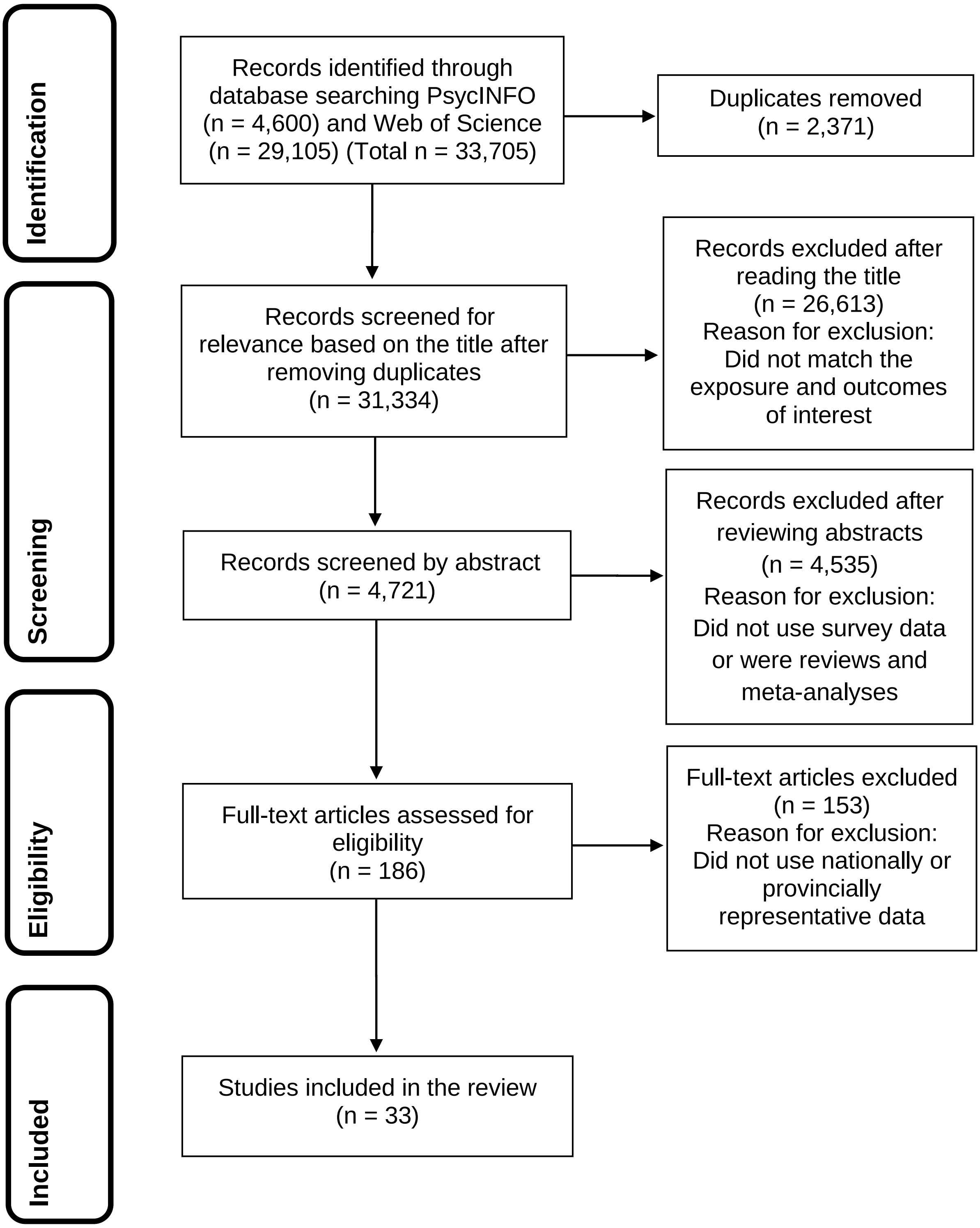
I used the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) 2020 statement to summarise the articles found (131). A flow chart of the search process is provided in Figure 2.1.

The literature search yielded 33,705 records. This included 4,600 articles from PsycINFO and 29,105 from the Web of Science. I screened the 31,334 articles retained after the removal of duplicates. These records were screened for relevance based on title and eligibility criteria, resulting in an exclusion of 26,613 records that did not match the inclusion criteria. These were excluded because they did not match the exposure and outcomes of interest. For example, pertaining to the exposure, the excluded articles examined blogs, online forums, gaming, use of social media for educational, marketing or business purposes and data privacy issues on social media. Pertaining to the outcomes, the excluded articles examined substance use, eating disorders, body image problems, personality attributes, cyberbullying and problematic internet use or internet addiction. These papers were outside the scope of my literature search because the focus was on social media as a tool for social networking (exposure) and indicators of mental health and well-being such as depression, anxiety, self-esteem and life satisfaction (outcomes). Some exceptions were made – these can be found in the footnotes of Table 2.1.

The remaining records (n = 4,721) were further screened by reading the abstracts, which resulted in the exclusion of 4,535 records. These were excluded because they did not use survey data (e.g., experimental or qualitative data) or they were reviews and meta-analyses rather than research studies.

186 full-text articles were assessed for eligibility, which resulted in the further exclusion of 153 articles as these did not use nationally or provincially representative survey data. For example, one paper examined mindfulness as a mediator in the relationship between social media engagement and depression in young adults who were enlisted through a general psychology participant pool at a public liberal arts college in Southeast USA (n = 371) (132). Overall, 33 articles met the inclusion criteria. These are described in the next section.

Figure 2.1: PRISMA flow diagram of literature search



2.3.2 Study characteristics of selected journal articles

Table 2.4 provides an overview of the studies' characteristics meeting the inclusion criteria set out in Section 2.2.2. The studies are organised by region and are described by the study author(s), publication year, study design, location of study, survey year(s), data source, sample size, mean age, age range and response rates. As indicated by the PRISMA 2020 checklist, one of the items pertains to presenting assessments of risk of bias for each included study (131). In line with this guideline, the response rates of each study were incorporated (as applicable) since they can serve as an indicator of study quality (133). Low response rates, for instance, can result in selection bias, which can compromise the external validity of the study's findings. Effect sizes were not reported due to variability in exposure(s) and outcome(s) measured in each study.

Table 2.4: Descriptive characteristics of journal articles

Author(s) and publication year	Study design	Location	Year(s) of data collection	Data source	Sample size (n); age	Response rates
Studies in Asia-Pacific						
Dui (2020)	CS	China	2018	CFPS	n = 8,666; 16-86yrs	Not reported
Lee, Ho and Lwin (2017)	CS	Singapore	Not stated	Pen & paper	n = 4,920; 13-17yrs	78-90%
Lai, Hsieh and Zhang (2019)	CS	Taiwan	2014	TCS	n = 1,121; 12-17yrs	Not reported
Neira and Barber (2014)	CS	Western Australia	Not stated	YAPS	n = 1,819; 13-21yrs	Not reported
Studies in the United Kingdom (UK)						
Plackett et al (2022)	LT	UK	2009-19	UKHLS	n = 3,228; 10-15yrs	74%
Twigg, Duncan and Weich (2020)	LT	UK	2009-17	UKHLS	n = 7,596; 10-15yrs	74%
Kelly et al. (2018)	CS	UK	2015-16	MCS	n = 10,904; 14yrs	61%
Orben et al (2019)	LT	UK	2009-16	UKHLS	n = 539 to 5,492; 10-15yrs	74%
Viner et al. (2019)	LT	England	2013-15	LSYPE	n = 12,866; 13-16yrs	Not reported
Booker, Kelly and Sacker (2018)	LT	UK	2009-15	UKHLS	n = 9,859; 10-15yrs	74%
Jagtiani et al. (2019)	CS	UK	2011-13	UKHLS	n = 2,229; 16-21yrs	73%
Booker et al. (2015)	CS	UK	2009	UKHLS	n = 4,899; 10-15yrs	74%
Studies in Europe						
Thorisdottir et al. (2020)	LT	Iceland	2017-19	LIFECOURSE	n = 2,211; 12-14yrs	61%
Thorisdottir et al. (2019)	CS	Iceland	2018	Class questionnaire	n = 10,563; 14-16yrs	84%
Reer, Tang and Quandt (2019)	CS	Germany	Not stated	Web survey	n = 1,865; 14-39yrs	Not reported
Buda et al. (2021)	CS	Lithuania	2018	HBSC	n = 4,191; 11,13,15yrs	81%
van der Velden et al. (2019)	LT	Netherlands	2016-17	LISS	n = 3,486; 16-74yrs	86%
Bányai et al. (2017)	CS	Hungary	2015	ESPAD	n = 5,961; 15-22yrs	89%
Casaló and Escario (2019)	CS	Spain	2014-15	ESTUDES	n = 37,486; 14-18yrs	85%
Andreassen, Pallesen & Griffiths (2017)	CS	Norway	2014	National open web-survey	n = 23,532; 16-88yrs	56%

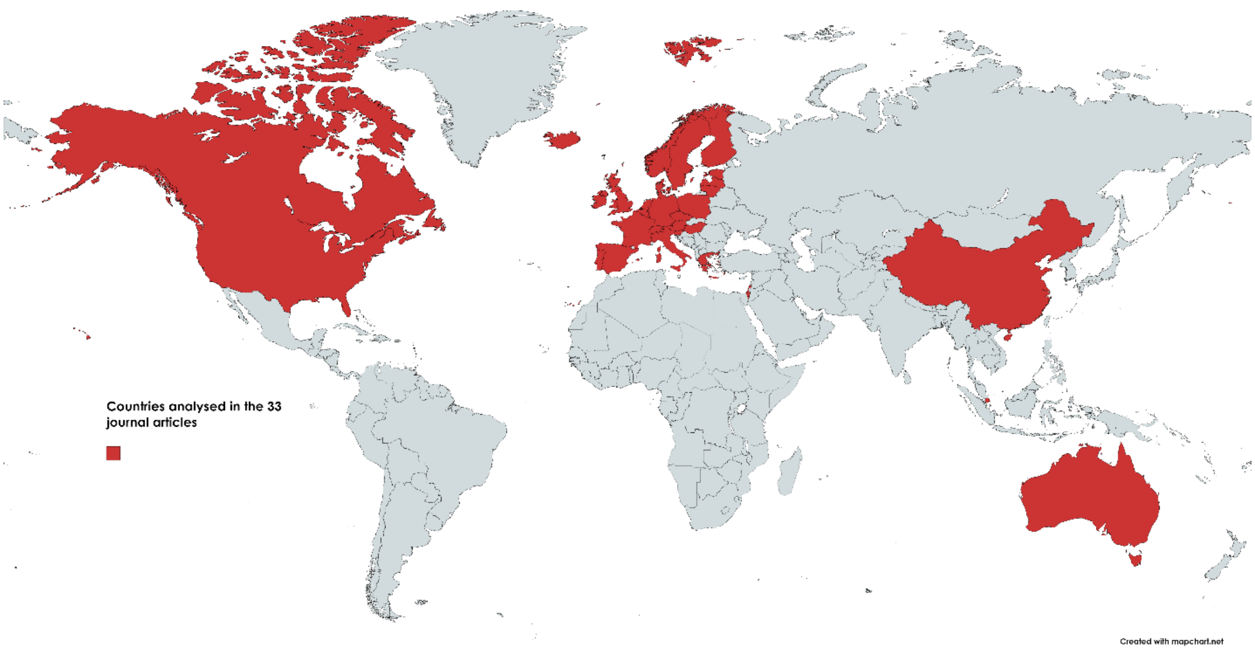
Studies in North America						
Primack et al. (2021)	LT	USA	2018	Web survey	n = 1,289; 18-30yrs	Not reported
Lee et al. (2022)	LT	USA	2013-18	PATH	n = 5,114; 12-14yrs	73%
Shensa et al. (2020)	CS	USA	2018	Web survey	n = 2,408; 18-30yrs	Not reported
Hardy and Castonguay (2018)	CS	USA	2016	GSS	n = 743; 18-50+yrs	Not reported
Riehm et al. (2019)	LT	USA	2013-16	PATH	n = 6,595; 12-17yrs	78%
Primack et al. (2017)	CS	USA	2014	GfK	n = 1,787; 19-32yrs	59%
Shensa et al. (2017)	CS	USA	2014	GfK	n = 1,749; 19-32yrs	59%
Studies in Canada						
Sampasa-Kanyinga et al. (2019)	CS	Ontario	2013	OSDUHS	n = 9,732; 11-20yrs	63%
Sampasa-Kanyinga & Lewis (2015)	CS	Ontario	2013	OSDUHS	n = 753; mean: 14.1yrs	70%
Sampasa-Kanyinga & Hamilton (2015)	CS	Ontario	2013	OSDUHS	n = 5,126; 11-20yrs	63%
Cross-national studies						
Boer et al. (2020)	CS	29 countries	2017-18	HBSC	n = 154,981; 11,13,15yrs	Not reported
Twenge and Martin (2020)	CS (UK); LT (US)	UK and USA	2009-16	National survey (UK); YRBSS and MtF (US)	n = 221,096; 13-18yrs	Not reported
Boniel-Nissim et al. (2015)	CS	8 countries[4]	2009-10	HBSC	n = 53,973; 11,13,15yrs	40-86%

Abbreviations: **Study design**: CS: cross-sectional; LT: longitudinal. **Data source**: CFPS: China Family Panel Studies; ESPAD: European School Survey Project on Alcohol and Other Drugs; ESTUDES: Spanish Survey on Drug Use in the School Population; GfK: Growth from Knowledge panel; GSS: General Social Survey; HBSC: Health Behaviour in School-aged Children survey; LIFECOURSE: Longitudinal Investigation For Epidemiologic Causes and Outcomes RiSing in Early Childhood and Adolescence study; LISS: Longitudinal Internet studies for the Social Sciences panel; LSYPE: Longitudinal Study of Young People in England; MCS: Millennium Cohort Study; MtF: Monitoring the Future survey; OSDUHS: Ontario Student Drug Use and Health Survey; PATH: Population Assessment of Tobacco and Health study; TCS: Taiwan Communication Survey; UKHLS: UK Household Longitudinal Study; YAPS: Youth Activity Participation Study; YRBSS: Youth Risk Behavior Surveillance System

[4] Canada, England, Scotland, Germany, Hungary, Italy, Israel, The Netherlands and Poland.

Research studies covering the eligibility criteria were identified from 31 countries, reflecting the global nature of the phenomenon under study. There were four studies from the Asia Pacific region (47, 134-136), eight studies from the UK (10, 43, 104, 107, 137-140), eight studies from Europe (40, 42, 45, 49, 105, 141-143), seven studies from North America (39, 41, 71, 144-147), three studies from Canada (148-150) and three cross-national studies (44, 151, 152) (Figure 2.2).

Figure 2.2: Countries included in the systematic literature review



The oldest study included in my literature review was surveyed in 2009 and the most recent studies (27.3%: 9/33 studies) included survey data from 2018 or later. 66.7% of the studies (22/33 studies) used cross-sectional study designs and 30.3% of the studies used longitudinal study designs (10/33 studies). The remaining study used both types of study designs (3.0%: 1/33 studies). Most of the 33 selected articles used nationally representative data (87.9%: 29/33 studies), with a minority (12.1%: 4/33 studies) using data representative at the province or region level (e.g., Ontario, Canada (148-150)) and Western Australia (47).

Pertaining to response rates, whilst there were some studies whose response rates were not reported (30.3%: 10/33 studies), most of the other studies (69.6%: 16/23 studies) had response rates over 70%.

Reflecting the eligibility criteria, most of the 33 selected studies sampled children, adolescents and/or young adults. Five studies did not limit the age range to young people. These five studies were included in the literature review for the following reasons:

1. One study used longitudinal survey data (105).
2. One study used an atypically large sample of Norwegians (n = 23,532) (49).
3. Two studies made a comparison by age group and so findings from young people were reported (134, 145).
4. One study researched potential mediators such as the fear of missing out and social comparison orientation (of relevance to my PhD) in the associations between social media engagement and well-being indicators (42).
5. In general, these studies could offer relevant insights and/or suggest possible datasets that could be adapted for use in the empirical chapters of my PhD.

Most sample sizes in the selected studies were large, ranging from 5,126 (150) to 23,532 participants (49) as shown in Table 2.4, reflecting their use of quantitative methods on large and representative data. Most studies used regression analyses. More advanced statistical methods included latent growth curve analysis, latent profile analysis, path analysis and structural equation modelling.

2.3.3 Analytical characteristics of articles that did not assess family factors

Table 2.5 sets out the study author(s), publication year, statistical analysis strategy, explanatory variable(s) (and other variables if relevant), outcome variable(s) and key results related to the associations between social media use and mental health and well-being outcomes for the subset of studies included in the literature review that did not consider family factors (26/33 studies).

Table 2.5: Analytical characteristics of journal articles that did not assess family factors

Author(s) and publication year	Statistical analysis	Explanatory variable(s)	Outcome variable(s)	Key results
Studies in Asia-Pacific				
Dui (2020)	Multiple linear regression	SNS dependence	Depressive symptoms (CES-D[5])	Greater SNS dependence was associated with greater depressive symptoms at ages 16-18 (larger association) and ages 19-40.
Lai, Hsieh and Zhang (2019)	Structural equation modelling (SEM)	**Main exposure:** Frequency and duration of Facebook use **Antecedents:** Number of Facebook friends; need to belong; perceived waste of time	**Subjective well-being:** social support, life satisfaction, social satisfaction	More Facebook friends and a greater need to belong were associated with greater Facebook use (stronger for males than females), whereas perceived waste of time was associated with lower Facebook use. Facebook use was associated with greater subjective well-being (stronger for males).
Neira and Barber (2014)	Hierarchical linear regression	SNS use; SNS frequency; SNS investment	Self-esteem, depressed mood[6], social self-concept	Greater SNS investment but not SNS frequency was associated with lower self-esteem and depressed mood. Gender did not moderate the relationships between a) frequency of SNS use and self-esteem/depressed mood, and b) SNS investment and self-esteem/depressed mood.
Studies in the UK				
Plackett, Sheringham and Dykxhoorn (2022)	Multilevel linear regression and path analysis with SEM	**Exposure:** Duration of chatting or interacting on SNSs **Potential mediator:** Self-esteem	Mental health (SDQ[7])	Duration of SNS use was not associated with poorer mental health. Self-esteem did not mediate the association between duration of SNS use and mental health in adjusted path analysis.

[5] Center for Epidemiologic Studies Depression Scale
[6] Depressed Mood Scale
[7] Strengths and Difficulties Questionnaire (25 items)

Kelly, Zilanawala, Booker, et al. (2018)	Linear regression and path analysis	**Exposure:** Duration of social media use (SMU) **Potential mediators:** Online harassment; sleep; self-esteem (RSES[8]); body image	Depressive symptoms (SMFQ[9])	Greater duration of SMU was associated with greater depressive symptoms (stronger for girls than boys). The magnitude reduced after accounting for online harassment, poorer sleep quality and quantity, self-esteem and body image (partial mediation).
Orben, Dienlin, and Przybylski (2019)	Random-intercept, cross-lagged panel modelling	Duration of chatting or interacting on SNSs	Life satisfaction[10]	Between-person effects: Boys who use SNS more have slightly lower life satisfaction in school and schoolwork whilst girls who use SNS more have slightly lower satisfaction with life and appearance. Within-person effects: boys who use SNS more had slight decreases in life and mean satisfaction, whilst girls who used SNS more had slightly lower satisfaction in all domains except appearance (school, schoolwork, mean and life satisfaction, friends, family).
Viner, Gireesh, Stiglic, et al. (2019)	Multinomial and ordinal logistic regressions and mediation analysis	**Main exposure:** Frequency of SMU **Potential mediators:** Cyberbullying; sleep adequacy; physical activity	Mental health (GHQ-12[11]), well-being (ONS[12])	Very frequent social media use was associated with poorer mental health and well-being in both genders. This relationship was no longer significant after cyberbullying, sleep and physical activity were adjusted for in girls but remained significant in boys. SMU frequency was not associated with well-being and positively associated with physical activity in boys.

[8] Rosenberg Self-Esteem Scale
[9] Moods and Feelings Questionnaire – Short Version
[10] 7-point Visual Analogue Scale
[11] 12-item General Health Questionnaire
[12] Personal well-being questions from Office for National Statistics (ONS) well-being surveys

Booker, Kelly and Sacker (2018)	Parallel latent growth curve analysis	Duration of chatting or interacting on SNSs	**Well-being:** Happiness, socioemotional difficulties (SDQ)	Longer duration of SNS use at age 10 was associated with poorer well-being over time in females only.
Booker, Skew, Kelly, et al. (2015)	Logistic regression	Duration of chatting or interacting on SNSs	**Well-being:** Happiness, socioemotional difficulties (SDQ)	Those who use SNS for 1-3 hours/day were about one-third less likely to be happy than those who use SNS for <1 hour/day. Young people who used SNS for 4 or more hours/day were at least twice as likely to have socioemotional difficulties than those who spent <1 hour/day.
Studies in Europe				
Thorisdottir, Sigurvinsdottir, Kristjansson, et al. (2020)	Linear mixed-effects regression	Duration of social media use	**Psychological distress:** physical and social anxiety (MASC[13]), depressed mood (OSC[14])	Greater duration of SMU was weakly but significantly associated with psychological distress over time, with a stronger association in females than in males, although the interaction effect was weak.
Thorisdottir, Sigurvinsdottir, Asgeirsdottir, et al. (2019)	Hierarchical linear regression	**Main exposures:** duration of SMU; active vs passive SMU[15] **Protective factors:** Offline peer support; self-esteem (RSES) **Risk factors:** Social comparison[16]; body image[17]	**Emotional distress:** physical and social anxiety (MASC), depressed mood (OSC)	Longer duration of SMU was associated with greater emotional distress. After controlling for social media duration and protective and risk factors, passive use was associated with greater emotional distress than active use in both genders, with a stronger relationship found in females. After controlling for social media duration and type of use, protective factors were negatively associated with emotional distress and risk factors were positively associated with emotional distress.

[13] Multidimensional Anxiety Scale for Children
[14] Depression dimension scale of the Original Symptom Checklist
[15] Adapted from the Multidimensional Scale of Facebook Use
[16] Iowa–Netherlands Comparison Orientation Measure
[17] Body image subscale of the Offer Self-Image Questionnaire

Buda, Lukoševičiūtė, Šalčiūnaitė, et al. (2021)	Logistic regression	Problematic social media use (PSMU)[18]	Life satisfaction[19]	PSMU was associated with greater odds of poor life satisfaction in both genders.
Reer, Tang and Quandt (2019)	Linear regression and mediation analyses	**Main exposure:** Frequency of social media engagement (SME) **Potential mediators:** Fear of Missing Out (FoMO); social comparison[20]	**Psychosocial well-being:** loneliness, depression, anxiety (PHQ-4[21])	Loneliness, depression and anxiety are associated with higher SME. Decreases in loneliness, depression and anxiety are associated with increases in FoMO and SCO and in turn higher SME (partial mediation for anxiety and depression). SCO mediated the connection between psychosocial well-being and FoMO. FoMO partially mediated the connection between SCO and SME.
Van der Velden, Setti, van der Meulen, et al. (2019)	Logistic and multiple regression	**Main exposure:** Duration of SNS use: reading, texting or calling, posting **Potential moderator(s):** age; loneliness[22]	Mental health (MHI-5[23]), sleep problems	SNS use was consistently associated with mental health and sleep problems, but this was no longer the case after controlling for prior mental health, sleep problems and loneliness.
Bányai, Zsila, Király, et al. (2017)	Latent profile analysis	Frequency of addictive SMU (BSMAS[24])	Self-esteem, depressive mood	The at-risk group of adolescents for social media addiction showed the lowest self-esteem, highest depressive symptoms and most time on SMU and these adolescents were mainly female.
Andreassen, Pallesen and Griffiths (2017)	Multilevel linear regression	Social media addiction (BSMAS)	Self-esteem (RSES), narcissism[25]	Lower self-esteem was significantly associated with higher social media addiction and these were mainly women and younger people.

[18] Social Media Disorder Scale
[19] Cantril Ladder
[20] Iowa–Netherlands Comparison Orientation Measure
[21] Patient Health Questionnaire-4
[22] 6-item De Jong Gierveld Loneliness Scale
[23] 5-item Mental Health Inventory (subscale of the Medical Outcomes Study (MOS) 36-item short-form health survey)
[24] Bergen Social Media Addiction Scale
[25] Narcissistic Personality Inventory-16

Studies in North America				
Primack, Shensa, Sidani, et al. (2021)	Logistic regression	Duration of SMU; depression	Risk of depression (PHQ-9[26]), duration of SMU	Among non-depressed participants at baseline, highest duration of SMU was associated with significantly higher odds of developing depression 6 months later in both genders. There was no association between being depressed at baseline and increasing duration of SMU 6 months later.
Lee, Lohrmann, Luo, et al. (2022)	Latent growth curve model	Frequency of SMU	Internalising mental health problems (GAIN-SS[27])	A higher frequency of social media use was associated with more internalising mental health problems for both genders.
Shensa, Sidani, Escobar-Viera, et al. (2020)	Factor analysis and logistic regression	Face-to-face emotional support (ES) and social media emotional support (SM-ES) (PROMIS[28])	Risk of depression (PHQ-9)	SM-ES was associated with slightly more odds of depression but ES was associated with slightly lower odds of depression, after controlling for ES and SM-ES, respectively. SM-ES was not negatively correlated with ES, which suggests that SM-ES was not necessarily displacing ES.
Hardy and Castonguay (2018)	Logistic regression	Number of SNSs	Anxiety	For young adults (18-29 years old), use of more SNSs is associated with lower anxiety (feeling of having a nervous breakdown).
Riehm, Feder, Tormohlen, et al. (2019)	Multinomial logistic regression and Mantel test for trend	Duration of SMU	**Past-year mental health problems:** Internalising and externalising problems (GAIN-SS)	Compared to non-users, spending >30 minutes on social media was associated with internalising and externalising problems in both genders, even after adjusting for prior internalising and externalising problems. As time on social media increased, the odds of internalising and comorbid problems increased proportionately (significant linear trend).
Primack, Shensa, Escobar-Viera, et al. (2017)	Ordered logistic regression	Use of multiple social media platforms	Depression and anxiety symptoms (PROMIS)	Participants who used 7-11 social media platforms had greater odds of depressive and anxiety symptoms than those who used <3 platforms, even after controlling for duration of

[26] Patient Health Questionnaire-9
[27] Global Appraisal of Individual Needs – Short Screener
[28] The Patient-Reported Outcomes Measurement Information System (PROMIS) was used to assess perceived face-to-face emotional support and this scale was adapted to assess perceived emotional support derived from social media.

				SMU. Use of multiple social media platforms had stronger associations with outcomes than duration of SMU.
Shensa, Escobar-Viera, Sidani, et al. (2017)	Ordinal logistic regression	Frequency of PSMU (adapted from BFAS[29])	Depressive symptoms (PROMIS)	PSMU was associated with greater odds of depressive symptoms, even after controlling for the duration and frequency of SMU.
Studies in Canada				
Sampasa-Kanyinga and Lewis (2015)	Multinomial logistic regression	Duration of social media use (heavy vs regular use)	Unmet need for mental health support, mental health, psychological distress (K-10[30]), suicidal ideation	Reporting an unmet need for mental health support was associated with daily SMU of >2 hours than those without this unmet need. Daily SMU of >2 hours was also associated with fair or poor self-rating of mental health and high levels of psychological distress.
Sampasa-Kanyinga and Hamilton (2015)	Logistic regression and mediation analysis	**Main exposure:** SNS use vs non-use **Mediator:** cyberbullying victimisation	Psychological distress (K-10, suicidal behaviour	Use of SNSs was associated with psychological distress. Risk of cyberbullying victimisation fully mediated the relationship between SNS use and psychological distress, so this relationship was no longer significant after adjusting for cyberbullying.
Cross-national studies				
Twenge and Martin (2020)	Linear regression	Duration of digital media use (including but not limited to SMU)	Mental health and well-being[31]	Moderate and heavy digital media use was significantly associated with mental health issues/low well-being and this association was stronger in females than in males. Heavy users of digital media (vs low users) were two times more likely to have mental health issues/low well-being in both genders.

[29] Bergen Facebook Addiction Scale
[30] Kessler Psychological Distress Scale
[31] 14-item Warwick-Edinburgh Mental Wellbeing Scale (WEMWBS) for the UK sample; depression and suicidal ideation for the Youth Risk Behavior Surveillance System (YRBSS) sample; overall happiness for the Monitoring the Future (MtF) sample

2.3.4 Social media use and mental health associations

Based on Table 2.5, I describe four ways in which social media use was assessed (briefly discussed in Section 1.2.3 of Chapter 1) with reference to indicators of mental health. This is briefly summarised below with a few key studies from the literature review. I also outline whether gender was observed to have moderated the key associations in these empirical studies.

Duration and frequency of social media use

Duration of social media use refers to a quantifiable measure of time that a user spends on social media (e.g., hours of use in a day) (39-41). Based on longitudinal data from the LIFECOURSE study conducted in 2017-19 among 12-14-year-olds in Iceland, Thorisdottir, Sigurvinsdottir, Kristjansson, et al. (2020) found that greater duration of social media use, assessed by the single-item question *“On average, how much time do you spend on social media each day (e.g., Facebook, Snapchat, Twitter and Instagram)?”*, was weakly but significantly associated with symptoms of physical and social anxiety, as well as depressed mood (β = 0.04 (95% CI: 0.02, 0.06); p=0.001), and these associations were stronger for females than males, although the authors reported that effect sizes were small and may not be of clinical importance (40).

Frequency of social media use refers to an unquantifiable measure of time that users spend on social media (e.g., three times a week) (42-44). Based on longitudinal data from Our Futures study conducted in 2013-15 among 13-16-year-olds in England, Viner, Gireesh, Stiglic et al. (2019) found that very frequent social media use, assessed by the frequency with which they habitually accessed or checked social media networks (ranging from never to more than three times a day), was associated with poorer mental health (high 12-item GHQ scores). This association was no longer significant after adjustment for cyberbullying, sleep and physical activity in females but it remained significant in males (43), suggesting that there could be other potential mediators that could explain the association between frequency of social media use and later mental health in adolescent males.

Active and passive social media use

As mentioned in Section 1.2.3 of Chapter 1, active social media use involves chatting, posting personal content (e.g., photos and status updates) to an audience and/or liking or commenting on posts from followers, whilst passive social media use refers to browsing and/or reading content from others without direct social interaction (45).

Based on a study conducted in 2018 among 14-16-year-olds in Iceland, Thorisdottir, Sigurvinsdottir, Asgeirsdottir, et al. (2019) found that passive social media use (versus active use) was associated with more symptoms of anxiety and depressed mood in both genders, even after controlling for duration of social media use, risk factors (social comparison, body image) and protective factors (offline peer support, self-esteem) (45). This relationship was stronger in females than males.

Investment in social media

Similar levels of frequency or duration of social media use may not equate to similar levels of investment in social media use, which refers to, for example, how important social networking sites are to adolescents (47). Based on a study using data from the Youth Activity Participation Study conducted (year unknown) among 13-21-year-olds in Western Australia, Neira and Barber (2014) found that greater investment in SNS use (e.g., perceived as being an integral part of daily life) instead of the frequency of SNS use was associated with higher depression (47). This association was not moderated by gender.

Social media addiction

Pertaining to addictive social media use (defined by the biopsychosocial model (48), described in Section 1.3.1 of Chapter 1), based on a study using data from the European School Survey Project on Alcohol and Other Drugs (ESPAD) conducted in 2015 among 15-22-year-olds in Hungary, Bányai, Zsila, Király, et al. (2017) found that the at-risk group of adolescents for social media addiction showed the highest level of depressive symptoms and were mainly female (142).

2.3.5 Social media use and well-being associations

Similar to the presentation above, I focus on well-being as the outcome in this section.

Duration and frequency of social media use

Based on a longitudinal study using data from the UKHLS conducted in 2009-16 among 10-15-year-olds in the UK, Orben, Dienlin and Przybylski (2019) found that greater duration of chatting or interacting on social networking sites was associated with lower life satisfaction in both genders (139).

In contrast, based on a study using data from the Taiwan Communication Survey conducted in 2014 among 12-17-year-olds in Taiwan, Lai, Hsieh and Zhang (2019) found that duration of Facebook use was associated with greater subjective well-being (measured by social support, life satisfaction and social satisfaction) and this association was stronger in males than females (136).

Based on a cross-national study using data from the Health Behaviour in School-aged Children (HBSC) survey conducted in 2017-18 among 11-, 13- and 15-year-olds, Boer, van den Eijnden, Boniel-Nissim et al. (2020) found that in countries with a low prevalence of intense social media use (measured as the frequency of online contact with anyone on social media), intense users reported lower life satisfaction, whereas, in countries with a high prevalence of intense social media use, intense users reported higher life satisfaction (151).

Investment in social media

Using data from the Youth Activity Participation Study conducted (year unknown) among 13-21-year-olds in Western Australia, Neira and Barber (2014) found that greater investment in SNS use (e.g., perceived as being an integral part of daily life) instead of the frequency of SNS use was associated with lower self-esteem (47). This association was not moderated by gender.

Active and passive social media use

No study in my literature review examined associations between active and passive social media use on well-being outcomes.

Social media addiction

Pertaining to addictive social media use, based on data from the Health Behaviour in School-aged Children (HBSC) survey conducted in 2018 among 11-, 13- and 15-year-olds in Lithuania, Buda, Lukoševičiūtė, Šalčiūnaitė, et al. (2021) found that problematic social media use was associated with twice or higher odds of poor life satisfaction in both genders (Males: OR = 2.07 (95% CI: 1.45, 2.97); Females: OR = 2.91 (95% CI: 2.14, 3.94)) (141).

2.3.6 Analytical characteristics of articles that assessed family factors

Table 2.6 sets out the study author(s), publication year, statistical analysis strategy, explanatory variable(s) (and other variables if relevant), outcome variable(s) and key results related to the associations between social media use and mental health and well-being outcomes for studies that considered family factors (21.2%: 7/33 studies).

Table 2.6: Analytical characteristics of journal articles that assessed family factors

Author(s) and publication year	Main analysis strategy	Explanatory variable(s)	Outcome(s)	Results
Studies in Asia				
Lee, Ho and Lwin (2017)	Covariance structure modelling	**Exogenous variables:** positive relationships with mother and father **Endogenous variables**: depression; loneliness; self-reactive outcome expectation; self-identity; deficient self-regulation; SNSs habit strength; duration of SNS use		Only positive relationship with father was linked to lower dependence on SNSs for identity formation. Positive relationships with both parents were associated with lower depression. Both depression and self-identity were associated with more deficient self-regulation and in turn greater time spent on SNSs.
Studies in the UK				
Twigg, Duncan and Weich (2020)	Multilevel regression	Duration of chatting or interacting on SNSs	Life satisfaction[32]	Heavy use of SNSs (vs non-users) was significantly associated with lower life satisfaction over time, with worse outcomes in females than in males and better outcomes in participants who come from supportive families.
Jagtiani, Kelly, Fancourt, et al. (2019)	Linear regression	**Main exposure:** Duration of chatting or interacting on SNSs **Moderator:** Family meal frequency	Mental well-being (SWEMWBS[33])	Heavy users (vs moderate users) and those having few or no family meals had lower well-being. Family meal frequency significantly moderated the association between SNS use and well-being: among those reporting no family meals, well-being scores were lower for heavy users (vs non-users) but similar across all SNS use categories among those having more family meals.

[32] 7-point visual analogue scale
[33] Short form (7-item) of the Warwick-Edinburgh Mental Wellbeing Scale

Studies in Europe				
Casaló and Escario (2019)	Logistic regression	Parents' rules at home and outside (frequency); parents' control: where and with whom adolescent is with at night; care from parents (frequency)	Excessive internet use[34]	Fixing clear home rules was not associated with excessive internet use, but greater frequency of fixing clear outside rules was associated with excessive internet use. Parents' knowledge of where and with whom their children are at night was associated with lower levels of excessive internet use. Receiving care and affection from parents significantly reduced excessive internet use prevalence.
Studies in Canada				
Sampasa-Kanyinga, Goldfield, Kingsbury, et al. (2019)	Logistic regression	Duration of SMU (heavy vs regular use)	Parent-child relationship quality	Longer duration of SMU was associated with higher odds of negative relationships in various parent-child dyads apart from mothers and sons, even after controlling for total screen time.
Cross-national studies				
Boer, van den Eijnden, Boniel-Nissim, et al. (2020)	Multilevel regression	Frequency of intense SMU (binary)[35] and problematic SMU (binary)[36]	**Mental well-being:** life satisfaction[37] and psychological complaints **School well-being:** school satisfaction and perceived school pressure **Social well-being[38]:** family and friend support	In countries with low prevalence of intense SMU, intense users had poorer mental well-being and lower levels of family support. In countries with high prevalence of intense SMU, intense SMU was weakly or not associated with psychological complaints and was positively associated with family support and life satisfaction. Intense SMU was associated with higher levels of friend support in all countries, and this association became stronger as prevalence of intense SMU increased. Problematic SMU was consistently associated with lower well-being in all countries.

[34] Similar items to Young's Internet Addiction Test (IAT)
[35] Scale adapted from EU Kids Online Survey
[36] 9-item Social Media Disorder Scale
[37] Cantril's ladder (visual analogue scale)
[38] Two 4-item subscales of the Multidimensional Scale of Perceived Social Support

Boniel-Nissim, Tabak, Mazur, et al. (2015)	Generalised linear model (GLM) and logistic regression	**Main exposure:** frequency of electronic media communication (EMC) **Moderator:** supportive communication with parents	Life satisfaction[39]	Except in Israel and The Netherlands, adolescents reporting a very low or very high frequency of EMC with friends had the lowest life satisfaction (curvilinear association). Supportive parent communication moderated the effect of frequency of EMC with friends on life satisfaction: The inverse relationship between life satisfaction and frequent EMC was the strongest in adolescents who perceived their communication with both parents as difficult. In countries where every day EMC was less frequent, the optimal frequency tended to be lower, whereas, in countries with very frequent daily EMC, higher frequencies seemed optimal.

[39] Cantril's ladder (visual analog scale)

The seven articles (Table 2.6) are organised below according to family factors as (i) moderators, (ii) antecedents, (iii) exposures and (iv) outcomes.

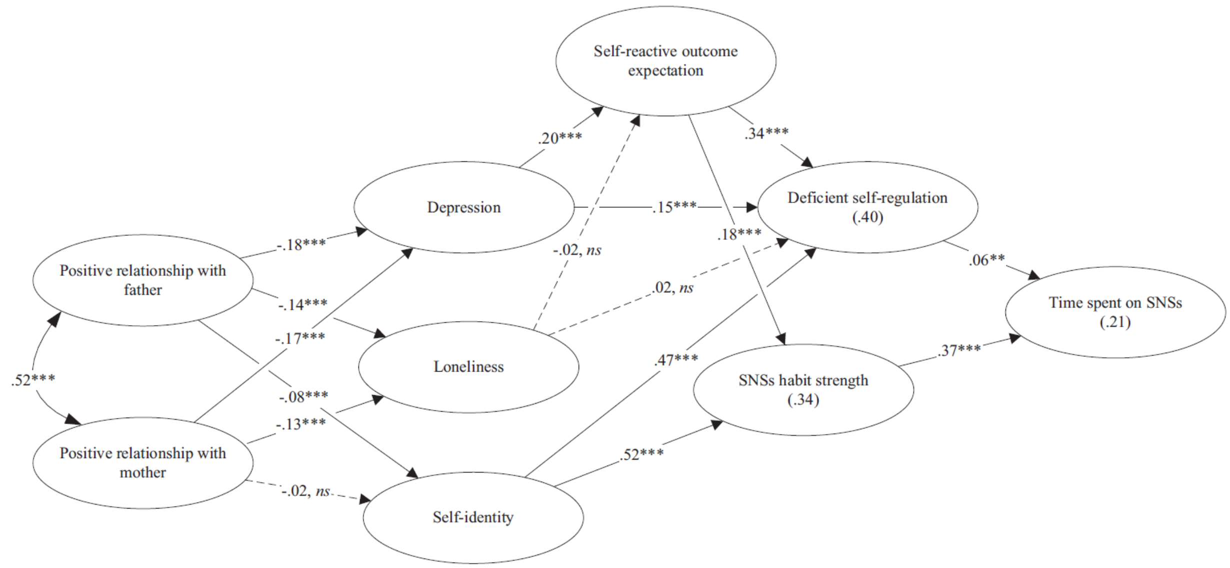
Family factors as moderators

As moderators, family variables may influence the direction and/or strength of the associations between the independent variable (e.g., social media use) and dependent variable (e.g., mental health outcomes). Using data from the UKHLS conducted in 2011-13 among 16-21-year-olds in the UK living with their parents, Jagtiani, Kelly, Fancourt et al. (2019) observed that evening shared family meal frequency significantly moderated the association between duration of SNS use and well-being; heavy users (4+ hours/weekday) had lower well-being on average than non-users among those not having any evening shared family meals, but well-being scores were similar across all SNS use categories among those having more shared evening family meals (107).

Family factors as antecedents

Ngai, Tao and Moon (2015) devised a causal-chain framework to illustrate the antecedents, mediators, moderators and outcomes of social media use (124). Antecedents are factors that precede a behavioural outcome and could encompass social factors, user attributes, and/or organisational attributes when examining the literature on social media (124). Family factors may be hypothesised to precede outcomes such as the duration or frequency of social media use. In the study conducted by Lee, Ho and Lwin (2017) among 13-17-year-olds in Singapore, adolescents' positive relationship with their fathers lowered their dependence on social networking sites for identity formation, leading to better self-regulation and in turn less time spent on social networking sites (135). In the same study, having a positive relationship with both parents was associated with lower depression, leading to better self-regulation and therefore less time spent on social networking sites (135). This suggests that positive parent-child relationships could lower the amount of time spent on social networking sites through these various mediators, as illustrated in Figure 2.3 below.

Figure 2.3: Extended social cognitive model examining the external and personal antecedents of SNS use among Singaporean adolescents



Source: Lee, Ho and Lwin (2017)

Family factors as exposures

Using data from the Spanish Survey on Drug Use in the School Population (ESTUDES) conducted in 2014-15 among 14-18-year-olds in Spain, Casaló and Escario (2019) found that greater parental care and knowledge about where and with whom their adolescent child goes out at night were associated with lower excessive internet use (143). However, a higher frequency of establishing clear rules outside the home increased the prevalence of excessive internet use, suggesting a salient difference in the associations between internet use and parenting approaches.

Family factors as outcomes

Based on a study using data from the Ontario Student Drug Use and Health Survey (OSDUHS) conducted in 2013 among 11-20-year-olds in Canada, Sampasa-Kanyinga, Goldfield, Kingsbury, et al. (2019) found that heavy social media use was associated with higher odds of negative relationships in various parent-child dyads (apart from the mother-son dyad), even after adjusting for total screen time.

Additionally, based on a cross-national study using data from the Health Behaviour in School-aged Children (HBSC) survey conducted in 2017-18 among 11-, 13- and 15-year-olds, Boer, van den Eijnden, Boniel-Nissim et al. (2020) found that low prevalence of problematic social media use (PSMU) strengthened the negative association between PSMU and social well-being, the latter being measured by family and friend support (151). Conversely, in countries with high levels of intense social media use (measured by how often one has online contact with anyone on social media), intense social media use was associated with higher life satisfaction and higher levels of family support than non-intense social media use (151).

2.3.7 The role of gender

Gender is a possible moderator of the associations between social media use and mental health or well-being. As described in Tables 2.5 and 2.6, and Sections 2.3.4 and 2.3.5, the studies presented in my literature review depicted mixed evidence between males and females in the associations between social media use and indicators of mental health or well-being. These are summarised below with recently published studies.

Larger negative associations in females than males: Among adolescents aged 14 years in the UK in 2015-16, Kelly, Zilanawala, Booker, et al. (2018) found that greater duration of social media use was associated with greater depressive symptoms (measured by the Moods and Feelings Questionnaire) and this association was stronger in females than males (104).

Positive associations in both males and females: Among adolescents aged 12 to 17 years in Taiwan in 2014, Lai, Hsieh and Zhang (2019) found that greater duration and frequency of Facebook use was associated with greater subjective well-being (measured by social support, life satisfaction and social satisfaction) in both genders but this association was stronger in males than females (136).

No difference in associations between males and females: Among adolescents aged 12 to 14 years in the USA in 2013-18, Lee, Lohrmann, Luo, et al. (2022) found that a higher frequency of social media use was associated with more internalising mental health problems (measured by the Global Appraisal of Individual Needs – Short Screener) in both genders (144). Similarly, among adolescents aged 11, 13 and 15 years in Lithuania in 2018, Buda, Lukoševičiūtė, Šalčiūnaitė, et al. (2021) found that problematic social media use (measured by the Social Media Disorder Scale) was associated with two times higher odds of poor life satisfaction (measured by the Cantril Ladder) in both genders (141).

2.3.8 The role of age

As mentioned in Chapter 1, young people at different stages of development may have different social contexts and support structures, which can interact with social media use to produce varying effects on mental health and well-being. Many of the studies in my literature review controlled for age in regression analyses, where appropriate, but did not discuss age as an independent predictor of mental health or well-being, nor how associations between social media use and mental health and well-being might differ across ages among young people. One exception was the study conducted by Booker, Kelly and Sacker (2018), who used parallel latent growth curve modelling to examine the relationship between duration of SNS use and well-being among 10-15-year-olds using UKHLS data from 2009 to 2015 (10). Change in well-being was estimated by age averaged across individuals (rather than by time). This study found that greater social media interaction at age 10 was associated with lower levels of well-being at later ages among females but not among males. These results among young people suggest that there might be differences in the association between social media use and mental health or well-being outcomes by gender and by age.

2.4 Discussion of literature review

2.4.1 Key findings

The systematic literature review presented in this chapter aimed to examine and summarise global evidence for the influence of social media use on key mental health and well-being outcomes among young people, including previous work that has explored aspects of family life (e.g., quality of parent-child relationships). Cross-national differences were also explored with data from different countries.

The findings of this systematic literature review suggest an intricate relationship between social media use and mental health and well-being, which can be influenced by various mediators and moderators. The empirical studies also differed in how they measured and defined social media use and mental health and well-being outcomes. I consolidate and critically analyse key findings from my literature review below.

Social media use may be analysed in terms of **duration** (a quantifiable measure of time), **frequency** (an unquantifiable measure of time), **investment** (amount of energy, time, effort and attention), **addiction** (level of difficulty managing social media use), **active use** (chatting, posting and/or commenting on content) and **passive use** (browsing and/or reading content). A key finding from this review is that the way social media is used may be more paramount than the frequency or duration of social media use per se in influencing symptoms of poor mental health or poor well-being. For example, Neira and Barber (2014) found that a higher investment in SNS use (instead of frequency of SNS use), characterised by how important participation in social networking sites was to the user, was associated with lower self-esteem and higher depressed mood among young people in Western Australia (47). Additionally, Thorisdottir, Sigurvinsdottir, Asgeirsdottir, et al. (2019) found that passive social media use was associated with more symptoms of anxiety and depressed mood than active use among adolescents in Iceland, even after controlling for the duration of social media use (45). These studies highlight that examining how social media is used can reveal more information on the factors that potentially negatively influence young people's mental health and well-being.

The manner and context of social media use are crucial to understanding its empirical associations with mental health and well-being outcomes, and how that differs between genders and family factors is likely to fall under scrutiny.

Pertaining to gender, whilst some empirical studies have found females to be at greater risk than males when using social media (104), other studies have found no gender differences (141, 144) or even positive associations in both genders (136). These differences could be due to systematic differences in the samples under study, for example, differences in participants' age, years of data collection and measures of exposure and outcome.

Pertaining to family factors, Jagtiani, Kelly, Fancourt et al. (2019) observed that evening shared family meal frequency significantly moderated the association between duration of SNS use and well-being: heavy users had lower well-being scores on average than non-users among those not having any evening shared family meals, but well-being scores were similar across all SNS use categories among those having more shared evening family meals (97). Additionally, Casaló and Escario (2019) found that among adolescents in Spain, fixing clear outside rules increased the prevalence of excessive internet use, but the opposite effect was found in parents with care and knowledge about where and with whom their child goes out at night (143). This finding suggests that an evaluative and flexible parenting approach is potentially more beneficial than an authoritarian approach for adolescents, as the latter group might feel the need to "escape" by going on the internet. Similarly, Boniel-Nissim, Tabak, Mazur et al. (2015) found that cross-nationally, the inverse relationship between life satisfaction and frequency of electronic media communication (EMC) was the strongest in adolescents who perceived their communication with both parents as difficult (44). This suggests that supportive parent-child communication may buffer against the negative effects of EMC with friends on life satisfaction.

The effects of social media use could also vary based on setting or context. For example, the cross-national study of adolescents by Boer, van den Eijnden, Boniel-Nissim et al. (2020) found that in countries with a low prevalence of intense social media use (measured as how often one has online contact with anyone on social media), intense users reported lower life satisfaction, whereas, in countries with a high prevalence of intense social media use, intense users reported higher life satisfaction (151). In contrast, problematic social media use was consistently associated with lower well-being in all countries (151). Specific to family factors, the low prevalence of problematic social media use strengthened the inverse association between problematic social media use and social well-being (measured as family and friend support). Conversely, in countries with high levels of intense SMU, intense SMU was associated with higher levels of family support than non-intense SMU (151).

The authors of this study identified normalisation theory as a potential explanation for these findings, which states that substance use may not be problematic in places where it is more pervasive (153-155). This could also be extended to intense and problematic social media use, whereby the optimal level of social media use in adolescents corresponds to the norm in the given country. Given that intense SMU is associated with higher life satisfaction and higher levels of family support than non-intense SMU in countries with a high prevalence of intense SMU, and intense SMU was associated with higher levels of friend support than non-intense SMU in all countries, intense SMU could reflect active involvement, engagement and social inclusion (151). The normalisation theory is also further supported by Boniel-Nissim, Tabak, Mazur et al. (2015), who found that in countries where daily EMC was less frequent, the frequency of EMC with the highest life satisfaction scores tended to be lower, whereas in countries where daily EMC was very frequent, the frequency of EMC with the highest life satisfaction scores tended to be higher. Such findings challenge the narratives of social media as an inherently risky tool.

Lastly, there is a possibility of bidirectional/cyclical associations between social media use and mental health and well-being (e.g., poor mental health leading to greater use of social media, which in turn leads to poorer mental health). Several studies included in this review attempted to account for this potentially cyclical association by statistically controlling for prior measures of mental health. For example, based on data from the Longitudinal Internet Studies for the Social Sciences panel (LISS) conducted in 2016-17 in the Netherlands, van der Velden, Setti, van der Meulen et al. (2019) found that SNS use was no longer associated with mental health problems after prior levels of mental health had been accounted for (105), indicating that higher levels of SNS use may be a result of mental health problems rather than a root cause. Those with mental health difficulties might have difficulty managing their use of social media, which could exacerbate their mental health. In contrast, based on data from the Population Assessment of Tobacco and Health (PATH) study conducted in 2013-16 in the USA, Riehm, Feder, Tormohlen, et al. (2019) found that adolescents who used social media for over 30 minutes a day had more mental health problems than non-users, characterised by comorbid internalising and externalising problems, even after adjusting for prior mental health problems (41). As such, findings on the potential cyclical relationship between social media use and mental health and well-being is mixed and no conclusive evidence is available.

2.4.2 Strengths and limitations

One of the strengths of this systematic review is the systematic exploration of different indicators of social media use (i.e., frequency and duration, active and passive use, investment and addiction), family factors (e.g., quality of parent-child relationships) and mental health and well-being outcomes among young people in different countries. Most of the studies used large and nationally representative samples, thereby enhancing generalisability to the wider population. That said, some limitations of the systematic review need to be considered when interpreting the results.

A limitation of the systematic review is that the observational studies included often did not account for the processes of social media use that impact the effects. In some cases, such as in the study by Thorisdottir, Sigurvinsdottir, Kristjansson, et al. (2020), this was due to the survey data only asking a single question on the frequency or duration of social media use (40). The processes could include, for example, how social media is used, when it is used, how often and how long it is used, if it is used instead of other activities, if it is used with others, with what intention it is used and the type of social media platform used.

Publication bias is a potential source of bias because studies that have significant and strong associations are more likely to be published. Moreover, most of the studies relied on self-reporting. This could have resulted in social desirability bias, which happens when participants underreport their levels of social media use or levels of mental health and well-being to levels they deem as socially desirable. Self-report data on time spent using social media might also lack accuracy because survey participants might use social media at different times of the day. As such, it might be difficult for participants to accurately estimate their use in time categories, unlike in studies using experience sampling methods.

Finally, most studies are correlational and a large proportion of the studies were based on cross-sectional data, meaning causal inferences could not be made. Residual confounding may also have influenced the observed associations, potentially leading to under- or over-estimations in the associations between social media use and mental health and well-being.

2.5 Conclusion and implications for my PhD

The studies from my systematic literature review reflect that the associations between social media use and mental health and well-being outcomes are complex and vary according to the way social media use is measured, the particular outcomes under investigation and differences by country, family, gender and age. The intricacies of the results indicate that it is crucial to comprehend the potential hazards, protective aspects, and mechanisms associated with social media use and mental health or well-being. Moreover, the focus has been on consolidating evidence and guidance regarding mental health and well-being in children, adolescents, and young adults (156), a group for whom social media use would be particularly prevalent and hence relevant.

Below I highlight four key themes that underpin the empirical research that will follow in my PhD, drawing on Bronfenbrenner's ecological framework and identifying gaps in the existing literature.

Longitudinal research

My systematic literature review has highlighted a need for more longitudinal analysis (124) to enable a better understanding of the associations between social media use and the rates of change in indicators of mental health and well-being among young people. This may yield more robust results that would better inform policy. As such, the focus of my PhD will be on conducting longitudinal research that examines associations between social media use, self-esteem and depression (choice of datasets will be discussed in Chapter 4). Longitudinal research also helps to account for the potential cyclical nature of these associations, if, for example, data on mental health and well-being are available prior to ascertaining levels of social media use and thus can be adjusted for in multivariate analyses.

Exploration of gender and family differences

Most papers in my literature review focused on individual-level variables. However, Bronfenbrenner's ecological framework (3) suggests that it is crucial to investigate the connections between young people's social media use and other important environments, such as the family. Studies have also suggested that future research should explore socio-cultural factors (28, 124, 125) and be specific about the constructs of mental health and well-being used (157). To expand the focus beyond individual-level variables and as illustrated in Figure 1.1, part of the focus of my thesis is on whether family structure and aspects of parent-child relationships (e.g., parenting styles) confound or modify any observed associations between social media use (e.g., SNS use) and mental health and well-being (self-esteem and depression).

Given the inconsistent findings pertaining to the role of gender, authors such as Booker and colleagues (2018) and Cara and colleagues (2022) have advocated for analyses to be stratified by gender or to formally test for the moderation of key associations by gender (10, 157). As such, my research considers gender differences in the key associations between social media use and mental health and well-being.

Cross-country comparisons

Bronfenbrenner's ecological framework also suggests that there is usefulness in examining cross-country differences, which form the macrosystem of the framework (illustrated in Figure 1.1 of Chapter 1).

Measurement of social media use

Being able to assess social media use based on different forms of activity is important because simply assessing the amount of time spent on social media, in general, does not provide information on the aspects of use which could be either beneficial or detrimental to mental health and/or well-being. For example, one of the studies in my literature review found that after controlling for the duration of social media use, passive use (e.g., browsing social media profiles of people you do not know) was associated with more symptoms of anxiety and depressed mood than active use (e.g., sending a private message, picture, video or chat) for both genders among adolescents aged 14 to 16 years in Iceland (45). In my PhD, I utilise data from the KCYPS, which enables the evaluation of social media based on various types of engagement, for example, making posts on social media versus texting on social networking sites. This will be expanded upon in Chapter 5.

Chapter 3: Aims and Objectives

This stand-alone chapter outlines the aims and objectives of my thesis.

Chapters 1 and 2 highlighted mixed findings on the potential moderating effect of gender on the associations between social media use and mental health and well-being. Moreover, the role of the family in these associations has not been well established. Hence, my thesis aims to delve into these areas by examining the longitudinal associations between social media use (SMU)/social networking site use (SNS use) and mental health and well-being outcomes among young people, while considering the role of gender and aspects of family life.

3.1 Aims

The aims of my thesis are to undertake empirical research among young people (children, adolescents and young adults) to:

1. Describe differences in levels of SMU/SNS use and mental health/well-being.
2. Quantify the cross-sectional and longitudinal associations between SMU/SNS use and mental health/well-being.
3. Identify any differences (moderation) in these associations by gender and aspects of family life.
4. Identify any differences in key findings across different populations of young people by comparing my findings across different countries.

3.2 Objectives

The objectives of my thesis are to:

1. Identify suitable longitudinal datasets of young people (children, adolescents and young adults) across countries containing relevant variables for the exposure (SMU/SNS use), outcome (mental health/well-being) and potential moderators of the exposure-outcome association.
2. Estimate differences across groups in baseline levels of SMU/SNS use and mental health/well-being.

3. Use appropriate statistical methods for the analysis of longitudinal data to test the independent associations between key variables and mental health/well-being and to test the potential moderating effects of gender and aspects of family life.
4. Examine any changes in the main findings after adjustment for prior levels of mental health/well-being.

Chapter 4: Research Methods

This chapter provides the background for the subsequent three empirical chapters (Chapters 5, 6 and 7). I first set out the research problem and a conceptual framework that presents the empirical associations that I will investigate later. Then, I discuss the process of compiling my datasets for the longitudinal analyses, along with the relevant details on each dataset and the modelling strategy employed. Finally, I provide a description of the ethical approval process for the selected studies and give details on participant consent.

4.1 Research problem

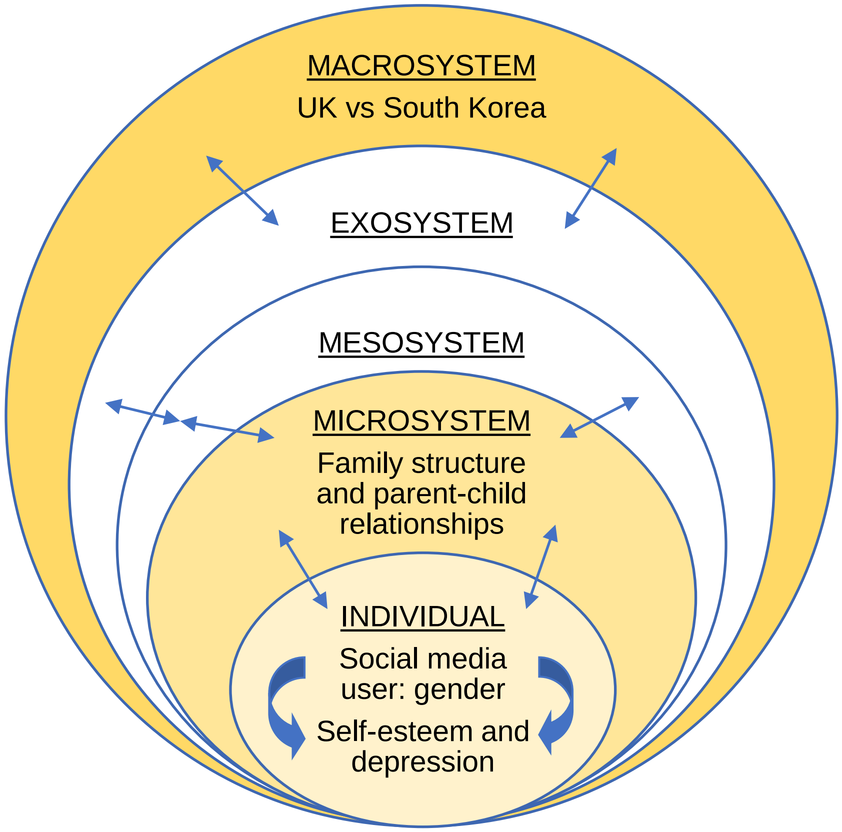
Whilst the literature on social media use, mental health and well-being is expanding rapidly, the role of the family and gender as potential moderators in this association remains a gap in the literature which my PhD seeks to address. In addition, my thesis examines data across two countries: the UK Household Longitudinal Study (UKHLS) and the Korean Children and Youth Panel Survey (KCYPS), enabling comparisons to be made and discussed more broadly. This is especially important because no study to date has explored the associations between social media use and mental health and well-being outcomes using the KCYPS. Previous studies that utilised the KCYPS in this area of research focused on mobile phone addiction (121) or internet use (123) to examine associations with mental health and behavioural outcomes.

It is worth acknowledging that there is a lack of consensus among international experts regarding the appropriate age range for the categorisation of children, adolescents and young people. For example, the World Health Organisation (WHO) defines ‘young people’ as those aged 10 to 24 years, while the United Nations (UN) defines ‘youth’ as those aged 15 to 24 years (158). Meanwhile, some authors suggest that ‘adolescents’ should be defined as those aged 10 to 24 years (159). In the context of my PhD and in light of data availability, I study (i) 10-21-year-olds in the UKHLS and (ii) 14-year-olds at baseline, followed up to the age of 18, in the KCYPS. Hence, the age range of my research participants aligns most closely with the WHO's delineation of young people, prompting me to adopt this definition throughout my PhD.

4.2 Conceptual framework

In Figure 4.1 below, I adapted Bronfenbrenner's Ecological Systems Model (3) to outline the factors that I will investigate in Chapters 5, 6 and 7. In Chapter 5, I will examine the cross-sectional and longitudinal associations between the duration of social networking site (SNS) use and self-esteem among young people aged 10 to 21 years, using data from the UKHLS. Additionally, I will investigate whether gender, family structure and parent-child relationship quality have a modifying effect on this association. In Chapter 6, I will study similar associations among young people aged 14 years at baseline, using data from the KCYPS. This chapter will analyse self-esteem as the outcome measure and will examine parenting styles as a potential moderator. Finally, in Chapter 7, I will use the same KCYPS cohort and research questions as in Chapter 6 to investigate depression as the outcome of interest.

Figure 4.1: Conceptual framework



Adapted from: Bronfenbrenner (1979), Ecological Systems Model

Exposures: In Chapter 5, I will use duration of SNS use as the exposure measure. As described in Table 1.1 of Chapter 1, SNS use is a subset of social media use (SMU). In Chapters 6 and 7, I will use the frequency of computer social media use (CSMU) and phone-based interpersonal communication[40] (PIC) as exposure measures. This approach adds to the literature by moving away from studies that rely on a single question/item on the amount of time spent on social media, to capture more specific types of social media activity, providing a more comprehensive view of the exposure measure.

[40] Includes both social networking and communication items – this will be elaborated upon in Chapter 6.

Outcomes: In Chapters 5 and 6, I will use self-esteem as the outcome measure, and in Chapter 7, I will use depression as the outcome measure. My choice of mental health and well-being outcomes was based on the discussions presented in Sections 1.1.1 and 1.1.2 of Chapter 1. Apart from including outcomes measures related to both mental health (i.e., depression) and well-being (i.e., self-esteem), these outcomes were also selected based on their availability in the datasets. For example, the Rosenberg Self-Esteem Scale was included in both the UKHLS and KCYPS, making it a suitable measure for examining changes in self-esteem over time across different populations.

Moderators: In Chapters 5 to 7, I will investigate gender as a potential moderator of the key associations. Family structure (household composition) will be examined as a potential moderator in each chapter. Parent-child relationship quality (talking to and quarrelling with mother and father) will be examined as a potential moderator in Chapter 5 (using the UKHLS) and parenting styles will be examined as a potential moderator in Chapters 6 and 7 (using the KCYPS). The choice of family factors was based on data availability (e.g., there were no questions that assessed parent-child relationship quality in the KCYPS). These potential moderators were selected based on the gaps in evidence identified in Chapters 1 and 2.

4.3 Research methods

In this section, I discuss the process of deriving my final datasets for longitudinal analyses in the empirical chapters, along with the relevant details on each dataset and the modelling strategy employed.

4.3.1 Overview of datasets

During the process of my systematic literature review, I identified potential datasets and evaluated the availability of my variables of interest. Table 4.1 presents the variables of interest (i.e., social media, mental health and/or well-being, and family) that were available in each of the longitudinal datasets examined.

Table 4.1: Summary of longitudinal datasets sourced for

Longitudinal datasets	Social media variables	Mental health and/or well-being variables	Family variables
UKHLS	√	√	√
KCYPS (baseline 2010)	√	√	√
KYPS (baseline 2008)	None	√	√
MCS 5 (Age 11)	√	√	None
MCS 6 (Age 14)	√	√	√
Pew American Trends Panel Wave 35	√	√	None
OSDUHS (grades 7-8, 9-12)	√	√	Limited
HBSC 2005-06	None	√	√
HBSC 2013-14	√	√	√
Next Steps 2015 (Age 25)	√	√	None

Abbreviations: HBSC: Health Behaviour in School-aged Children Study; KCYPS: Korean Children and Youth Panel Survey; KYPS: Korean Youth Panel Survey; MCS: Millennium Cohort Study; OSDUHS: Ontario Student Drug Use and Health Survey; UKHLS: UK Household Longitudinal Study

To conduct longitudinal analyses related to my research aims, I selected the UKHLS and KCYPS datasets based on the availability of variables and years of data collection. Specifically, these datasets provided access to all three key sets of variables (social media use, mental health and/or well-being, and family). Whilst the UK Millennium Cohort Study (MCS) was also considered, only one sweep (MCS 6) had all three key sets of variables available at the time of sourcing for longitudinal datasets, making the UKHLS a more suitable choice for my research in the UK. apart from the MCS, the HBSC also offered a diverse range of variables, but the data are cross-sectional and so did not align with one of the main objectives of my research, which involves analysing longitudinal data.

4.3.2 Datasets chosen (UKHLS and KCYPS)

The UKHLS (Understanding Society) is a large-scale, multi-topic and nationally representative longitudinal survey which interviews approximately members of 40,000 households annually (160, 161). The Great Britain sample is a proportionately stratified and geographically clustered sample of residential addresses; the Primary Sampling Units (PSUs) are postal sectors which are stratified by (i) region (nine English regions, Scotland and Wales), (ii) population density and (iii) minority ethnic density. The Northern Ireland sample was drawn from a list of domestic properties and was not clustered. At each wave, those aged 10 to 15 years in sampled households are invited to complete what the UKHLS team describe as a 'youth' self-completion questionnaire, whilst household members aged 16 years and over (adults) complete their detailed interview either face-to-face with an interviewer or through a self-completion online survey (160). The UKHLS households recruited at the first round of data collection are visited each year to collect information on changes to their household and individual circumstances. At the time of this study, ten waves of UKHLS data were available (wave 1: 2009-11 through wave 10: 2018-20). UKHLS data (SN: 6614) was obtained from the UK Data Service (Project Number: 178728) (162).

The KCYPS (2010-16) was a follow-up study of the Korean Youth Panel Survey (2003-08) and is a nationally representative study of the growth and development of Korean children and youth conducted by the National Youth Policy Institute (NYPI) from 2010 to 2016 (106). The KCYPS was developed based on Bronfenbrenner's ecological framework (3) and the survey questions were divided into two categories: personal development and development environment (106). The personal development segment encompasses 12 sub-categories (e.g., health, academic achievement, emotional problems, etc.) (106). The development environment encompasses six environmental factors that exert important effects on adolescents' socialisation, including the family environment (family members, parenting styles, etc.) and the media environment (computer, mobile phones, cyber delinquency and adult media) (106).

The KCYPS was a seven-year prospective panel study of a representative sample of Korean students in three cohorts: (i) Grade 1 (1st year in elementary school: **E1 cohort**; 2003 birth cohort), (ii) Grade 4 (4th year in elementary school: **E4 cohort**; 2000 birth cohort) and (iii) Grade 7 (1st year in middle school: **M1 cohort**; 1997 birth year cohort) (106). In total, there were seven waves of KCYPS data (wave 1 in 2010 through to wave 7 in 2016). Overall, 7,071 participants were recruited at the first wave of data collection for KCYPS: 2,342 in the **E1 Cohort**, 2,378 in the **E4 Cohort** and 2,351 in the **M1 Cohort**. Retention rates for the study were relatively high. For example, over 90% of the participants in the M1 Cohort at wave 1 took part in the study at wave 3 (n = 2,259); 83% of the participants in the M1 Cohort who took part at wave 3 took part in the study at wave 7 (n = 1,872).

The KCYPS employed a multi-stage stratified cluster sampling method, with schools as the primary sampling unit (PSU). The schools were selected using a probability proportional to size sampling method. The sample population has been described as geographically representative of Korea. The survey was conducted on all students and parents from the selected grade levels. At the baseline survey, four trained research staff visited participating schools during regular school hours. Self-report questionnaires were administered to the students who were encouraged to complete all items. For the Grade 7 panel of the KCYPS (**M1 Cohort**; the cohort analysed in my PhD), baseline measures were collected from October to November 2009. Follow-up data collection took place annually between October and December. Students who took part at baseline and agreed to continue in the study were contacted via telephone at follow-up. After obtaining verbal consent, the research staff then had a face-to-face meeting with each student followed by an interviewer with caregivers to collect demographic information. According to the NYPI data user guide (106), incentives were provided to students who participated in each panel. The details of the goals, design and sampling of the KCYPS are published in the NYPI Youth and Children Data Archive:

https://www.nypi.re.kr/archive/board?menuId=MENU00329.

Data from the KCYPS was sent to me (24/01/2020) by Sung Eun Kim from the Korean National Youth Policy Institute (NYPI) with the message that the data was open to all researchers through the Institution's homepage. I consented to the regulations for data usage via the data consent application on the Institution's homepage:

https://www.nypi.re.kr/archive/mps/program/examinDataCode/dataDwloadAgreeView?menuId=MENU00226.

The documentation for the KCYPS is in Korean, so I translated the key information I required with the help of a native Korean speaker. I also used Google translate and back-translate to ensure that the translations were as accurate as possible. In some cases, descriptive statistics were compared with published studies to check the accuracy of the translation and statistical coding.

Table 4.2 summarises the similarities and differences of the key variables used in each empirical chapter.

Table 4.2: Variables to be used in the UKHLS and the KCYPS

Key variables in analyses	Datasets	
	UKHLS (Chapter 5)	**KCYPS (Chapters 6 and 7)**
Age at baseline	10 to 21 years at wave 4	14 years at wave 3
Time of data collection	2012-14 to 2018-20	2012-16
Social media use	Duration of social networking use	Frequency of computer social media use; frequency of phone-based interpersonal communication
Mental health and well-being	Rosenberg Self-Esteem Scale (8-item)	**Chapter 6**: Rosenberg Self-Esteem Scale (10-item) **Chapter 7**: Center for Epidemiologic Studies Depression Scale Revised (CESD-R) (10-item)
Objective family indicator	Family structure (number of parents in the household)	Family structure (number of parents in the household)
Subjective family indicator	Parent-child relationship quality as measured by: • Frequency of talking to mother • Frequency of talking to father • Frequency of quarrelling with mother • Frequency of quarrelling with father	Parenting styles as measured by the revised version of Heo's Parenting Styles Scale: • Positive parenting styles (supervision, affection and rational explanation subscales) • Negative parenting styles (inconsistency, unreasonable expectation and over-involvement subscales)

Abbreviations: KCYPS: Korean Children and Youth Panel Survey; UKHLS: UK Household Longitudinal Study

The target sample for the UK study consisted of 'youths' (aged 10-15 years) and 'young adults' (aged 16-21 years) from the UKHLS dataset at wave 4. The 'young adult' questionnaire is a sub-section of the adult questionnaire, specifically designed for individuals aged 16 to 21 years. It includes question items that are relevant to this age group and is administered alongside questions asked in the adult questionnaire content in each wave. To increase sample sizes, data from both age groups were harmonised and pooled together for analysis (age range throughout the study period: 10 to 21 years). This approach was particularly useful for models that were estimated separately by gender to highlight any potential moderation of the association between SNS use and self-esteem. Wave 4 was selected as the baseline for this study because it was the first occasion when self-esteem questions were included for both ‘youths’ and ‘young adults’.

The target sample for the South Korean studies was derived solely from the M1 cohort because, unlike the UKHLS, it was not possible to pool the other cohorts due to inconsistent variable availability across waves in the other cohorts. Consequently, the oldest cohort (**M1 cohort**; aged 14 years at baseline to 18 years) was selected because adolescence is a critical developmental stage marked by increasing autonomy and significant changes in social and emotional development (7). Children may not yet have fully developed social comparison abilities, and mental health issues also tend to emerge more frequently during adolescence (25). As such, adolescence is an essential period to examine the associations between social media use and mental health and well-being outcomes.

The years of data collection for my analyses were largely similar, with some variations in the later years. Specifically, in my main analyses, I analysed data from 2012 to 2020 in the UKHLS and from 2012 to 2016 in the KCYPS.

The availability of variables pertaining to social media use differed between the UKHLS and the KCYPS. In the UKHLS, only a single question on the duration of social networking site (SNS) use was asked, which limits our understanding of the types of social networking activity in which participants engage in, such as which platforms they use or how they use SNSs (e.g., active or passive use (45)). In contrast, the KCYPS provides a more detailed assessment of social media use which captures different forms of social media activity, with computer social media use including items such as posting content on social media sites, and phone-based interpersonal communication including items such as texting friends and family on social networking sites. This provides valuable information on how users spend their time on social media beyond merely measuring the time spent.

Regarding the outcomes, both the UKHLS and the KCYPS employed a comparable measure of self-esteem. The UKHLS assessed self-esteem as the sole well-being indicator in the ‘youth’ and ‘young adult’ questionnaires (there were no mental health indicators asked in both questionnaires). A second chapter using the KCYPS data will use depression as an indicator of mental health. This will allow me to investigate whether the associations between social media use and self-esteem versus depression are consistent or divergent in the same sample, thereby expanding the scope of my research.

Lastly, both datasets included an objective family indicator, family structure, but the variable of interest was derived differently in each dataset. The two datasets also differed in terms of subjective family indicators. The UKHLS included indicators of parent-child relationship quality (i.e., frequency of talking to and quarrelling with mothers and fathers), whilst the KCYPS included indicators of parenting styles (i.e., positive and negative parenting styles). These will be discussed in detail in Chapters 5 and 6, respectively.

Table 4.3 outlines when each key variable was covered through waves 1 to 10 of the ‘youth’ and ‘young adult’ panels in the UKHLS (Chapter 5).

Table 4.3: Key variables in the UKHLS according to study wave

	Study wave									
	1 2009 /11	2 2010 /12	3 2011 /13	4 2012 /14	5 2013 /15	6 2014 /16	7 2015 /17	8 2016 /18	9 2017 /19	10 2018 /20
Self-esteem		√[a]		√[a] √[b]		√[a] √[b]		√[a] √[b]		√[a] √[b]
SNS use	√[a]	√[a]	√[a] √[b]	√[a] √[b]	√[a] √[b]	√[a] √[b]	√[a] √[b]	√[a] √[b]	√[a] √[b]	√[a] √[b]
Family structure	√[c]	√[c]	√[c]	√[c]	√[c]	√[c]	√[c]	√[c]	√[c]	√[c]
Parent-child relationship quality	√[a]		√[a] √[b]		√[a] √[b]		√[a] √[b]		√[a] √[b]	

Notes: [a]'youth' self-completion questionnaire (10-15-year-olds); [b]'young adults' self-completion questionnaire (16-21-year-olds); [c] available in the *egoalt* file at each wave which outlines kin and other relationships between enumerated pairs of individuals in the household (161).

Table 4.4 outlines when each key variable was covered through waves 1 to 7 of the M1 cohort in the KCYPS (Chapters 6 and 7).

Table 4.4: Key variables in the KCYPS according to study wave (M1 cohort)

	Study wave						
	1	2	3	4	5	6	7
	2010	2011	2012	2013	2014	2015	2016
Self-esteem (Chapter 6)	√		√		√	√	√
Depression (Chapter 7)		√	√	√		√	√
Social media use	√	√	√	√	√	√	√
Family structure	√	√	√	√	√	√	√
Parenting Styles	√			√		√	√

4.3.3 Linear mixed-effects modelling

Similar to previous studies (40), the empirical chapters of my thesis will use longitudinal modelling of continuous outcomes using linear mixed-effects models. Linear mixed-effects models contain two parts: a fixed part and a random part. In the fixed part of the model, coefficients represent the estimated average relationship between an independent and a dependent variable. In the random part of the model, random effects (level-2 or person-specific residuals) allow for residual/unexplained person-specific variation in (i) intercepts (levels of the continuous outcome when all independent variables (e.g., including follow-up time) are set at zero or their references levels) and

(ii) slopes (allowing the strength of the association between an independent variable and a continuous outcome to vary between participants) (163).

Statistical techniques such as linear mixed-effects modelling are suitable when the data is longitudinal (i.e., different values of the same continuous outcome over time for the same individuals). The longitudinal nature of the UKHLS and the KCYPS datasets meant that participants at baseline had possible repeated measurements of the continuous mental health (depression in the KCYPS) and well-being (self-esteem in the UKHLS and KCYPS) outcomes. When the data consists of multiple levels or hierarchies (e.g., the same measurements over time nested within persons), participant-level observations are not statistically independent because repeated observations on the same outcome by the same participant are typically more similar than observations from different participants (163). Inference from standard (single level) regression techniques which ignore the correlated nature of such data is not valid.

Linear mixed-effects models with time-since-baseline as timescale (expressed in years) will be used in the empirical chapters of my thesis to estimate the associations between SMU/SNS use and the change in self-esteem and depression over the study period. A longitudinal study of a single birth cohort (e.g., M1 cohort in the KCYPS) does not allow us to investigate the effect of more than one timescale (e.g., separate calendar time and chronological age effects), as such, the chosen time metric was time-since-baseline in my analyses of the UKHLS and the KCYPS. I accounted for the broad age range of participants in the UKHLS (aged 10-21 years) by examining age as an independent predictor of self-esteem.

Such models (estimated by maximum likelihood) use all available data and hence do not require participants to respond at every wave. These models account for intraindividual correlation (i.e., correlation between repeated observations within the same participant). In my study, random intercepts and random slopes (for the time-since-baseline term) were included (via random effects or level-2 residuals) to allow for unexplained/residual variation between participants in the continuous outcomes at baseline and in its rate of change, respectively. An additional term in the random part of the model estimated intercept-by-slope covariance (163).

Using linear mixed-effects models, the analytical strategy employed in the following empirical chapters is similar to the analyses by Thorisdottir, Sigurvinsdottir, Kristjansson, et al. (2020), which examined the longitudinal association between social media use and psychological distress in adolescents (40).

First, the tests of hypotheses that are related to the research questions (set out in each chapter) will involve the coefficients in the fixed part of the models and will mainly focus on the associations between SMU/SNS use (time-varying) and the outcomes. In contrast to the study by Thorisdottir, Sigurvinsdottir, Kristjansson, et al. (2020), family factors will be treated as both potential moderators and control variables in my analyses (40). However, similar to their study, family structure will be treated as time-invariant, whilst subjective family indicators (parent-child relationship quality and parenting styles) will be treated as time-variant in my analyses.

Second, time-since-baseline in the aforementioned paper was treated continuously and was entered into the models by a single term (i.e., a linear trend). The tests of hypotheses related to (i) differences across groups (e.g., SMU categories, gender, etc.) in the outcome at baseline (intercept): these were examined by the main effects of the variables of interest and (ii) differences across groups in the estimated rate of change in the outcome for a one-unit increase in time (slope): these were examined by the inclusion of interaction terms (e.g., social media use by time).

These interaction terms assessed, for example, whether any differences in the average levels of the outcome across SMU categories increased or decreased for a unit increase in time (or equivalently as participants grew older by one year (40)). For example, widening differences over time might indicate a greater decline in average self-esteem over time for heavy social media users versus light or moderate social media users.

Finally, two-way interaction terms (as in the aforementioned paper) were included in the fixed-effects part of the model to assess if the associations between social media use and the outcomes (differences in the intercept) differed between males and females, and by family factors. Three-way interaction terms were included in the fixed-effects part of the model to assess if the associations between social media use and the outcomes (e.g., differences in the rate of change across SNS categories) differed between males and females, and/or by family factors. For example, a moderating effect by gender may be present if any greater decline in average self-esteem for heavy users of social media versus light or moderate users was more pronounced in females than in males.

4.4 Ethical approval and consent to participate

As set out in the UKHLS user guide (161), the collection, use and sharing of data in research studies with people require that ethical and legal obligations are respected. Study protocols and research programmes for the UKHLS are scrutinised by research ethics committees to assure that ethical and legal obligations are always respected. The Ethics Committee of the University of Essex provided ethical approval of the UKHLS main survey (161). As stated by Booker, Kelly and Sacker (2018), verbal consent from all respondents was required for participation. 'Youth' participation required the interviewer to ask the parent/guardian for their verbal consent, receive an affirmative response and then ask the young person for their consent, at which point the young person was free to agree or refuse (10).

Ethical approval for the KCYPS was obtained by Statistics Korea for baseline and follow-up data collection (approval number: 40202). Prior to data collection, informed written consent was obtained from the parent/main guardian of each student and verbal assent was obtained from the participants. All data in the KCYPS is de-identified (106).

4.5 Conclusion

To summarise, this chapter introduced the research problem and conceptual framework. I then discussed the process of choosing and deriving the final datasets for my longitudinal analyses and provided relevant details on each dataset as well as the modelling strategy employed. Finally, I described the ethical approval process for the selected datasets.

Chapter 5: SNS use and self-esteem in the UK

Chapter 5 represents the first empirical investigation in my thesis, focusing on exploring the relationship between the duration of social networking site use and self-esteem among young people in the UK. The chapter also aims to examine whether gender and family factors play a moderating role in this association. To set the context, the chapter begins with a review of relevant literature, followed by a statement of research questions and hypotheses. A detailed account of the methods is provided, which includes describing the participant demographics, measures used, analytical techniques employed and how missing data were addressed. The chapter then presents the study's findings and offers a brief discussion of the results, highlighting specific strengths and limitations. A more comprehensive analysis of the results, as well as a broader discussion of the study's strengths and limitations, will be presented in the Discussion chapter (Chapter 8).

5.1 Background

In Chapters 1 and 2, I explored the importance of self-esteem in young people and how levels of self-esteem could potentially be associated with various aspects of social media use. For example, lower self-esteem was found to be associated with greater social media addiction in two studies conducted in 2014-15, one among 15-22-year-olds in Hungary (142) and another among participants aged 16 years and over in Norway (49). Additionally, researchers have argued that social media is particularly important to study in relation to user self-esteem. This is attributed to the user's potential to compare themselves and their lives to the content posted by others within their network (21), which is predominantly characterised by positive and idealised portrayals (22).

Based on my literature review in Chapter 2, six studies published in peer-reviewed journals used data from the UKHLS to explore the associations between duration of SNS use and various aspects of mental health and well-being (10, 107, 137-140). These are summarised below.

Plackett, Sheringham and Dykxhoorn (2022) used UKHLS data from ten waves (2009-19) and found that the duration of SNS use was not associated with poorer mental health (socioemotional difficulties) in 10-15-year-olds, and self-esteem did not mediate this association in adjusted path analysis (137). From seven waves of UKHLS data (2009-17), Twigg, Duncan and Weich (2020) found that heavy SNS use was associated with lower life satisfaction over time in 10-15-year-olds, and very high SNS use was associated with lower levels of life satisfaction in females only (138). The authors of this study also found that being in a supportive family increased life satisfaction over two time points.

Combining data from waves 3 and 4 of the UKHLS (2011-13), Jagtiani, Kelly, Fancourt et al. (2019) found that among 16-21-year-olds living with family members, heavy SNS use was associated with lower well-being on average and that sharing no evening family meals was associated with lower well-being for heavy SNS users compared to non-users (107). Using eight waves of UKHLS data (2009-16), Orben, Dienlin and Przybylski (2019) showed that among 10-15-year-olds, greater SNS use was associated with slightly lower levels of life satisfaction in both genders (139).

Using data from five waves (2009-15), Booker, Kelly and Sacker (2018) observed that longer duration of SNS use at age 10 was associated with worse socio-emotional difficulties with increasing age in females only and that worse well-being was associated with longer duration of SNS use at age 10 in females only (10). Booker, Skew, Kelly, et al. (2015) used UKHLS data from 2009 and observed that among 10-15-year-olds, longer duration of SNS use was associated with lower odds of happiness and higher odds of socio-emotional difficulties (140).

Despite the aforementioned research and drawing on Bronfenbrenner's ecological framework (Section 1.4.1), more longitudinal work is needed, especially studies that investigate the influence of family factors such as family structure (138) in relation to the associations between social media use and mental health and well-being. Research has highlighted the importance of investigating interrelated features of a child's proximal family environment alongside examining patterns in children's behaviour across childhood (110). Moreover, the extant literature on the relationship between social media use and mental health and well-being has primarily concentrated on outcomes such as depression, anxiety (146) and happiness (138). Few studies have explored self-esteem as an outcome of well-being in the analysis of social media use.

5.2 Research questions and hypotheses

In line with the aims and objectives listed in Chapter 3, this chapter uses data from the UKHLS to investigate the cross-sectional and longitudinal associations between duration of SNS use and self-esteem in young people (i.e., 'youths' (aged 10-15 years) and 'young adults' (aged 16-21 years)). I also explore whether gender, family structure and parent-child relationship quality may confound or moderate this relationship. Due to the wide age range in this analytical sample, I also consider age as an independent predictor of self-esteem.

There were five main research questions and hypotheses considered in this chapter. These were set in light of the gaps in the literature highlighted in Chapter 2, that is, exploring gender and family factors using longitudinal data. The analytical strategy for addressing these research questions will be elaborated upon in Section 5.3.3.

The research questions (**RQ**) and accompanying hypotheses (**H**) are set out below.

RQ1: Descriptive analyses of self-esteem and SNS use

RQ1a: Do baseline levels of self-esteem vary on average by the duration of SNS use, gender, family structure and parent-child relationship quality?

RQ1b: Does the duration of SNS use at baseline vary on average by gender, family structure and parent-child relationship quality?

H1: Descriptive analyses of self-esteem and SNS use

H1a: Baseline self-esteem is lower on average for heavy SNS users, females, participants not belonging to a two-parent household, participants who talked

less to their mothers and fathers about things that matter and participants who quarrelled more with their mothers and fathers.

H1b: The prevalence of heavy SNS use at baseline is higher for females, participants not belonging to a two-parent household, participants who talked less to their mothers and fathers about things that matter, and participants who quarrelled more with their mothers and fathers.

RQ2: Gender as moderator of the SNS use and self-esteem association

RQ2: Does gender moderate the association between the duration of SNS use and self-esteem?

H2: Gender as moderator of the SNS use and self-esteem association

H2: Gender moderates the association between the duration of SNS use and self-esteem, with a stronger association in females than males.

RQ3: Independent associations between key variables and self-esteem

RQ3: Are duration of SNS use, family structure and parent-child relationship quality independently associated with self-esteem?

H3: Independent associations between key variables and self-esteem

H3a: Longer duration of SNS use (e.g., heavy versus light use) is significantly associated with lower self-esteem at baseline (main effects) and a faster rate of decline in self-esteem (interaction with time-in-study) while holding various confounding variables and family variables constant.

H3b: Participants not belonging to a two-parent household, participants who talked less to their mothers and fathers about things that matter, and participants who quarrelled more with their mothers and fathers are associated with lower self-esteem at baseline and a faster rate of decline in self-esteem while holding various confounding variables and family variables constant.

RQ4: Family factors as moderator of the SNS use and self-esteem association

RQ4: Do family structure and parent-child relationship quality moderate the association between the duration of SNS use and self-esteem?

H4: Family factors as moderator of the SNS use and self-esteem association

H4: Family structure and parent-child relationship quality moderate the association between duration of SNS use and self-esteem, for example, heavy versus light SNS use is associated with a faster rate of decline in self-esteem among participants who talked less to their mothers and fathers about things that matter, holding all else constant.

RQ5: Supplementary analysis

RQ5: After controlling for prior (wave 4) self-esteem and other confounding variables, is the duration of SNS use associated with self-esteem?

H5: Supplementary analysis

H5: Longer duration of SNS use is significantly associated with lower self-esteem at baseline (wave 6; main effects) and a faster rate of decline in self-esteem (interaction with time-in-study) while holding prior (wave 4) self-esteem and other confounding variables constant.

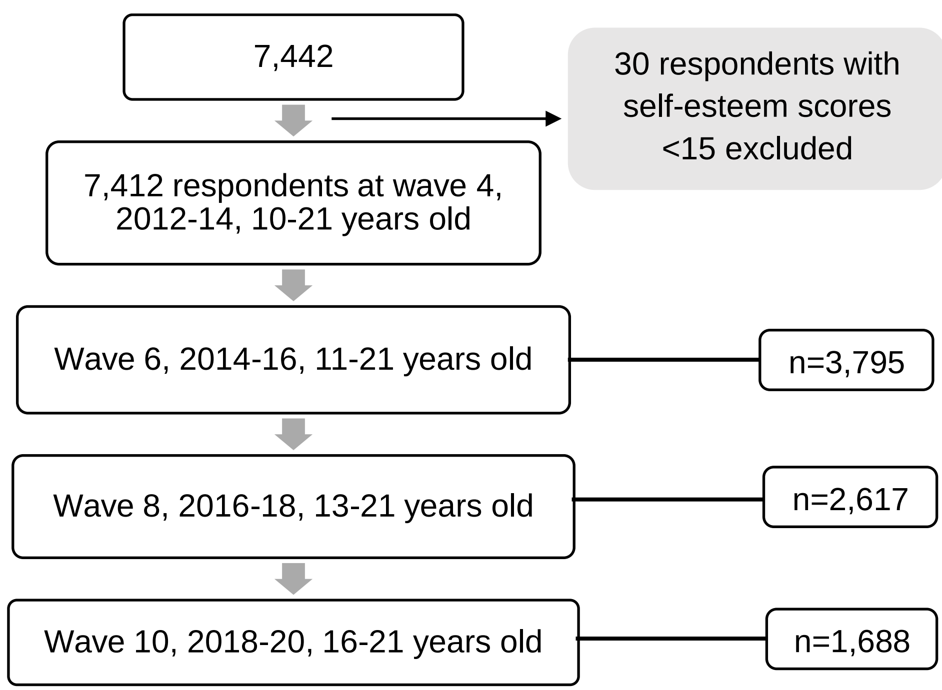
5.3 Methods

5.3.1 Analytical sample

The target sample for this study was derived from UKHLS ‘youths’ (aged 10-15 years) and ‘young adults’ (aged 16-21 years) at wave 4. Details of the dataset is provided in Section 4.3.2 of Chapter 4 and is not repeated here. At each wave, the data from ‘youths’ and ‘young adults’ were harmonised and pooled together to create a single dataset for analysis. Wave 4 was selected as the baseline for this study because this was the first occasion when questions on self-esteem were asked among ‘youths’ and ‘young adults’. Participants with valid data on self-esteem at wave 4 (see below) came from the UKHLS main study, which collects information from the UK General Population Sample (GPS) and the Ethnic Minority Boost Sample (EMBS). From wave 2 onwards, the main study also included information from continuing participants of the British Household Panel Study (BHPS). Questions on self-esteem were asked in even-numbered waves of the ‘youth’ and ‘young adult’ panels only.

Those with a valid self-esteem score at wave 4 (n = 7,412) were followed up to wave 10. Of those at baseline, 51% (n = 3,795) had a valid self-esteem score at wave 6, 35% (n = 2,617) had a valid self-esteem score at wave 8 and 23% (n = 1,688) had a valid self-esteem score at wave 10. Hence, I had a total of n = 15,512 non-missing (person-wave) observations on self-esteem over the four waves (4, 6, 8, and 10) from the 7,412 participants with a valid self-esteem score at wave 4. 15% (n = 1,075) of participants had valid self-esteem scores at all four waves and 39% (n = 2,901) of participants had valid self-esteem scores only at baseline (wave 4). The process of deriving my analytical sample for the analyses in this chapter is illustrated in Figure 5.1.

Figure 5.1: Analytical sample of the UKHLS



The respondents from the ‘youth’ and ‘young adult’ panels with valid self-esteem scores at wave 4 were asked similar questions on survey items such as SNS use (see below). They were followed up to wave 10 in this study: at wave 4, participants were 10 to 21 years old; at wave 6, participants were mostly 11 to 21 years old; at wave 8, participants were mostly 13 to 21 years old, and at wave 10, participants were mostly 16 to 21 years old. Participants older than 21 years became ineligible for the self-esteem analysis because the self-esteem questions were only included in the ‘youth’ and ‘young adult’ panels.

There were 30 respondents with self-esteem scores less than 15 at wave 4 and these were excluded from the analytical sample (see below for details).

5.3.2 Measures

In this section, I describe how each measure relevant to this empirical study was measured in the UKHLS. These measures are self-esteem, social networking site (SNS) use, family structure, parent-child relationship quality and confounders.

Outcome variable: Self-esteem

Self-esteem is assessed in the UKHLS using a revised version of the Rosenberg Self-Esteem Scale (RSES-R) (11). It is measured by a set of eight items which capture how best individuals feel about themselves, rated on a four-point Likert scale, from “Strongly agree” (coded 1) to “Strongly disagree” (coded 4). The scale measures both positive and negative feelings about the self (e.g., “*I am able to do things as well as most other people*” and “*At times I feel I am no good at all*”), as set out below (Table 5.1). ‘Youth’ and ‘young adult’ participants were asked the self-esteem items via self-completion and interview, respectively.

Table 5.1: Self-esteem items from the RSES-R

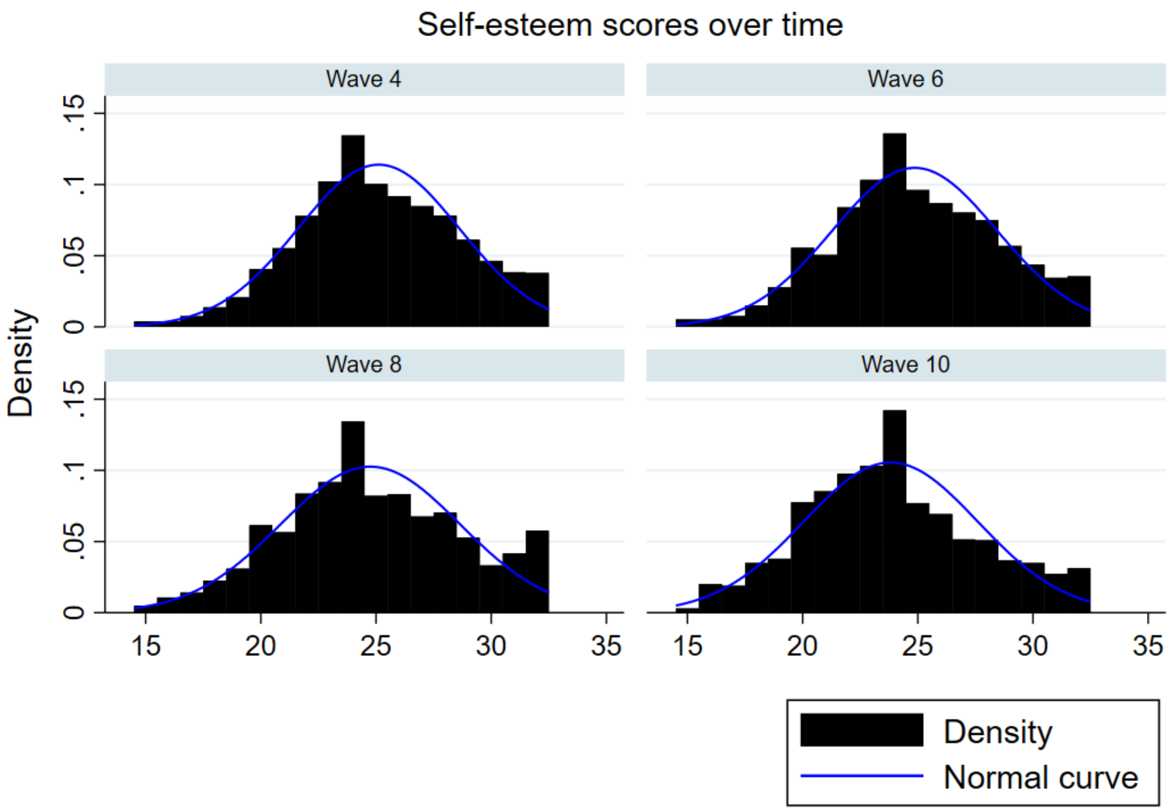
Self-esteem items	Strongly agree	Agree	Disagree	Strongly disagree
1. I feel that I have a number of good qualities.	1	2	3	4
2. I feel that I do not have much to be proud of.	1	2	3	4
3. I certainly feel useless at times.	1	2	3	4
4. I am able to do things as well as most other people.	1	2	3	4
5. I am a likeable person.	1	2	3	4
6. I can usually solve my own problems.	1	2	3	4
7. All in all, I am inclined to feel I am a failure.	1	2	3	4
8. At times I feel I am no good at all.	1	2	3	4

The four positively worded items (shaded in grey in Table 5.1) were reverse coded; higher scores on the scale reflected a greater level of self-reported overall self-esteem. Responses on all eight items were summed to form an overall self-esteem score (range: 8 to 32).

The histograms of the raw self-esteem scores at baseline (wave 4) depicted a slight negative skew in its distribution, mainly due to the low scores of a minority of participants (scores <15: n = 30). As a result, I included only participants with self-esteem scores greater than or equal to 15 to obtain an approximately normal distribution for the continuous outcome.

Figure 5.2 shows the distribution of self-esteem scores at each of the even-numbered waves for those in the analytical sample. Internal reliability of this scale, as assessed by Cronbach's alpha, was high in the present study (α=0.78 on the 7,412 participants with valid answers on all eight items of self-esteem at wave 4).

Figure 5.2: Distribution of self-esteem scores by study wave



Exposure variable: Duration of SNS use

As mentioned in Chapter 1, it is important to conceptually distinguish between the duration of social media use (e.g., “how many hours per day do you spend using…”) and the general frequency of social media use (e.g., “how often do you spend using….”). The single-item question on the amount of time spent on social networking sites included in the UKHLS refers to the duration of SNS use.

Participants in the ‘youth’ questionnaire were asked via self-completion:

“Do you belong to a social web-site such as Bebo, Facebook or MySpace?” Response categories for this item were:

1: Yes

2: No

Those responding positively were asked: *"How many hours do you spend chatting or interacting with friends through a social web-site like that on a normal school day?"* Response categories for this item were:

1: None
2: Less than 1 hour
3: 1-3 hours
4: 4-6 hours
5: 7 or more hours

Respondents in the 'young adult' questionnaire were asked during the main interview:

"Do you belong to any social networking web-sites?" Response categories for this item were yes and no. Those answering positively were asked: *"How many hours do you spend chatting or interacting with friends through social web-sites on a normal weekday, that is Monday to Friday?"* Response categories for this item are the same as those in the 'youth' questionnaire.

Responses were recoded into four categories as follows to achieve sufficient numbers for analysis: (i) those not belonging to any social networking website and spent no hours on it (classified as **'non-users'**); (ii) those using SNSs for 1 hour or less (**'light users'**), (iii) those using SNSs for 1-3 hours (**'moderate users'**) and (iv) those using SNSs for 4+ hours (**'heavy users'**). As my analysis involved tracking participants from 'youth' to 'young adulthood', I assumed that a normal school day (wording in the 'youth' questionnaire) refers to Monday to Friday as this ensures consistency with the SNS use question asked in the 'young adult' questionnaire (normal weekday).

Potential moderator: Family structure

The concept of family structure in studies such as those by Park and Lee (2020) refers to the family members that children or adolescents were observed to be living with at the time of data collection (family composition) (165). Using data from the 2018 Korean Youth Risk Behavior Web-based Survey (KYRBS), Park and Lee (2020) investigated associations between family structure, health behaviours, mental health and academic achievement in Korean adolescents. In this paper, the list of family members that participants were living with was used to classify family structure into four groups: “two-parent family (intact family)”, “single-mother family”, “single-father family” and “restructured family” (defined as families with stepfathers or stepmothers but could also contain one or two parents) (p. 3) (165).

In my study, I investigated whether family structure was independently associated with the initial levels of self-esteem and the rate of change in self-esteem (**RQ3**). In addition, I investigated whether family structure moderated the association between the duration of SNS use and self-esteem (**RQ4**). Family structure was assessed in my study only at baseline (wave 4) and therefore treated as time-invariant in the modelling to avoid making assumptions about the directionality of changes in family structure over time, as such changes can represent both positive and negative transitions.

<u>Household information: number of parents present in the household</u>

In the UKHLS, the head of the household is asked to describe the relationship of each member of the household to every other member (using a showcard) with the 30 options below[41]:

1: Husband/Wife
2: Partner/Cohabitee
3: Civil partner
4: Natural son/daughter
5: Adopted son/daughter
6: Foster child
7: Stepson/Stepdaughter
8: Son-in-law/Daughter-in-law
9: Natural parent
10: Adoptive parent
11: Foster parent

[41] This question was asked for all households consisting of more than one person and no assumptions were made about any relationship.

12: Stepparent
13: Parent-in-law
14: Natural brother/sister
15: Half-brother/sister
16: Stepbrother/sister
17: Adopted brother/sister
18: Foster brother/sister
19: Brother/Sister-in-law
20: Grandchild
21: Grandparent
22: Cousin
23: Aunt/Uncle
24: Niece/Nephew
25: Other relative
26: Employee
27: Employer
28: Lodger/Boarder/Tenant
29: Landlord/Landlady
30: Other non-relative

This information is provided to users of the UKHLS data in the *egoalt* file. At each wave, the *egoalt* file can be used to create household composition variables which can be attached to the survey items (e.g., gender, SNS use and self-esteem) to examine their associations with family structure. I used the *egoalt* file to identify whether participants were living with any parent(s) at baseline (wave 4 for the present study) and so were classified in the dataset as a (i) natural son/daughter, (ii) adopted son/daughter, (iii) foster child or (iv) stepson/stepdaughter (in relation to a specific adult living in the same household).

In assessing the aspects of parent-child relationships, the parent could be a natural parent, step-parent, adoptive parent, or foster parent. Whilst there is considerable debate around the terms natural parent and birth parent, I have decided to follow the term used in the UKHLS (i.e., natural parent), to denote a child born to his/her biological parent. The UKHLS mainstage questionnaire documentation (166) states that the instruction given for the question pertaining to relationships between members in the household was to treat relatives of cohabiting members of the household as though the cohabiting couple were married unless they were a same-sex couple. Hence, the UKHLS defined a step-parent as a co-resident and married adult partner of the natural parent for heterosexual couples.

For each person living in the household, there is one row in the *egoalt* dataset for each pair of individuals in the household. For example, two children living with both natural parents would each be represented by three rows: one for each natural parent and one for their sibling. By adding and merging files using the relevant study identifiers, I summarised the relevant relationship between each other member of the household for each participant. To classify family structure at baseline, I derived a variable based on the number of parents that each participant was living with (values 0, 1, 2+); hence, participants were classified at wave 4 as (i) living with no parents, (ii) living with one parent, or (iii) living with two or more parents.

Potential moderator: Parent-child relationship quality

The following section describes how I operationalised parent-child relationship quality in this study chapter. Subjective indicators of parent-child relationship quality were asked at odd-numbered waves (i.e., waves 1, 3, 5, 7 and 9). There were no specifications regarding how participants defined who their parents were (e.g., biological, adopted, etc.). The only guidance given was to include their parents even if they lived in a different household from the participant. As such, no assumptions were made regarding the specifications of the parent-child dyad. Measures were derived based on participants' responses to four questions in the 'youth' (self-completion) and 'young adult' (interview) questionnaires which related to the talking and quarrelling aspects of parent-child relationships[42]. These questions were as follows:

[42] Variables that assessed parents' involvement with their children's school (e.g., parents' interest in how their children do at school and how often they go to school parent evenings) were not used as these

"The next few questions are about your relationship with your parents even if either of them lives in a different household to you."

Talking to mother: *"How often do you talk to your mother, about things that matter to you?"* Response categories were as follows:

1: Most days
2: More than once a week
3: Less than once a week
4: Hardly ever
5: Do not have a mother

Talking to father: Same question and response categories as above.

Quarrelling with mother: *"How often do you quarrel with your mother?"* Response categories are the same as above.

Quarrelling with father: Same question and response categories as above.

I chose not to combine these into a composite score so that I could assess the differences between parents (e.g., mother-child versus father-child) and the aspects of relationship quality (e.g., talking versus quarrelling).

Responses were recoded so that higher scores indicated more frequent talking and quarrelling (1: "hardly ever", 2: "less than once a week", 3: "more than once a week", 4: "most days"). Participants who stated that they did not have a mother/father were scored as 0 on these variables[43]. As in similar studies (30), these variables (which reflect the subjective aspects of family life) were treated as time-varying in the longitudinal models. As these questions were only asked at the odd-numbered waves,

factors may not be directly linked to parent-child relationship quality, as opposed to the communication aspects of the questions asked above.

[43] Of those who answered the questions on quarrelling at wave 3, 53 participants (1%) reported that they did not have a mother and 387 participants (7%) reported that they did not have a father.

scores on the parent-child relationship quality variables were carried forward to the following wave (when the self-esteem items were administered).

Confounders

To identify potential confounders in the association between SNS use and self-esteem, I considered previous studies collated in Chapter 2, as well as variables that showed statistically significant p-values in the descriptive analyses. Confounders are variables that are associated with both the exposure and outcome and are not on the causal pathway. By selecting these variables, I aimed to minimise the risk of spurious associations and increase the internal validity of my study.

Self-reported responses for gender, age (in years) and ethnicity were included, with 18 ethnic identities being collapsed into five categories (White, Black, Asian, Mixed, and other ethnicities).

Total gross household income in the previous month was chosen as a marker of socioeconomic position (SEP). The income variable in the UKHLS datasets was equivalised for household composition and was grouped into quintiles from lowest to highest. This was computed after obtaining the analytical sample of participants with valid self-esteem scores at wave 4.

Parental educational qualification was provided by the parent(s) in the adult interview. I merged mother’s and father’s highest educational qualification level (with six categories: no qualification, other qualification, GCSE, A level, other higher qualification, and degree) into a single variable based on the highest qualification achieved by either parent. This variable was recoded as parents’ highest educational qualification level (with five categories: no qualification, GCSE, A level, degree, other (higher) qualification). This variable was missing if no parent(s) took part in the study at wave 4. Further details of item missingness for the variables are provided in Section 5.3.4. Living area (urban/rural) was not chosen as a confounder due to the statistically insignificant bivariate associations in the descriptive analyses. All confounders were assessed in this study only at baseline (wave 4); hence, they were treated in the longitudinal analyses as time-invariant.

5.3.3 Analytical strategy

Descriptive analyses

To answer the research questions set out in Section 5.2 (**RQ1**), I conducted two sets of bivariate analyses based on the analytical sample at wave 4.

First, I explored differences in the mean levels of self-esteem at baseline by categories of SNS use, gender, family variables and potential confounders such as age, ethnicity, and household income. Statistical significance for the difference in means of self-esteem was examined using linear regression models and Wald tests.

Second, I explored differences in SNS use at baseline by demographics, family variables and potential confounders. Statistical significance was examined using Pearson's chi-square test for a two-way table (test for independence between two variables). Participants who reported not having a mother/father were excluded from the tests when examining the significance of the associations for the parent-child relationship quality variables. All tests of statistical significance were based on two-tailed probability ($p<0.05$).

Analyses were performed using Stata V17 (StataCorp, Texas, USA), accounting for the complex survey design of the UKHLS by using a weight which consisted of the wave 4 cross-sectional 'youth' interview weight (*d_ythscub_xw*) and the wave 4 cross-sectional adult self-completion interview weight (*d_indscub_xw*)[44]. The descriptive analyses were computed using the *svy* commands, taking into account differential non-response (*d_ythscub_xw*; *d_indscub_xw*) and the clustering (d_psu) and stratification (d_strata)

[44] There were 336 participants in the 'youth' panel and 315 participants in the 'young adult' panel with a weight of zero: they were assigned a value on the weight variable by using the average weight for their respective panels. For the analytical sample, the proportions of 10-15- and 16–21-year-olds were 52% and 48%, respectively, before and after weighting (Table 5.4).

variables that were determined at the time of sampling. These analyses set out to describe the key sample characteristics as well as to identify potential confounders to include in the linear mixed-effects models estimated on the longitudinal data.

Linear mixed-effects modelling

To answer the research questions set out in Section 5.2 (**RQ2-5**), I performed linear mixed-effects modelling in four stages. Linear mixed-effects models with time-since-baseline as timescale (expressed in years, coded as 0, 2, 4 and 6) were used to estimate the associations between the duration of SNS use and the change in self-esteem over the study period. Differences in age between the participants were accounted for in the analyses by adjusting for age at baseline (range 10 to 21 years). This method of analysis is described in detail in Section 4.3.3 of Chapter 4.

Moderation by gender

As explained in the Introduction, any potential moderating effect of gender on the associations between SNS use and self-esteem was tested for by adding gender by SNS use interaction terms (**RQ2**).

First, three-way (SNS use × gender × time-since-baseline) and two-way (SNS use × gender) interaction terms were included to decide whether the subsequent regression models would be stratified by gender.

Once this was decided, I undertook the modelling in four stages.

Models 1-3 were estimated to examine **RQ3** (independent associations with self-esteem).

- **Model 1** included the main exposure (**SNS use** as a categorical variable) and year as independent variables (main effects) plus the interaction SNS use × time to allow the estimated 1-year rate of change in self-esteem to vary by SNS use categories, after controlling for confounders.

- **Model 2** included the terms in Model 1 plus the objective family variable, **family structure** and its interaction with time to allow the estimated 1-year rate of change in self-esteem to vary by the categories of family structure.

- **Model 3** included the terms in Model 2 plus the subjective family variables assessing **parent-child relationship quality** (talking to and quarrelling with mother and father) and their interactions with time to allow the estimated 1-year rate of change in self-esteem to vary by the subjective family variables. Moreover, the aim of my research questions (**RQ3** and **RQ4**) was to examine each subjective family variable while controlling for the other in the same model.

Models 4a and 4b were estimated to examine **RQ4** (moderation by family factors).

- **Model 4a** included the terms in Model 3 plus three-way interaction terms (family variables × SNS use × time) to allow the estimated change in self-esteem to vary by combinations of family variables and SNS use.

- **Model 4b** included the terms in Model 3 plus two-way interaction terms (family variables × SNS use) to allow the baseline levels of self-esteem to vary by combinations of family variables and SNS use.

The mixed-effects models were estimated using Stata, with the datasets in long form (i.e., each row represented one wave per participant). Estimation via mixed models in Stata requires any specified weighting variable to not be time-varying within individuals.

Longitudinal weights are developed by the UKHLS team mainly for monotone attrition, i.e., for participants who have participated in consecutive waves (a balanced panel), although advice is available for users to create a tailored longitudinal weight for a specific combination of waves (167). As mentioned earlier, only 15% of participants had valid self-esteem scores at all four waves. To maximise inclusion in the mixed-effects models, and as cross-sectional weights in the UKHLS are derived from the longitudinal weights (and so account for attrition to some degree) (168), the models were estimated using the derived cross-sectional weight at wave 4 using the mixed command in Stata with the option *pweight*.

Supplementary analysis: adjustment for prior self-esteem

As stated by Kelly and colleagues (2018), any longitudinal investigations of associations between social media use and mental health and well-being outcomes need to acknowledge the possibility of a bidirectional or cyclical relationship between social media use and mental health (104): not only may heavy social media use negatively influence well-being, but also young people who experience poor well-being might be more likely to use social media for extended periods of time. This highlights the importance of conducting a supplementary analysis to estimate the associations between social media use and self-esteem after adjustment for prior levels of mental health or well-being.

To examine the presence of any such cyclical relationships, previous investigations have adjusted for values of the outcome variable assessed prior to the first wave when participants were classified into categories of social media use (104, 164). Hence, to address **RQ5**, I re-ran my analysis using self-esteem scores at wave 6 as the baseline score so that I could statistically adjust for self-esteem scores at wave 4. This allowed me to estimate whether prior self-esteem played any role in confounding the associations between the duration of SNS use and self-esteem.

All models adjusted for confounders and their interactions with time-since-baseline.

5.3.4 Missing data

Multiple imputation is increasingly used as a method to fill in missing values for variables (item non-response) as it reflects the uncertainty around the true value, in contrast to simpler methods such as mean imputation. These imputed values are then used in the analysis of interest, such as in a linear mixed-effects model, and the results of each imputed dataset are combined into an overall estimate using Rubin’s rules (169).

I used multiple imputation to avoid dropping cases with missing data (e.g., item non-response) on the exposure variables and potential confounders using chained equations (MICE). MICE uses a separate conditional distribution for each imputed variable; there is one imputation model for each variable with missing values. MICE is suitable for *"imputing incomplete, large, national, public datasets"* (p. 6) (170).

The MICE distributions available in Stata are (i) binary, ordered and multinomial logistic regression for categorical variables, (ii) linear regression and predictive mean matching (PMM) for continuous variables and (iii) Poisson and negative binomial regression for count variables. Multinomial logistic regression was a clear choice for the categories of SNS use, household income quartiles, ethnicity, parent-child relationship quality (talking to and quarrelling with mother and father) and highest parental educational qualification. Binary logistic regression was used for the area of residence (rural/urban). I created 20 imputed datasets, similar to the study by Kelly, Zilanawala, Booker, et al. (2018) which investigated the associations between social media use and depressive symptoms among 14-year-olds using the UK Millennium Cohort Study (104). Table A1 in the Appendices provides a summary of the variables used in the imputation models and the number of missing observations for each imputed variable.

5.4 Results

5.4.1 Non-response and attrition

As explained by Bu (2022), in longitudinal studies, non-response typically refers to initial non-response at the first wave of data collection, whereas attrition refers to non-response at later wave, for example due to refusal to continue taking part in the study (171). Any systematic differences in response and/or attrition rates across groups potentially reduces sample representativeness and can lead to biased estimates of parameters (171).

Members of the UKHLS team examined the extent and correlates of non-response at waves 1 and 2 (172). For example, for the general population sample (all wave 1 enumerated[45] individuals aged 10 to 15 years, i.e., all persons who were eligible for the wave 1 'youth' questionnaire), response to the 'youth' self-completion questionnaire at wave 1 was presented by individual characteristics (gender, age and region) (172).

[45] Enumerated persons are persons in a household where at least one person was interviewed (160).

Overall, 77% of 10–15-year-olds were observed to have completed the ‘youth’ self-completion questionnaire. Response rates were slightly lower among males (76% males versus 78% females) and were lower among 10-year-olds and 15-year-olds (172).

In addition, attrition at wave 2 relative to wave 1 was examined across sociodemographic characteristics assessed at wave 1. An analysis of the probability of being re-interviewed at wave 2 conditional on having completed the individual interview at wave 1 showed an overall response rate (full interview, excluding proxies) of 75%, with lower probabilities among respondents aged under 30 years, those in urban rather than rural areas, renters rather than owners and those living in flats rather than houses (172).

To examine patterns in participation in this study, I conducted similar analyses to examine possible differences in the propensity to respond. For all wave 4 enumerated individuals aged 10 to 21 years (n=10,855), inclusion in my analytical sample at wave 4 (i.e., having a valid self-esteem score) was examined by gender, age and Government Office Region (Table 5.2).

Table 5.2: Inclusion in the analytical sample at wave 4 by characteristics of enumerated individuals at wave 4

	Valid self-esteem	Base
	N (inclusion %)	**N**
Total	7442 (68.6)	10,855
Sex		
Male	3663 (66.6)	5,499
Female	3779 (70.6)	5,356
Age		
10	565 (65.8)	859
11	661 (71.8)	920
12	616 (72.3)	852
13	694 (73.5)	944
14	656 (71.9)	913
15	648 (70.1)	925
16	633 (69.6)	910
17	665 (71.0)	936
18	636 (69.4)	916
19	615 (64.5)	954
20	540 (62.3)	867
21	513 (59.7)	859
Region		
North East	237 (65.1)	364
North West	676 (66.2)	1021
Yorkshire & The Humber	602 (66.2)	910
East Midlands	596 (72.7)	820
West Midlands	626 (70.3)	891
East of England	611 (74.0)	826
London	977 (62.3)	1568
South East	837 (71.7)	1167
South West	505 (72.8)	694
Wales	543 (66.5)	817
Scotland	667 (72.3)	923
Northern Ireland	564 (66.4)	849

Notes: Base is all wave 4 enumerated individuals aged 10 to 21 years. Completion (inclusion in the analytical sample) is defined as having a valid score on the self-esteem scale (including the 30 participants with scores <15). This analysis was not weighted.

Overall, 69% of 10-21-year-olds (enumerated individuals at wave 4) had self-esteem scores at wave 4 (included in my analytical sample). Response rates were lower among males (67% males versus 71% females), 10-year-olds, 19-21-year-olds and those living in London.

To examine attrition, I examined inclusion in the analytical sample at wave 4 among those 10-21-year-old participants who participated at the preceding wave by gender, age and region (Table 5.3).

Table 5.3: Inclusion in the analytical sample at wave 4 by characteristics of individuals who took part at wave 3

	Valid self-esteem	Base
	N (inclusion %)	**N**
Total	5770 (62.3)	9,269
Sex		
Male	2800 (61.6)	4,548
Female	2970 (62.9)	4,721
Age		
10	531 (73.8)	720
11	502 (73.3)	685
12	577 (74.0)	780
13	533 (73.0)	730
14	537 (69.2)	776
15	517 (70.2)	736
16	594 (71.4)	832
17	570 (65.4)	871
18	536 (60.2)	891
19	465 (58.7)	792
20	397 (54.6)	727
21	11 (1.5)	729
Region		
North East	192 (58.7)	327
North West	533 (60.2)	885
Yorkshire & The Humber	432 (58.6)	737
East Midlands	459 (63.8)	719
West Midlands	492 (65.8)	748
East of England	455 (65.2)	698
London	741 (57.7)	1285
South East	642 (62.3)	1030
South West	398 (61.8)	644
Wales	434 (62.1)	699
Scotland	531 (65.2)	815
Northern Ireland	460 (67.8)	678

Notes: Base is all individuals aged 10 to 21 years who participated at wave 3 ('youth' or individual interview). Completion (inclusion in the analytical sample) is defined as having a valid score on the self-esteem scale (including participants with scores <15). This analysis is not weighted.

Overall, 9,269 participants aged 10 to 21 years took part in the study at wave 3. Of those, 5770 participants (62%) had a valid self-esteem score at wave 4 (and so were included in my analytical sample).[46] Response rates were slightly lower among males (62% males versus 63% females) and were lower among 17-to-20-year-olds and those living in the North East, Yorkshire & The Humber, and London. The considerably lower response rate for those aged 21 years at wave 3 is attributable to some extent to study design, as the self-esteem questions are not asked for those aged over 21 years.

5.4.2 Participants

A breakdown of the baseline (wave 4) characteristics of the sample used in my main analysis is given in Tables 5.5 and 5.6. As the items on parent-child relationship quality were included in the UKHLS at odd-numbered waves only, the tables show the bivariate associations between parent-child relationship quality as measured at wave 3 and self-esteem and duration of SNS use as measured at wave 4. Both analyses were weighted using the 'youth' cross-sectional weight and 'young adult' cross-sectional interview weight provided with the datasets at wave 4. Both tables also include the results of bivariate statistical tests outlined in the analytical strategy in Section 5.3.3 using the complex survey design features of the UKHLS.

RQ1a: Baseline levels of self-esteem

Table 5.4 shows the means and standard deviations (SD) of self-esteem by the duration of SNS use (four categories: non-users, light users, moderate users, heavy users), family variables and confounders.

[46] Overall, 7442 participants aged 10-21 had a valid self-esteem score at wave 4. 1672 participants in the analytical sample at wave 4 did not participate at the preceding wave. Possible reasons for this include being below the minimum age limit (10 years old) for the 'youth' questionnaire (and so not eligible at wave 3) and non-response at wave 3.

Table 5.4: Mean self-esteem at wave 4 by SNS use, family variables, confounders

Characteristics	Self-esteem		
	n (column %)	Mean (SD)	P-value
Overall	7,412 (100)	25.1 (3.5)	-
SNS use:			
No profile/hours (non-user)	1,855 (24)	25.4 (3.5)	<0.001
<1 hour (light user)	2,184 (30)	25.2 (3.4)	
1-3 hours (moderate user)	2,077 (28)	25.0 (3.5)	
4+ hours (heavy user)	1,283 (18)	24.6 (3.8)	
Missing*	13 (0)		
Family structure (wave 4):			
Living with no parents	521 (6)	24.6 (3.9)	<0.001
Living with one parent	1,851 (26)	24.8 (3.5)	
Living with 2+ parents	5,040 (67)	25.3 (3.5)	
Talking to mother (wave 3):			
No mother*	15 (0)	24.3 (4.7)	<0.001
Hardly ever	980 (13)	24.3 (3.6)	
Less than once a week	1,103 (15)	25.0 (3.6)	
More than once a week	1,379 (19)	25.3 (3.3)	
Most days	1,928 (26)	25.4 (3.5)	
Missing*	2,007 (26)		
Talking to father (wave 3):			
No father*	172 (3)	24.3 (3.8)	<0.001
Hardly ever	1,826 (25)	24.6 (3.5)	
Less than once a week	1,305 (17)	25.1 (3.4)	
More than once a week	1,058 (15)	25.6 (3.3)	
Most days	855 (11)	25.6 (3.6)	
Missing*	2,196 (29)		
Quarrelling with mother (wave 3):			
No mother*	53 (1)	25.2 (4)	<0.001
Hardly ever	2,721 (37)	25.5 (3.4)	
Less than once a week	1,283 (18)	24.9 (3.5)	
More than once a week	873 (12)	24.5 (3.4)	
Most days	505 (7)	23.9 (3.7)	
Missing*	1,977 (26)		
Quarrelling with father (wave 3):			
No father*	387 (6)	24.4 (3.6)	<0.001
Hardly ever	3,099 (41)	25.4 (3.5)	
Less than once a week	1,049 (14)	25.0 (3.5)	
More than once a week	558 (8)	24.6 (3.3)	
Most days	331 (4)	24.1 (3.8)	
Missing*	1,988 (26)		
Gender:			
Males	3,654 (52)	25.5 (3.4)	<0.001
Females	3,758 (48)	24.7 (3.6)	

Table 5.4 continued

Characteristics	Self-esteem		
	n (column %)	Mean (SD)	P-value
Age:			
10-15 years	3,826 (52)	25.2 (3.4)	0.003
16-21 years	3,586 (48)	25.0 (3.6)	
Ethnicity:			
White	5,789 (84)	25.0 (3.4)	<0.001
Black	368 (3)	26.3 (4.1)	
Asian	905 (8)	25.4 (4.4)	
Mixed	303 (4)	25.3 (3.8)	
Other*	39 (1)	26.1 (3.4)	
Missing*	8 (0)		
Parents' highest educational qualification:			
None	434 (5)	24.7 (3.9)	<0.001
GCSE	1,367 (19)	24.9 (3.4)	
A-Level	1,339 (18)	25.2 (3.4)	
Degree	2,198 (30)	25.6 (3.5)	
Other higher qualification	1,430 (20)	24.9 (3.4)	
Missing*	644 (8)		
Equivalised household income:			
1 lowest	1,311 (18)	24.8 (3.5)	<0.001
2	1,412 (19)	24.7 (3.6)	
3	1,431 (19)	25.2 (3.6)	
4	1,593 (21)	25.3 (3.5)	
5 highest	1,665 (23)	25.4 (3.4)	
Type of living area:			
Urban	5,688 (78)	25.1 (3.5)	0.420
Rural	1,723 (22)	25.0 (3.5)	
Missing*	1 (0)		

Abbreviations: SD: standard deviation; SNS: social networking sites. *Notes:* Column percentages are weighted: sample sizes are unweighted. P-values were calculated by Wald test for difference in means. *Excluded from Wald test because of low frequencies or deemed not to be of substantive interest. The high number of missing cases for the parent-child relationship quality variables was attributed to participants who responded to the self-esteem questions at wave 4 but not to the talking/quarrelling questions at wave 3.

The baseline analytical sample comprised n = 7,412 participants who were 10-21 years old at wave 4 (2012-14) and who had a valid self-esteem score of 15 or more (Table 5.4). Males and females were roughly evenly split in this sample at baseline (52% and 48%, respectively). Overall, the mean self-esteem at wave 4 was 25.1 (SD 3.5).

Mean self-esteem varied by the duration of SNS use ($p<0.001$), being lowest for heavy SNS users (4+ hours on a normal weekday) and highest for non-users (24.6 versus 25.4, respectively). Mean self-esteem varied by family structure (as assessed at wave 4: $p<0.001$): self-esteem was lowest on average for those living with no parents and was highest for those living with 2+ parents (24.6 versus 25.3, respectively).

Mean self-esteem also varied by each indicator of parent-child relationship quality (as assessed at wave 3: $p<0.001$). Self-esteem was lowest for those who hardly ever talked to their mother about things that mattered and was highest for those who talked on most days (24.3 versus 25.4, respectively). The pattern was similar for talking to their father. Self-esteem was lower on average for participants who quarrelled with their mother/father more frequently. For example, the average self-esteem for those who reported that they hardly ever quarrelled with their mother was 25.5 compared with an average of 23.9 for those who quarrelled with their mother on most days.

With respect to the covariates, females had lower self-esteem on average than males (24.7 versus 25.5, respectively; $p<0.001$); those aged 16 to 21 years had lower self-esteem than those aged 10 to 15 years (25.0 versus 25.2, respectively; $p=0.003$) and self-esteem varied by minority ethnic group ($p<0.001$), being lowest for those in the White group and highest for those in the Black group (25.0 versus 26.3, respectively).

Self-esteem also varied by parental educational status ($p<0.001$), being lowest for those whose parent(s) had no qualifications and highest for those whose parent(s) had a degree (24.7 versus 25.6, respectively). A similar socioeconomic gradient in self-esteem was found by household income quintile (24.8 versus 25.4 in the lowest and highest income quintiles, respectively; $p<0.001$).

In summary, Hypothesis 1a was supported by the data as baseline self-esteem was significantly lower for heavy SNS users, females, participants not belonging to a two-parent household and participants who talked less to and quarrelled more with their mothers and fathers.

RQ1b: Baseline levels of duration of SNS use

Table 5.5 shows the count and row percentages of the duration of SNS use (four categories: non-users, light users, moderate users, heavy users) by family variables and confounders. It excludes 13 participants (n = 7,399) from the analytical sample at baseline due to missing data on SNS use.

Table 5.5: Use of social networking sites (hours/weekday) by family variables and confounders

		Chatting on social websites (hours/weekday)				
		None	<1 hour	1-3 hours	4+ hours	P-value
	Total n	n (row %)	n (row %)	n (row %)	n (row %)	
Overall	7,399	1,855 (25)	2,184 (30)	2,077 (28)	1,283 (18)	-
Family structure (wave 4):						
Living with no parents	521	90 (19)	142 (28)	166 (32)	123 (22)	<0.001
Living with one parent	1,848	403 (21)	504 (29)	550 (30)	391 (20)	
Living with 2+ parents	5,030	1,362 (26)	1,538 (30)	1,361 (27)	769 (16)	
Talking to mother (wave 3):						
No mother*	15	6 (41)	4 (29)	2 (11)	3 (19)	<0.001
Hardly ever	980	182 (19)	259 (26)	308 (31)	231 (24)	
Less than once a week	1,101	218 (19)	345 (31)	341 (32)	197 (18)	
More than once a week	1,377	275 (18)	446 (32)	423 (32)	233 (18)	
Most days	1,925	466 (23)	575 (30)	563 (30)	321 (17)	
Missing*	2,001					
Talking to father (wave 3):						
Don't have father*	172	42 (27)	61 (37)	43 (24)	26 (12)	<0.001
Hardly ever	1,823	360 (19)	507 (27)	560 (31)	396 (22)	
Less than once a week	1,304	248 (18)	421 (33)	422 (32)	213 (17)	
More than once a week	1,058	222 (20)	340 (32)	317 (31)	179 (18)	
Most days	852	254 (28)	254 (29)	227 (29)	117 (15)	
Missing*	2,190					
Quarrelling with mother (wave 3):						
No mother*	53	17 (34)	13 (27)	11 (16)	12 (22)	<0.001
Hardly ever	2,719	627 (22)	853 (31)	783 (30)	456 (17)	
Less than once a week	1,283	242 (17)	393 (31)	429 (34)	219 (17)	
More than once a week	870	176 (19)	254 (29)	260 (29)	180 (22)	
Most days	503	93 (18)	120 (23)	157 (32)	133 (27)	
Missing*	1,971					

Table 5.5 continued

		Chatting on social websites (hours/weekday)				
		None	<1 hour	1-3 hours	4+ hours	P-value
	Total n	n (row %)	n (row %)	n (row %)	n (row %)	
Quarrelling with father (wave 3):						
No father*	387	75 (19)	109 (30)	115 (29)	88 (22)	0.125
Hardly ever	3,098	698 (21)	950 (30)	910 (30)	540 (18)	
Less than once a week	1,047	210 (19)	309 (30)	349 (33)	179 (18)	
More than once a week	556	109 (18)	167 (31)	161 (30)	119 (21)	
Most days	329	64 (18)	95 (26)	100 (32)	70 (24)	
Missing*	1,982					
Gender:						
Males	3,644	1,038 (28)	1,151 (31)	930 (26)	525 (15)	<0.001
Females	3,755	817 (21)	1,033 (28)	1,147 (31)	758 (20)	
Age:						
10-15	3,813	1,384 (37)	1,317 (34)	828 (22)	284 (8)	<0.001
16-21	3,586	471 (12)	867 (25)	1,249 (35)	999 (28)	
Ethnicity:						
White	5,779	1,311 (23)	1,703 (30)	1,697 (29)	1,068 (19)	<0.001
Black	368	93 (27)	109 (29)	101 (27)	65 (17)	
Asian	902	351 (37)	267 (30)	192 (23)	92 (9)	
Mixed	303	88 (32)	89 (30)	76 (23)	50 (15)	
Other*	39	9 (20)	14 (39)	9 (22)	7 (19)	
Missing*	8					
Parents' highest educational qualification:						
None	432	118 (24)	111 (26)	119 (27)	84 (22)	<0.001
GCSE	1,364	315 (23)	386 (28)	392 (29)	271 (20)	
A level	1,337	323 (23)	367 (27)	412 (31)	235 (18)	
Degree	2,193	638 (29)	716 (33)	558 (25)	281 (13)	
Other higher qualification	1,429	342 (23)	427 (30)	399 (29)	261 (18)	
Missing*	644					

Table 5.5 continued

		Chatting on social websites (hours/weekday)				
		None	<1 hour	1-3 hours	4+ hours	P-value
	Total n	n (row %)	n (row %)	n (row %)	n (row %)	
Household income:						
1 (lowest)	1,308	355 (25)	398 (31)	332 (27)	223 (17)	0.342
2	1,407	373 (26)	394 (29)	384 (27)	256 (18)	
3	1,429	372 (26)	398 (27)	423 (29)	236 (18)	
4	1,592	385 (24)	476 (30)	458 (29)	273 (17)	
5 (highest)	1,663	370 (22)	518 (31)	480 (29)	295 (18)	
Type of living area:						
Urban	5,677	1,435 (24)	1,640 (29)	1,570 (28)	1,032 (18)	0.027
Rural	1,721	420 (25)	543 (31)	507 (29)	251 (15)	
Missing*	1					

Notes: Column percentages are weighted: sample sizes are unweighted. P-values were calculated by Pearson's chi-square test. *Excluded from Pearson's chi-square test because of low frequencies or deemed not to be of substantive interest. The high number of missing cases for the parent-child relationship quality variables was attributed to participants who responded to the SNS use questions at wave 4 but not to the talking/quarrelling questions at wave 3.

At baseline (wave 4), 25% of participants were classified as non-users of SNS whilst 18% were classified as heavy users (4+ hours/weekday). Duration of SNS use varied by family structure ($p<0.001$), 16% of those living with 2+ parents at wave 4 were heavy SNS users compared with 22% of those not living with any parents.

The duration of SNS use also varied by the indicators of parent-child relationship quality. For example, 17% of those who talked to their mother on most days about the things that mattered most to them were heavy SNS users compared with 24% of those who hardly ever talked to their mother ($p<0.001$). A similar pattern was found for talking to fathers (15% versus 22%, respectively; $p<0.001$). Duration of SNS use also varied by frequency of quarrelling with mothers: 17% of those who hardly ever quarrelled with their mothers were heavy SNS users compared with 22% of those who quarrelled with their mothers on most days ($p<0.001$). The duration of SNS use did not vary significantly with the frequency of quarrelling with fathers ($p=0.125$).

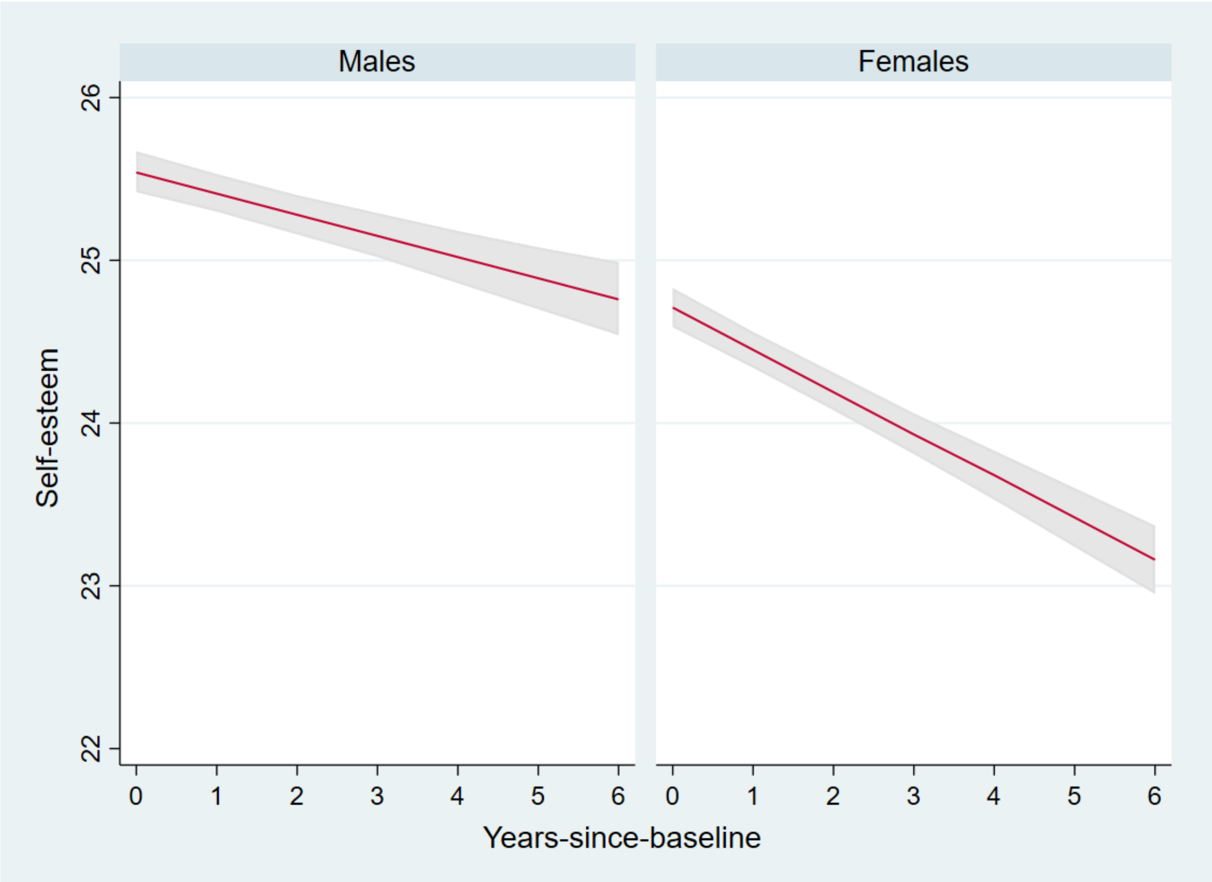
With respect to the covariates, females were more likely than males to be heavy SNS users (20% versus 15%, respectively) and less likely to be non-users (21% versus 28%, respectively; $p<0.001$). Those aged 16 to 21 years at wave 4 were more likely to be heavy SNS users than those aged 10 to 15 years (28% versus 8%, respectively; $p<0.001$). Duration of SNS use also varied by ethnicity ($p<0.001$), with those in the Asian group having the lowest prevalence of heavy SNS use (9%) and the highest prevalence of non-use (37%). The duration of SNS use varied by parental educational status ($p<0.001$), with the proportions of heavy SNS use being lowest among those with parent(s) with a degree (13%) and highest among those with parent(s) with no qualifications (22%). The proportions of heavy SNS use were similar across household income quintiles ($p=0.342$). Finally, the duration of SNS use varied significantly by area of residence ($p=0.027$), with the prevalence of heavy SNS use being higher among those in urban than rural areas (18% versus 15%).

In summary, Hypothesis 1b was largely supported by the data as heavy SNS use was higher for females, participants not belonging to a two-parent household, participants who talked less to their mothers and fathers and participants who quarrelled more with their mothers.

5.4.3 Trajectories of self-esteem by gender

Based on a linear mixed-effects model that estimated the (linear) 1-year rate of change in self-esteem separately by gender (i.e., time-since-baseline × gender), females had significantly lower self-esteem on average than males at baseline (24.7 versus 25.5, respectively; $p<0.001$) and females also had a significantly faster 1-year rate of decline in self-esteem than males (-0.26 versus -0.13, respectively; $p<0.001$ for time-since-baseline and gender interaction). Self-esteem trajectories by gender based on the predicted values from this model are presented in Figure 5.3.

Figure 5.3: Self-esteem trajectories by gender



Notes: self-esteem was assessed only at even-numbered waves (4, 6, 8 and 10); hence, time-since-baseline was entered in the model as a continuous variable with scores 0, 2, 4 and 6.

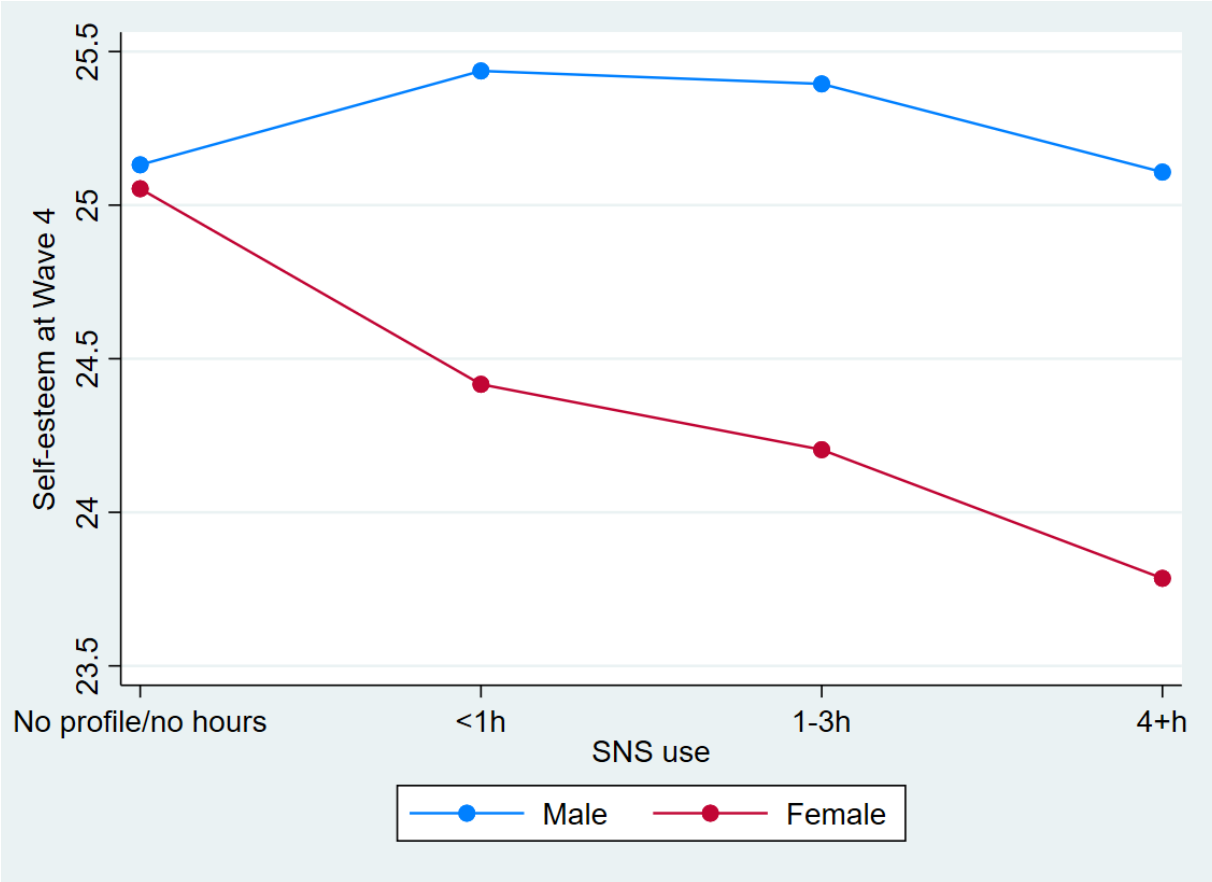
5.4.4 Longitudinal analyses

RQ2: Moderation by gender

Based on the linear mixed-effects model, evidence suggested a significant moderating effect of gender on the associations between the duration of SNS use and baseline levels of self-esteem (gender × SNS use: $p<0.001$, data not shown) but no statistically significant three-way interaction of SNS use, gender, and year (gender × SNS use × time: $p=0.420$, data not shown). As such, to answer **RQ3-5**, I stratified the regression models by gender.

Hypothesis 2 was supported by the data. Results from the linear mixed-effects model containing the gender × SNS use two-way interaction term suggested no significant gender difference in average levels of self-esteem at baseline (wave 4) among non-users, but lower levels of self-esteem on average among females as the duration of SNS use increased from light (<1hr/weekday) to heavy use (4+hrs/weekday) (Figure 5.4).

Figure 5.4: Self-esteem by SNS use and gender at baseline



Tables 5.6 (males) and 5.7 (females) show the multivariate associations between the duration of SNS use, family variables and self-esteem. **Model 1** contained the SNS use terms (main effect and interaction with time-since-baseline), **Model 2** included the terms in Model 1 plus family structure (assessed at wave 4 and treated as time-invariant) and **Model 3** included the terms in Model 2 plus the terms for parent-child relationship quality (treated as time-varying but measured at the wave preceding the assessment of self-esteem).

Table 5.6: Results from the linear mixed-effects models for the associations between SNS use, family structure, parent-child relationship quality and self-esteem among males

	Model 1			Model 2			Model 3		
	B	**95% CI**	**P**	**B**	**95% CI**	**P**	**B**	**95% CI**	**P**
Intercept	25.7	(25.1, 26.4)	<0.001	25.7	(25.0, 26.4)	<0.001	26.4	(25.6, 27.1)	<0.001
Time-since-baseline	-0.26	(-0.53, 0.00)	0.052	-0.24	(-0.51, 0.03)	0.081	-0.22	(-0.51, 0.06)	0.126
Age	-0.02	(-0.06, 0.02)	0.434	-0.01	(-0.05, 0.03)	0.715	-0.01	(-0.05, 0.04)	0.726
Age x time	0.01	(-0.01, 0.03)	0.184	0.01	(-0.01, 0.03)	0.216	0.01	(-0.01, 0.03)	0.361
SNS use (hours/weekday):									
Non-users	-0.26	(-0.54, 0.03)	0.082	-0.25	(-0.54, 0.04)	0.089	-0.28	(-0.57, 0.01)	0.055
<1 hour (ref)	-	-	-	-	-	-	-	-	-
1-3 hours	-0.03	(-0.32, 0.25)	0.809	-0.04	(-0.32, 0.24)	0.780	-0.01	(-0.29, 0.27)	0.935
4+ hours	-0.26	(-0.63, 0.11)	0.165	-0.27	(-0.64, 0.10)	0.146	-0.23	(-0.60, 0.14)	0.218
P value			*0.210*			*0.212*			*0.156*
SNS use × time:									
Non-users	-0.01	(-0.14, 0.12)	0.912	-0.01	(-0.14, 0.12)	0.906	-0.01	(-0.14, 0.12)	0.844
<1 hour (ref)	-	-	-	-	-	-	-	-	-
1-3 hours	-0.02	(-0.12, 0.09)	0.772	-0.01	(-0.12, 0.09)	0.785	-0.02	(-0.13, 0.09)	0.703
4+ hours	-0.03	(-0.15, 0.09)	0.661	-0.02	(-0.14, 0.10)	0.695	-0.03	(-0.15, 0.09)	0.589
P value			*0.977*			*0.983*			*0.958*
Family structure (wave 4):									
Living with no parents				-0.39	(-1.08, 0.31)	0.275	-0.38	(-1.08, 0.33)	0.293
Living with one parent				-0.04	(-0.37, 0.29)	0.828	0.05	(-0.30, 0.39)	0.798
Living with 2+ parents (ref)				-	-	-	-	-	-
P value						*0.549*			*0.489*
Family structure × time:									
Living with no parents				-0.02	(-0.41, 0.37)	0.930	0.00	(-0.42, 0.42)	0.997
Living with one parent				-0.04	(-0.15, 0.08)	0.523	-0.01	(-0.13, 0.11)	0.818
Living with 2+ parents (ref)				-	-	-	-	-	-
P value						*0.816*			*0.973*
Talk to mother:									
No mother*							-0.71	(-3.65, 2.23)	0.635
Hardly ever							-0.37	(-0.81, 0.07)	0.097
Less than once a week							-0.19	(-0.64, 0.26)	0.414
More than once a week							0.02	(-0.38, 0.43)	0.904
Most days (ref)							-	-	-

P value			*0.283*
Talk to mother × time:			
No mother*	1.17	(0.00, 2.33)	0.050
Hardly ever	0.07	(-0.11, 0.25)	0.444
Less than once a week	0.10	(-0.06, 0.27)	0.220
More than once a week	0.03	(-0.11, 0.18)	0.641
Most days (ref)	-	-	-
P value			*0.608*
Talk to father:			
No father*	-0.61	(-1.58, 0.37)	0.219
Hardly ever	-0.37	(-0.86, 0.12)	0.139
Less than once a week	-0.28	(-0.81, 0.25)	0.294
More than once a week	0.04	(-0.44, 0.52)	0.865
Most days (ref)	-	-	-
P value			*0.186*
Talk to father × time:			
No father*	-0.06	(-0.49, 0.37)	0.782
Hardly ever	-0.08	(-0.27, 0.12)	0.446
Less than once a week	-0.07	(-0.27, 0.14)	0.533
More than once a week	-0.03	(-0.22, 0.16)	0.741
Most days (ref)	-	-	-
P value			*0.864*
Quarrel with mother:			
No mother*	0.22	(-1.07, 1.52)	0.732
Hardly ever (ref)	-	-	-
Less than once a week	-0.15	(-0.49, 0.18)	0.370
More than once a week	-0.57	(-0.95, -0.19)	0.003
Most days	-0.70	(-1.23, -0.16)	0.010
P value			*0.008*
Quarrel with mother × time:			
No mother*	-0.09	(-0.57, 0.39)	0.715
Hardly ever (ref)	-	-	-
Less than once a week	0.02	(-0.10, 0.13)	0.758
More than once a week	0.02	(-0.12, 0.16)	0.779
Most days	0.16	(-0.08, 0.39)	0.191
P value			*0.646*

Quarrel with father:							
No father*					-0.40	(-1.10, 0.30)	0.265
Hardly ever (ref)					-	-	-
Less than once a week					-0.32	(-0.72, 0.08)	0.112
More than once a week					-0.41	(-0.89, 0.07)	0.096
Most days					-0.48	(-1.09, 0.14)	0.129
P value							*0.156*
Quarrel with father × time:							
No father*					-0.11	(-0.36, 0.14)	0.390
Hardly ever (ref)					-	-	-
Less than once a week					0.08	(-0.05, 0.20)	0.245
More than once a week					0.01	(-0.16, 0.18)	0.919
Most days					-0.07	(-0.36, 0.22)	0.632
P value							*0.579*
Random effects:							
Level-2 intercept	2.35	(2.2, 2.5)	2.35	(2.2, 2.5)	2.27	(2.12, 2.42)	
Level-2 slope	0.36	(0.28, 0.44)	0.35	(0.28, 0.44)	0.34	(0.27, 0.44)	
Correlation: Int-slope	-0.09	(-0.26, 0.08)	-0.09	(-0.26, 0.09)	-0.09	(-0.27, 0.09)	
Level-1 residual	2.55	(2.45, 2.66)	2.55	(2.45, 2.66)	2.55	(2.46, 2.66)	

Abbreviations: ref: reference category; SNS: social networking site. Notes: males (n = 3,654); person-wave observations (n = 7,519); **Model 1**: SMU + confounders; **Model 2**: SMU + family structure + confounders; **Model 3**: SMU + family structure + child-parent relationship quality. Confounding variables included in each model are age, ethnicity, household income quintiles and parental educational qualification. *Excluded from Wald test.

Table 5.7: Results from the linear mixed-effects models for the associations between SNS use, family structure, parent-child relationship quality and self-esteem among females

	Model 1			Model 2			Model 3		
	B	**95% CI**	**P**	**B**	**95% CI**	**P**	**B**	**95% CI**	**P**
Intercept	25.6	(24.9, 26.3)	<0.001	25.8	(25.1, 26.5)	<0.001	26.8	(26.1, 27.6)	<0.001
Time-since-baseline	-1.06	(-1.31, -0.81)	<0.001	-1.06	(-1.31, -0.80)	<0.001	-1.06	(-1.33, -0.78)	<0.001
Age	-0.05	(-0.09, -0.01)	0.014	-0.05	(-0.09, -0.01)	0.014	-0.06	(-0.1, -0.02)	0.005
Age x time	0.05	(0.04, 0.07)	<0.001	0.05	(0.04, 0.07)	<0.001	0.05	(0.03, 0.07)	<0.001
SNS use (hours/weekday):									
Non-users	0.38	(0.08, 0.69)	0.015	0.37	(0.06, 0.68)	0.019	0.34	(0.03, 0.64)	0.030
<1 hr (ref)	-	-	-	-	-	-	-	-	-
1-3 hours	-0.26	(-0.52, 0.00)	0.048	-0.26	(-0.52, 0.00)	0.049	-0.21	(-0.47, 0.04)	0.101
4+ hours	-0.49	(-0.81, -0.17)	0.003	-0.48	(-0.80, -0.16)	0.003	-0.30	(-0.62, 0.02)	0.069
P value			*<0.001*			*<0.001*			*0.002*
SNS use × time:									
Non-users	0.04	(-0.12, 0.20)	0.637	0.04	(-0.12, 0.21)	0.599	0.03	(-0.13, 0.20)	0.677
<1 hour (ref)	-	-	-	-	-	-	-	-	-
1-3 hours	0.09	(-0.01, 0.19)	0.090	0.09	(-0.01, 0.19)	0.080	0.09	(-0.02, 0.19)	0.102
4+ hours	0.06	(-0.05, 0.17)	0.262	0.06	(-0.05, 0.17)	0.261	0.03	(-0.08, 0.14)	0.569
P value			*0.398*			*0.374*			*0.377*
Family structure (wave 4):									
Living with no parents				0.11	(-0.48, 0.69)	0.722	0.26	(-0.32, 0.83)	0.382
Living with one parent				-0.33	(-0.65, 0.00)	0.051	-0.16	(-0.49, 0.17)	0.350
Living with 2+ parents (ref)				-	-	-	-	-	-
P value						*0.088*			*0.288*
Family structure × time:									
Living with no parents				0.22	(-0.05, 0.49)	0.104	0.16	(-0.12, 0.45)	0.262
Living with one parent				-0.02	(-0.13, 0.08)	0.674	-0.02	(-0.13, 0.09)	0.686
Living with 2+ parents (ref)				-	-	-	-	-	-
P value						*0.206*			*0.431*
Talk to mother:									
No mother*							-1.85	(-4.12, 0.43)	0.110
Hardly ever							-0.95	(-1.38, -0.52)	<0.001
Less than once a week							-0.54	(-0.93, -0.15)	0.008
More than once a week							-0.26	(-0.60, 0.08)	0.139
Most days (ref)							-	-	-

P value			*<0.001*
Talk to mother × time:			
No mother*	0.33	(-0.68, 1.35)	0.514
Hardly ever	0.18	(0.03, 0.32)	0.020
Less than once a week	0.06	(-0.06, 0.18)	0.352
More than once a week	0.02	(-0.09, 0.14)	0.667
Most days (ref)	-	-	-
P value			*0.113*
Talk to father:			
No father*	-0.66	(-1.65, 0.32)	0.186
Hardly ever	-0.44	(-0.88, 0.00)	0.048
Less than once a week	-0.24	(-0.66, 0.18)	0.257
More than once a week	0.01	(-0.40, 0.42)	0.957
Most days (ref)	-	-	-
P value			*0.082*
Talk to father × time:			
No father*	0.05	(-0.31, 0.41)	0.788
Hardly ever	-0.03	(-0.17, 0.11)	0.718
Less than once a week	0.01	(-0.13, 0.15)	0.884
More than once a week	0.02	(-0.11, 0.16)	0.720
Most days (ref)	-	-	-
P value			*0.859*
Quarrel with mother:			
No mother*	-0.40	(-1.71, 0.91)	0.545
Hardly ever (ref)	-	-	-
Less than once a week	-0.46	(-0.76, -0.16)	0.003
More than once a week	-0.59	(-0.94, -0.24)	0.001
Most days	-1.12	(-1.62, -0.62)	<0.001
P value			*<0.001*
Quarrel with mother × time:			
No mother*	0.03	(-0.51, 0.58)	0.909
Hardly ever (ref)	-	-	-
Less than once a week	0.02	(-0.07, 0.12)	0.627
More than once a week	0.01	(-0.11, 0.12)	0.917
Most days	0.11	(-0.07, 0.28)	0.221
P value			*0.646*

Quarrel with father:									
No father*							-0.44	(-1.00, 0.13)	0.131
Hardly ever (ref)							-	-	-
Less than once a week							-0.23	(-0.54, 0.09)	0.158
More than once a week							-0.23	(-0.63, 0.17)	0.258
Most days							-0.70	(-1.29, -0.10)	0.022
P value									*0.072*
Quarrel with father × time:									
No father*							0.02	(-0.17, 0.21)	0.838
Hardly ever (ref)							-	-	-
Less than once a week							-0.01	(-0.11, 0.09)	0.831
More than once a week							-0.01	(-0.15, 0.13)	0.860
Most days							0.09	(-0.14, 0.31)	0.446
P value									*0.839*
Random effects									
Level-2 intercept	2.40	(2.27, 2.55)		2.40	(2.27, 2.54)		2.25	(2.11, 2.39)	
Level-2 slope	0.35	(0.29, 0.43)		0.35	(0.29, 0.43)		0.33	(0.26, 0.41)	
Correlation: Int-slope	-0.14	(-0.30, 0.01)		-0.15	(-0.30, 0.01)		-0.10	(-0.28, 0.09)	
Level-1 residual	2.51	(2.42, 2.59)		2.51	(2.42, 2.59)		2.51	(2.43, 2.6)	

Abbreviations: ref: reference category; SNS: social networking site. Notes: females (n = 3,758); person-wave observations (n = 7,993); **Model 1**: SMU + confounders; **Model 2**: SMU + family structure + confounders; **Model 3**: SMU + family structure + child-parent relationship quality. Confounding variables included in **each model** are age, ethnicity, household income quintiles and parental educational qualification. *Excluded from Wald test.

RQ3: Main effects

Results for males (Table 5.6)

Among males, average levels of self-esteem did not significantly decrease over time in the fully adjusted model (Model 3: β = -0.22 units per year-since-baseline (95% CI: -0.51, 0.06); p=0.126). Age was not significantly associated with baseline levels of self-esteem (Model 3: p=0.726) nor with the rate of change in self-esteem (Model 3: p=0.361).

SNS use: Overall, the duration of SNS use was not significantly associated with baseline levels of self-esteem (Model 3: p=0.156), although non-users had marginally lower self-esteem on average at baseline than light-users (Model 3: β = -0.28 (95% CI: -0.57, 0.01); p=0.055). Duration of SNS use was also not associated with the rate of change in self-esteem (Model 3: p=0.958).

Family structure: Family structure at wave 4 (living with 0, 1 or 2+ parents) was not associated with baseline levels of self-esteem (Model 3: p=0.489) nor with the rate of change in self-esteem (Model 3: p=0.973).

Parent-child relationship quality:

The frequency of talking to mothers and fathers about the things that mattered was not associated with baseline levels of self-esteem (Model 3: p=0.283 and p=0.186, respectively) nor with the rate of change in self-esteem (Model 3: p=0.608 and p=0.864, respectively).

In contrast, baseline levels of self-esteem varied by the frequency of quarrelling with mother (Model 3: p=0.008). Compared to those who reported that they hardly ever quarrelled with their mother (reference), self-esteem at baseline was significantly lower on average among those who quarrelled more than once a week (Model 3: β = -0.57 (95% CI: -0.95, -0.19); p=0.003) and among those who quarrelled on most days (Model 3: β = -0.70 (95% CI: -1.23, -0.16); p=0.010). Frequency of quarrelling with mother was not associated with the rate of change in self-esteem (Model 3: p=0.646). Frequency of quarrelling with father was not associated with baseline levels of self-esteem (Model 3: $p=0.156$) nor with the rate of change in self-esteem (Model 3: $p=0.579$).

Results for females (Table 5.7)

Among females, levels of self-esteem on average decreased significantly over time (Model 3: $\beta = -1.06$ units per year-since-baseline (95% CI: -1.33, -0.78); $p<0.001$). Age at baseline was significantly associated with baseline levels of self-esteem: older females had lower self-esteem at baseline than younger females (Model 3: $\beta = -0.06$ (95% CI: -0.1, -0.02); $p=0.005$). Age was also significantly associated with the rate of change in self-esteem: self-esteem declined at a faster rate for younger females (Model 3: $\beta = 0.05$ (95% CI: 0.03, 0.07); $p<0.001$). For example, holding all else constant, the estimated 1-year rate of change in self-esteem was -0.39 among 10-year-old females compared to -0.10 among 16-year-old females.

SNS use: In the fully-adjusted model, duration of SNS use was significantly associated with baseline levels of self-esteem (Model 3: $p=0.002$): compared to light-users (reference: <1hr/weekday), non-users had higher self-esteem at baseline (Model 3: $\beta = 0.34$ (95% CI: 0.03, 0.64); $p=0.030$), whilst moderate users (Model 3: $\beta = -0.21$ (95% CI: -0.47, 0.04); $p=0.101$) and heavy users (Model 3: $\beta = -0.30$ (95% CI: -0.62, 0.02); $p=0.069$) had lower self-esteem at baseline. Duration of SNS use was not associated with the rate of change in self-esteem (Model 3: $p=0.377$).

Family structure: In Model 2, females living with 1 parent had lower self-esteem at baseline than those living with 2+ parents (Model 2: $\beta = -0.33$ (95% CI: -0.65, 0.00); $p=0.051$) but this difference was no longer statistically significant after adjustment for the indicators of parent-child relationship quality (Model 3: $p=0.350$).

Parent-child relationship quality:

Frequency of talking to mothers about the things that mattered was significantly associated with baseline levels of self-esteem (Model 3: $p<0.001$). Compared to those who talked with their mother on most days, those who reported that they hardly ever talked to their mother (Model 3: $\beta = -0.95$ (95% CI: -1.38, -0.52); $p<0.001$) and those who talked to their mother less than once a week (Model 3: β = -0.54 (95% CI: -0.93, -0.15); p=0.008) had significantly lower self-esteem at baseline. However, compared to those who talked with their mother on most days about the things that mattered, the estimated decrease in self-esteem over time was slightly lower in magnitude for those who hardly ever talked with their mother (Model 3: $\beta_{hardly\text{-}ever*time\text{-}since\text{-}baseline}$ = 0.18 (95% CI: 0.03, 0.32); p=0.020). Compared to those who talked with their father on most days, those who hardly ever talked with their father about things that mattered most to them had significantly lower self-esteem at baseline (Model 3: β = -0.44 (95% CI: -0.88, 0.00); p=0.048). Frequency of talking to mother and father was not significantly associated with the rate of change in self-esteem (Model 3: p=0.113 and p=0.859, respectively).

In a similar pattern to males, baseline levels of self-esteem varied by frequency of quarrelling with mothers (Model 3: p<0.001). Compared to those who hardly ever quarrelled with their mother, self-esteem at baseline was significantly lower among those who quarrelled less than once a week (Model 3: β = -0.46 (95% CI: -0.76, -0.16); p=0.003), among those who quarrelled more than once a week (Model 3: β = -0.59 (95% CI: -0.94, -0.24); p=0.001) and among those who quarrelled on most days (Model 3: β = -1.12 (95% CI: -1.62, -0.62); p<0.001). Compared to those who hardly ever quarrelled with their father, self-esteem at baseline was significantly lower among those who quarrelled with their father on most days (Model 3: β = -0.70 (95% CI: -1.29, -0.10); p=0.022). Frequency of quarrelling with mother and father was not significantly associated with the rate of change in self-esteem (Model 3: p=0.646 and p=0.839, respectively).

RQ4: Moderation by family factors

After including terms to Model 3

I found little evidence of statistical moderation by the family variables when looking at associations between the duration of SNS use and self-esteem. P-values for the three-way and two-way interaction terms are shown in Table 5.8.

Table 5.8: Results from the linear mixed-effects models for the potential moderation by family variables on the associations between SNS use and self-esteem

	Males P-values	Females P-values
Model 4a (three-way interactions):		
SNS × family structure × time-since-baseline	0.581	0.303
SNS × talking to mother × time-since-baseline	0.943	0.980
SNS × talking to father × time-since-baseline	0.962	0.728
SNS × quarrelling with mother × time-since-baseline	0.426	0.486
SNS × quarrelling with father × time-since-baseline	0.418	0.940
Model 4b (two-way interactions):		
SNS × family structure	0.354	0.022
SNS × talking to mother	0.769	0.787
SNS × talking to father	0.658	0.967
SNS × quarrelling with mother	0.886	0.535
SNS × quarrelling with father	0.814	0.900

Abbreviations: SNS: social networking sites (SNS); *Notes*: three-way interaction terms investigate moderation in the 1-year rate of change in self-esteem; two-way interaction terms investigate moderation in the levels of self-esteem at baseline. Estimates in red denote p-value <0.05.

There was one exception found in females: the association between the duration of SNS use and self-esteem at baseline was moderated by family structure (p=0.022). To aid interpretation, predicted values from this model (average levels of self-esteem at baseline by combinations of SNS use and family structure) are presented in Figure 5.5.

Figure 5.5: Self-esteem by SNS use and family structure in females at baseline

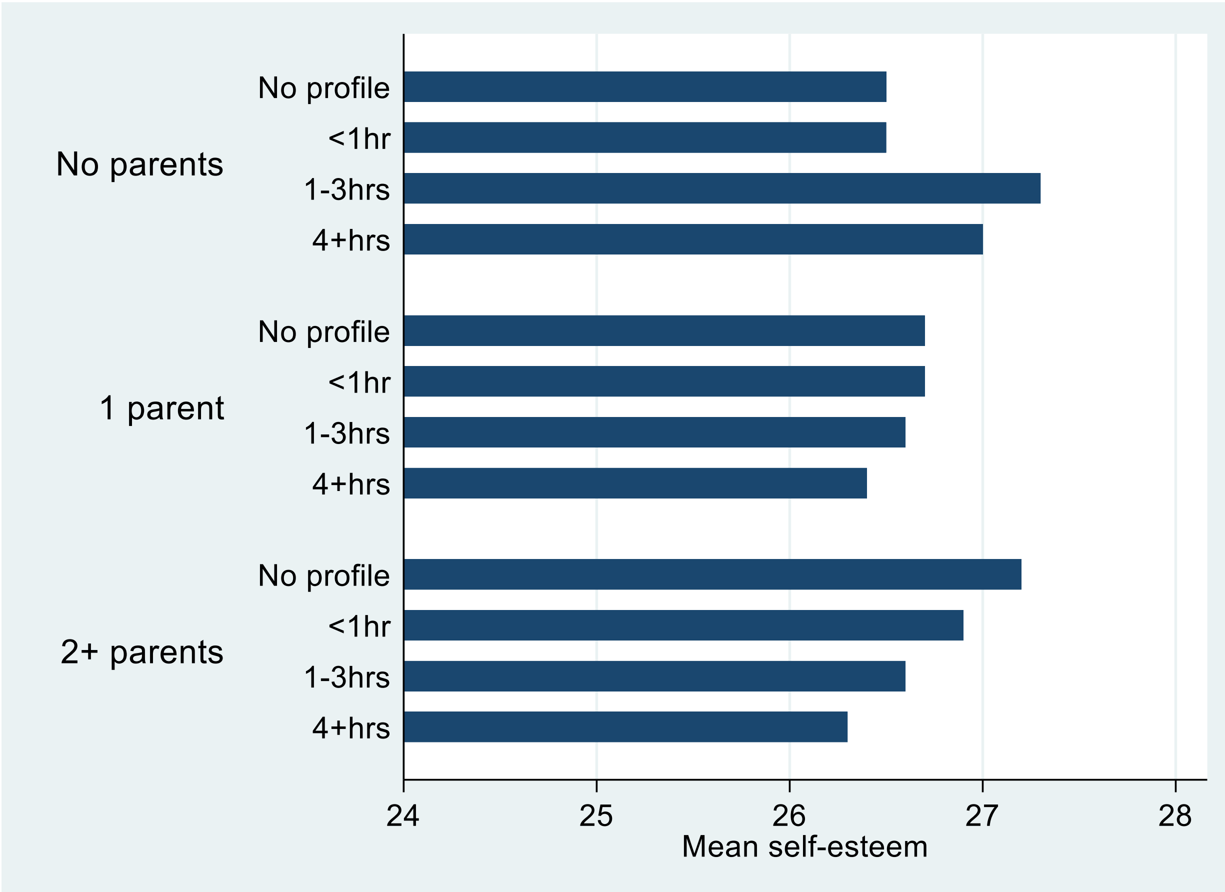


Figure 5.5 shows that for females living with 1 or 2+ parents at wave 4, average self-esteem at baseline slightly decreased with greater SNS use. In contrast, moderate (1-3hrs/weekday) and heavy (4+hrs/weekday) SNS users had higher baseline self-esteem than non-users and light users (<1hr/weekday) among those females living with no parents.

5.4.5 Supplementary analysis

Several previous studies have attempted to account for the potentially bidirectional or cyclical associations between social media use and mental health/well-being outcomes by controlling for prior measures of mental health/well-being. For example, the study by van der Velden, Setti, Meulen, et al. (2019) conducted in the Netherlands on adults (aged 16+ years) based on data from the Longitudinal Internet Studies for the Social Sciences panel (LISS) found that the hours spent on social networking sites was no longer associated with mental health problems after prior mental health problems were adjusted for (105). The authors concluded that this finding highlighted the necessity of controlling for prior measurements of the outcome variable to prevent overestimations of any positive or negative associations between SNS use and mental health/well-being.

RQ5: Supplementary analysis

As a supplementary analysis, I re-ran my analysis, using self-esteem scores at wave 6 as the baseline score so that I could statistically adjust for self-esteem scores at wave 4. Table 5.9 shows the associations between SNS use and self-esteem after adjusting for prior self-esteem.

Table 5.9: Results from the linear mixed-effects models on the associations between SNS use, family structure, parent-child relationship quality and self-esteem (after adjusting for prior levels of self-esteem and other confounders)

	Males			Females		
	B	**95% CI**	**P**	**B**	**95% CI**	**P**
Intercept	15.7	(14.2, 17.2)	<0.001	13.6	(12.1, 15.2)	<0.001
Time-since-baseline	-0.36	(-0.88, 0.17)	0.182	-1.45	(-1.94, -0.95)	<0.001
Age	-0.05	(-0.1, 0.01)	0.116	0.07	(0.01, 0.13)	0.025
Age x time	0.02	(-0.01, 0.06)	0.198	0.08	(0.04, 0.11)	<0.001
Self-esteem (wave 4)	0.43	(0.39, 0.47)	<0.001	0.43	(0.39, 0.47)	<0.001
SNS use (hours/weekday):						
Non-users	-0.15	(-0.58, 0.28)	0.493	0.40	(-0.10, 0.89)	0.114
<1 hour (ref)	-	-	-	-	-	-
1-3 hours	-0.01	(-0.34, 0.33)	0.962	-0.12	(-0.46, 0.22)	0.499
4+ hours	-0.06	(-0.53, 0.41)	0.804	-0.35	(-0.75, 0.05)	0.086
P value			*0.909*			*0.040*
SNS use × time:						
Non-users	-0.17	(-0.42, 0.08)	0.182	0.07	(-0.24, 0.39)	0.649
<1 hour (ref)	-	-	-	-	-	-
1-3 hours	-0.05	(-0.24, 0.13)	0.576	0.13	(-0.05, 0.32)	0.161
4+ hours	-0.11	(-0.33, 0.11)	0.313	0.09	(-0.11, 0.29)	0.359
P value			*0.550*			*0.570*

Abbreviations: ref: reference category; SNS: social networking site. *Notes*: males (n = 2,200; person-wave observations 3,858); females (n = 2,296; person-wave observations 4,219). Variables included in each model are family structure, parent-child relationship quality, age, ethnicity, household income quintiles and parental educational qualification.

In agreement with the main analysis, among males, duration of SNS use was not significantly associated with initial levels of self-esteem nor with its 1-year rate of change after adjustment for prior levels of self-esteem. Among females, duration of SNS use remained significantly associated with baseline levels of self-esteem but with lower effect sizes (p=0.040 for the Wald test) and wider 95% confidence intervals after adjustment for prior self-esteem. For example, compared to light SNS users (reference: <1hr/weekday), moderate users (Model: β = -0.12 (95% CI: -0.46, 0.22); p=0.499) and heavy users (Model: β = -0.35 (95% CI: -0.75, 0.05); p=0.086) had lower self-esteem on average at baseline in the fully adjusted model for females.

There was a slight difference pertaining to the independent associations of age and self-esteem among females. In contrast to the main analysis, older females had higher self-esteem at baseline than younger females (β = 0.07 (95% CI: 0.01, 0.13); p=0.025) after controlling for prior levels of self-esteem. Consistent with the main analysis, age was significantly associated with the rate of change in self-esteem: self-esteem declined at a faster rate for younger females (β = 0.08 (95% CI: 0.04, 0.11); $p<0.001$) after controlling for prior levels of self-esteem. For example, the estimated 1-year rate of change in self-esteem was -0.42 among 10-year-old females compared to 0.03 among 16-year-old females.

5.5 Discussion

In this section, I summarise the main findings and the strengths and limitations of the work presented in this chapter. A lengthier discussion, including comparisons with other studies (e.g., the Korean Children and Youth Panel Survey) and a consideration of the policy implications of the findings, is provided in greater detail in Chapter 8 (Discussion).

5.5.1 Main findings

My main findings from the descriptive analyses were that those with the lowest mean self-esteem scores at baseline were females, heavy SNS users, participants not belonging to a two-parent household and participants who talked less and quarrelled more with their mothers and fathers. Females were more likely to be heavy SNS users (4+hours/weekday) than males and had a lower baseline self-esteem on average than males. Moreover, older females had lower baseline self-esteem than younger females in the main analysis but higher baseline self-esteem after prior levels of self-esteem were controlled for. Average levels of self-esteem declined at a faster rate for younger females in both the main and supplementary analyses.

Pertaining to the main analyses, my study produced three main findings: (1) the significant interaction of SNS use and gender on self-esteem (**RQ2**), (2) the significant independent main effect of parent-child relationship quality on self-esteem (**RQ3**) and (3) the significant interaction of SNS use and family structure on self-esteem in females (**RQ4**).

Firstly, independent of the duration of SNS use, talking less often and quarrelling more often with mothers were significantly associated with lower baseline self-esteem for females, whilst quarrelling more often with mothers was significantly associated with lower baseline self-esteem for males. One possible reason for these associations could be that having supportive family relationships can serve as a form of protection against the negative impact of stress, while also promoting resilience and self-confidence (173). I will further discuss these findings in Chapter 8.

Secondly, females had significantly lower levels of self-esteem on average as the duration of SNS use increased from light to heavy use at baseline, however, there was no such association for males, both at baseline and with the rate of change in self-esteem. This result suggests that a greater duration of SNS use may be detrimental to young women's self-esteem. In Chapter 8, I will discuss previous studies that have yielded gender-specific findings regarding the associations between social media use and mental health and well-being, drawing comparisons and contrasts between them. I will delve into potential explanations for why females may be more affected by SNS use in this regard than males.

Thirdly, for females living with at least one parent at wave 4, average self-esteem at baseline decreased slightly with greater duration of SNS use. Conversely, for females living with no parents at wave 4, moderate and heavy SNS users had higher baseline self-esteem than non-users and light users. An explanation for this finding is the possibility of unobserved confounding (selection bias) in which these females are likely to be older and living independently.

The supplementary analyses (**RQ5**) showed that after controlling for prior self-esteem, similar results hold, suggesting that there is little evidence in this dataset of a cyclical association between SNS use and self-esteem and that the direction is most likely one way (SNS use to self-esteem).

My findings also indicated that the associations between age and self-esteem were gender-specific. In Chapter 8, I will contextualise these findings by comparing them to those of other studies, noting variations in findings related to participants' age and the specific mental health and well-being measures being examined.

5.5.2 Strengths of this study

My study utilised the UK Household Longitudinal Study (UKHLS), a nationally representative and comprehensive longitudinal survey. By analysing data from the UKHLS, I was able to track changes in self-esteem over six years, providing insights into the trajectory of self-esteem over time, rather than just a one-time, cross-sectional snapshot. Additionally, using self-reported data from participants themselves on both SNS use and self-esteem provided greater accuracy and reliability than relying on data collected from parents or teachers, for example.

Self-esteem is an important indicator of subjective well-being (16-18), which refers to how individuals perceive their quality of life and can encompass cognitive evaluations (i.e., life satisfaction) and emotional responses (i.e., positive affect) (19). Indicators of subjective well-being can offer a valuable alternative to more objective, medical-oriented metrics (20). An understanding of the associations between SNS use and self-esteem through this study will hopefully fill some of the gaps in the literature that looked at the relationships between SNS use and other indicators of well-being (136, 152).

To further investigate the relationship between SNS use and self-esteem, I conducted gender-stratified analyses and explored the potential moderating effects of family factors. This approach contributes to the existing literature by examining how gender and family factors influence the association between SNS use and self-esteem. Notably, this study is among the first to conduct gender-stratified analyses and investigate family dimensions within the context of social media research.

Additionally, a supplementary analysis was conducted to address potential bidirectional/cyclical relationships between SNS use and self-esteem by controlling for prior levels of self-esteem. This analysis provided insight into the directionality of the association between SNS use and self-esteem in this analytical sample. Additionally, I was able to handle missing data by using multiple imputation. The benefits of this approach will be discussed in Chapter 8.

5.5.3 Limitations of this study

Due to limitations of the data collected by the UKHLS, this study was only able to examine the duration of SNS use, rather than other aspects of social media use such as active versus passive use (65). Consequently, the nature of the relationship between SNS use and self-esteem remains unclear. For example, it is possible that individuals with low self-esteem turn to online support groups or applications for mental health support to chat or interact online and form friendships, potentially leading to a positive impact on their well-being. Unfortunately, the UKHLS data did not include detailed questions on these aspects of SNS use. Moreover, the question assessing the duration of SNS use was restricted to regular weekdays/schooldays, rather than weekends or non-school days, where usage might be more frequent. This could result in an inaccurate classification of the amount of time that the participants spent on social networking sites. Additionally, the use of mobile applications for social media interaction was not explicitly captured, which could have led to an underestimation of the duration of SNS use. These limitations prevented me from making firm conclusions about the nature of the relationship between SNS use and self-esteem in this study.

Additionally, the data on SNS use in this study was collected from 2012-14 (wave 4) to 2018-20 (wave 10, latest wave). It is important to note that social media and its use have undergone significant changes over this period and they continue to evolve. Hence, whilst this study provides some insights into the relationship between SNS use and self-esteem during this period, it is necessary to consider the changing nature of social media when interpreting the results. I will provide a detailed discussion of these changes and their potential implications for our understanding of the relationship between SNS use and self-esteem in Chapter 8.

To increase the sample size, participants from both the ‘youth’ and ‘young adult’ panels were combined, resulting in an age range of 10 to 21 years at baseline. However, this approach has a limitation: the characteristics of children and adolescents may differ significantly from young adults. For instance, their purposes for using SNSs may vary and the associations between SNS use and mental health and well-being may differ by developmental age (132). My analyses adjusted for age (at baseline); I examined age as an independent predictor of self-esteem, finding a faster rate of decline in self-esteem among younger compared to older females. However, I felt that the sample sizes were too small (especially for gender-stratified analyses) to conduct analyses of the SNS use and self-esteem associations separately for different age groups (e.g., 10-15- and 16-21-year-olds). Therefore, the potential differences in SNS use and its relationship with self-esteem among different age groups should be acknowledged.

My study also had a shortfall of missing data, in particular for the parent-child relationship quality variables, as these were only collected at odd-numbered waves, whilst the items on self-esteem were only asked at even-numbered waves (and were asked only of 'youth' aged 10-15 years and 'young adults' aged 16-21 years). The forced exclusion of participants from the analytical sample as they reached the age of 22, in addition to the observed higher rates of attrition among 'young adults', limited representativeness to some extent.

Lastly, whilst multiple imputation was used to fill in missing values to avoid the limitations of a complete-case analysis, it has some limitations. These will be discussed in Chapter 8.

5.6 Conclusion

This study analysed seven waves of UKHLS data spanning eight years (2012-20) and shed light on the associations between SNS use and self-esteem in young people aged 10 to 21 years at baseline in the UK. This study emphasised the significance of analysing gender-specific factors that may influence how females and males use social media and how it may impact their self-esteem differently. Whilst technological solutions and educational initiatives aimed at enhancing digital safety and well-being can be helpful, policies that enhance both online and offline relationships and consider how social media is being utilised may also be vital in fostering resilience and promoting self-esteem in the context of SNS use.

Chapter 6: Computer social media use, phone-based interpersonal communication and self-esteem in South Korea

Chapter 6 represents the second empirical investigation in my thesis, focusing on exploring the relationships between the frequency of computer social media use and phone-based interpersonal communication on self-esteem among young people (aged 14 years at baseline and followed up to the age of 18) in South Korea. The chapter also aims to examine whether gender and family factors play a moderating role in this association. To set the context, the chapter begins with a brief introduction, followed by a statement of research questions and hypotheses. An account of the methods is provided, which includes describing the participant demographics, measures used, analytical techniques employed and how missing data were addressed. The chapter then presents the findings of the study and offers a brief discussion of the results, highlighting specific strengths and limitations. A more comprehensive analysis of the results, as well as a broader discussion of the strengths and limitations of the study, will be presented in the Discussion chapter (Chapter 8).

6.1 Introduction

In line with the aims and objectives of Chapter 3, I use the Korean Children and Youth Panel Survey (KCYPS) in this study chapter to investigate the cross-sectional and longitudinal associations between the frequency of computer social media use (CSMU) and phone-based interpersonal communication (PIC) on self-esteem in a Korean cohort of young people (aged 14 years at baseline and followed up to the age of 18). Similar to Chapter 4, I also examine whether gender, family structure and parenting styles confound or moderate these relationships in order to ascertain whether findings differ across countries (UK versus South Korea) for the same outcome (self-esteem). This also fills a gap in the evidence since most existing studies using the KCYPS have only explored internet (123) or phone use (121) more generally rather than examining aspects of social media use and family life.

6.2 Research questions and hypotheses

Five main research questions (**RQ**) and accompanying hypotheses (**H**) were considered in this chapter. These were set in light of the gaps in the literature as discussed in Chapters 1 and 2, that is, whether gender and aspects of family life influence (modify) the associations between social media use/phone-based interpersonal communication and mental health and well-being.

These research questions and accompanying hypotheses are set out below.

RQ1: Descriptive analyses of self-esteem and CSMU/PIC

RQ1a: Do baseline levels of self-esteem vary on average by the frequency of computer social media use (CSMU), the frequency of phone-based interpersonal communication (PIC), gender, family structure and parenting styles?

RQ1b: Does the frequency of CSMU and PIC at baseline vary by gender, family structure and parenting styles?

H1: Descriptive analyses of self-esteem and CSMU/PIC

H1a: Baseline self-esteem is lower on average for more frequent computer social media users, females, participants not living in a household with two biological parents, participants with lower scores on a positive parenting scale and higher scores on a negative parenting scale. Baseline self-esteem is higher on average for more frequent PIC users.

H1b: Baseline levels of CSMU are higher for females and participants not living in a household with two biological parents. Baseline levels of CSMU are higher and baseline levels of PIC are lower for participants with lower scores on a positive parenting scale and higher scores on a negative parenting scale.

RQ2: Gender as a moderator of the CSMU/PIC and self-esteem associations

RQ2: Does gender moderate any association between the frequency of CSMU/PIC and self-esteem?

H2: Gender as a moderator of the CSMU/PIC and self-esteem associations

H2: Gender moderates any association between the frequency of CSMU/PIC and self-esteem, with a stronger association between CSMU/PIC and self-esteem in females than in males.

RQ3: Independent associations between key variables and self-esteem

RQ3: Are levels of CSMU and PIC frequency, family structure and parenting styles independently associated with self-esteem?

H3: Independent associations between key variables and self-esteem

H3a: More frequent CSMU and less frequent PIC are significantly associated with lower self-esteem at baseline (main effects) and a slower rate of increase in self-esteem (interaction with time-in-study) while holding various confounding variables and family variables constant.

H3b: Participants not living in a household with two biological parents, participants with lower scores on a positive parenting scale and higher scores on a negative parenting scale are associated with lower self-esteem at baseline and a slower rate of increase in self-esteem while holding various confounding variables, and frequency of CSMU and PIC constant.

RQ4: Family factors as moderator of the CSMU/PIC and self-esteem associations

RQ4: Do family structure and parenting styles moderate any association between the frequency of CSMU/PIC and self-esteem?

H4: Family factors as moderator of the CSMU/PIC and self-esteem associations

H4: Family structure and parenting styles moderate the association between the frequency of CSMU/PIC and self-esteem. For example, more frequent CSMU is hypothesised to be associated with a slower rate of increase in self-esteem among participants who rank higher on negative parenting, holding all other variables constant.

RQ5: Supplementary analysis

RQ5: After controlling for prior (wave 1) self-esteem and other confounding variables, is the frequency of CSMU and/or PIC associated with self-esteem?

H5: Supplementary analysis

H5: More frequent CSMU and/or less frequent PIC is significantly associated with lower self-esteem at baseline (wave 3; main effects) and a slower rate of increase in self-esteem (interaction with time-in-study), while holding prior (wave 1) self-esteem and other confounding variables constant.

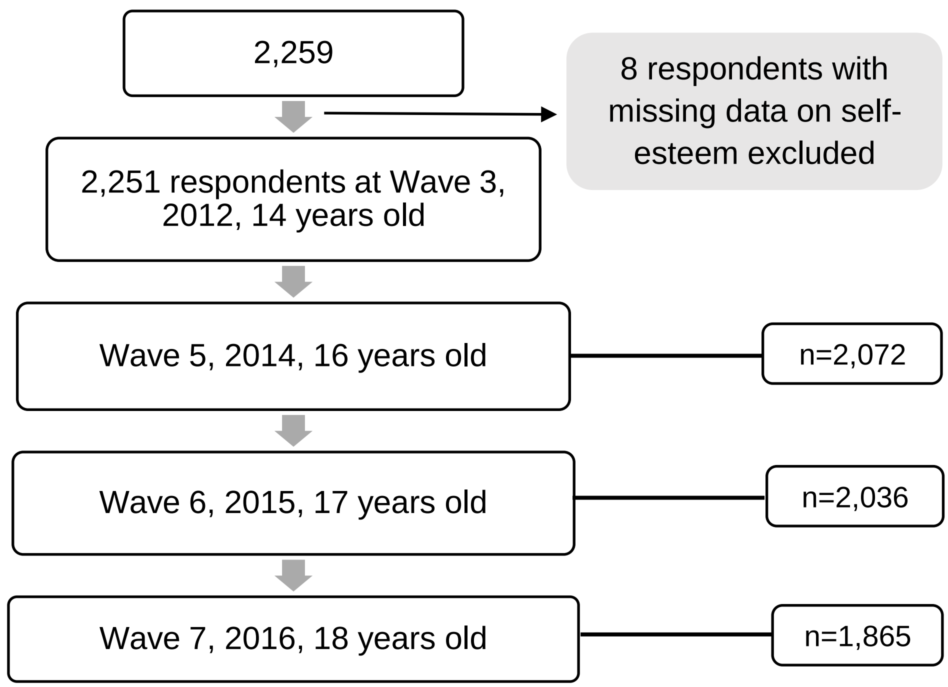
6.3 Methods

6.3.1 Analytical sample

In the main analysis, participants were selected from the M1 cohort of the KCYPS (see Section 4.3.2 of Chapter 4). Data for the KCYPS was collected annually. The M1 Cohort included 2,351 participants at wave 1 (2010). After a loss-to-follow-up of 92 participants and the exclusion of 8 participants with missing data on self-esteem (as described below), the final sample for this study was 2,251 participants at wave 3, which was selected as the baseline. The wave 3 sample of the M1 Cohort consisted of Grade 9 students who were 14 years old. Those with a valid self-esteem score at wave 3 (n = 2,251) were followed up to wave 7, which was the final year of data collection for the KYCPS 2010. During wave 7, the same group of students moved to their fresh(wo)man year of college and turned 18 years old.

Of those 2,251 participants with a valid self-esteem score at wave 3, 92% (2,072 participants) had a valid score at wave 5, 90% (2,036 participants) had a valid score at wave 6 and 83% (1,865 participants) had a valid score at wave 7. Hence, the 2,251 participants with valid self-esteem at wave 3 contributed a total of 8,224 person-wave observations of self-esteem at waves 3, 5, 6 and 7 (questions on self-esteem were not asked at wave 4). 1,776 participants (79%) had valid scores of self-esteem at each of these four waves. The process of deriving my analytical sample for the analyses in this chapter is illustrated in Figure 6.1.

Figure 6.1: Analytical sample of the KCYPS



6.3.2 Measures

Wave 3 of the M1 Cohort was selected as the baseline wave because it was the second wave to include self-esteem in the study content, which allowed me to statistically adjust for prior self-esteem levels (wave 1) in the supplementary analysis. Table 4.4 in Chapter 4 provides a summary of when each variable of interest was assessed across waves 1 to 7 for the M1 cohort. In the main analysis (M1 Cohort: wave 3 to wave 7), questions on self-esteem were asked at waves 3, 5, 6 and 7, questions on CSMU/PIC and family structure were asked at each wave and questions on parenting styles were asked at waves 1, 4, 6 and 7.

Outcome: Self-esteem

As with the UKHLS, self-esteem was assessed by a revised version of the Rosenberg Self-Esteem Scale (RSES-R) (11). The RSES-R was revised by the National Youth Policy Institute and consisted of 10 items which capture how best individuals feel about themselves, rated on a four-point Likert scale, from “Strongly agree” (coded 1) to “Strongly disagree” (coded 4) (Table 6.1). Participants were asked the items on self-esteem via a self-completion survey:

“This is a question about what the student thinks of himself. Please circle the appropriate box for each item below.”

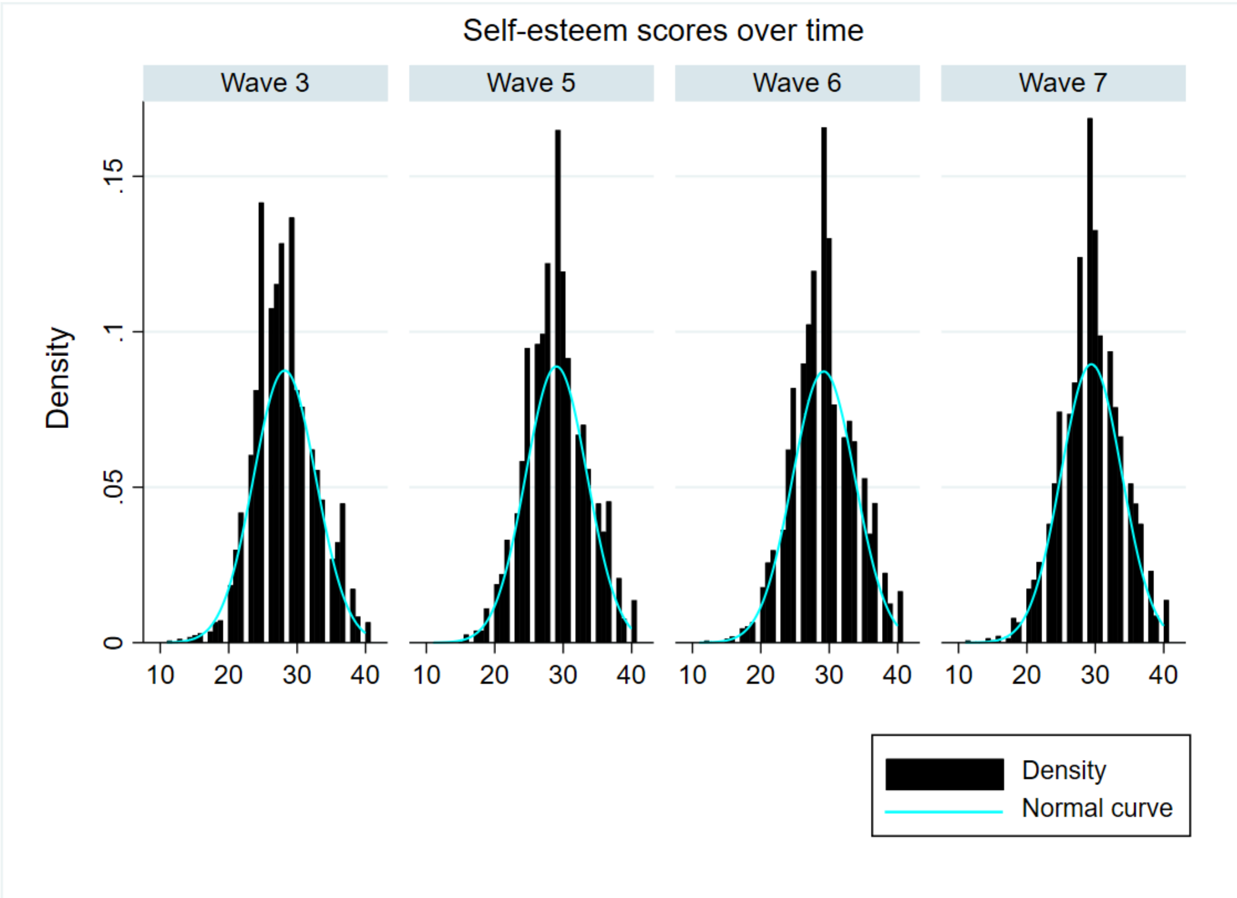
Table 6.1: Self-esteem items from the RSES-R

Self-esteem items	Strongly agree	Agree	Disagree	Strongly disagree
1. I am satisfied with myself.	1	2	3	4
2. I certainly feel useless at times.	1	2	3	4
3. I feel that I have a number of good qualities.	1	2	3	4
4. I am able to do things as well as most other people.	1	2	3	4
5. I feel that I do not have much to be proud of.	1	2	3	4
6. At times I think I am no good at all.	1	2	3	4
7. I feel that I am a person of worth, at least on an equal plane with others.	1	2	3	4
8. I wish I had more respect for myself.	1	2	3	4
9. I am inclined to feel like I am a failure.	1	2	3	4
10. I take a positive attitude towards myself.	1	2	3	4

Five positively worded items (shaded in grey above) were reverse coded: therefore, higher scores on the scale reflected a greater level of self-reported overall self-esteem. Internal reliability of this scale as assessed by Cronbach’s alpha was high in the present study: $\alpha=0.82$ on the 2,251 participants with valid answers (i.e. 1 to 4) on all 10 items of the RSES-R at wave 3. At each wave, responses on all 10 items were summed to form an overall self-esteem score (range in the analytical sample: 11 to 40).

The histograms of the self-esteem scores at each of the four waves indicated a very slight negative skew (Figure 6.2). As such, unlike Chapter 5, all participants with a positive score on the self-esteem scale were included in the analysis.

Figure 6.2: Distribution of self-esteem at waves 3, 5, 6 and 7 (M1 Cohort)



Exposure: CSMU and PIC

A limitation of the study presented in Chapter 5 based on UKHLS data was that information on social media use was collected using a single question on the duration of SNS use (e.g., in the ‘youth’ questionnaire: *“How many hours do you spend chatting or interacting with friends through a social web-site like [Bebo, Facebook or MySpace] on a normal school day?”*). I could not, for example, separate the amount of time usually spent on social media doing different activities such as posting on social media and texting friends and family on social networking platforms such as WhatsApp.

Simply measuring the amount of time spent on social media is not sufficient, as it does not provide information on specific aspects of use that may impact mental health and well-being, which could be either positive or negative. For example, as discussed in Chapter 2, research by Thorisdottir, Sigurvinsdottir, Asgeirsdottir, et al. (2019) found that passive use (e.g., browsing social media profiles of people you do not know) related to more symptoms of anxiety and depressed mood than active use (e.g., sending a private message, picture, video or chat) among adolescents aged 14 to 16 years in Iceland, after controlling for duration of social media use (45). In a similar vein to the examination of active versus passive social media use, investigating the various ways in which social media may be utilised can thus offer more insights into the specific aspects of social media use that could potentially impact mental health and well-being. In the KCYPS, ten questions assessed the frequency of computer use and nine questions assessed the frequency of phone use. These questions are set out below.

"Do you use the computer or not?" Response categories for this item were:

1. Yes
2. No

"How often do you use the computer:

1. *To search for information for studying and learning purposes*
2. *To search for non-academic information (listen to music, watch films, etc.)*
3. ***For games and entertainment***
4. ***For chatting or messaging***
5. *For E-mails*
6. ***For online community activities***
7. ***For personal homepages (blog, Facebook, Twitter, MySpace/Minihompi, etc.)***
8. *For online selling and buying (products, games, music, etc)*
9. ***To leave comments***
10. *To visit adult sites (over 18 years old)"*

"Do you use the phone or not?" Response categories for this item were:

1. Yes
2. No

“How often do you use your phone:

1. ***To call/talk to your family***
2. ***For text messages with family (including KakaoTalk, Line, etc.)***
3. ***To call/talk to friends***
4. ***For text messages with friends (including KakaoTalk, Line, etc.)***
5. *For games and entertainment*
6. *To take a photo*
7. *To watch videos*
8. *To listen to music*
9. *To view the time”*

Responses for the items assessing the frequency of computer and phone use were on a four-point Likert scale. The response options were as follows: 1=*Often*, 2=*Occasionally*, 3=*Rarely* and 4=*Never*. Those who answered *“No”* on the binary questions about the use of a computer and the use of a phone were scored as *“Never”* on the above items (6% and 4% of those with valid answers on all the self-esteem items at wave 3 reported not using the computer and not using a phone, respectively). These items were reverse coded so that higher scores indicated more frequent use.

Use of specific items

To generate a score specifically for computer social media use (CSMU), items 3, 4, 6, 7 and 9 were retained. Items 1 to 4 of phone use were retained for a score I describe hereafter as phone-based interpersonal communication (PIC).

Given the wording of the questions’ items, I could **not** consider these measures as simply being different modes of accessing social media (i.e., computer vs phone). Moreover, for phone-based interpersonal communication, I could not specifically separate interpersonal communication via social media (such as texting or calling on SNSs) from more traditional communications (such as calling a friend and family member with a SIM card). Nevertheless, I included frequency of PIC as an exposure of interest as two of the items related to texting on social networking sites (SNSs) such as KakaoTalk and Line. These platforms also provide calling options and may involve more than a two-way communication (e.g., group chats and calls) and so may capture aspects of social support potentially available by SNSs that are different to those captured by the items I chose to measure frequency of computer social media use. Reliability scores based on Cronbach's alpha (assessed at wave 3) were $\alpha=0.73$ for the five chosen items of CSMU and $\alpha=0.86$ for the four chosen items of PIC.

Single scores of CSMU and PIC were obtained by calculating the mean of the individual (non-missing) items (range 1 to 4): higher scores indicated more frequent use. For descriptive analysis, I grouped the continuous scores into tertiles for ease of interpretation. For the purposes of modelling, the scores were entered as a single continuous (time-varying) variable.

To avoid any misleading direct comparisons and masking of associations, CSMU and PIC were treated separately in the modelling.

Potential moderator: Family structure

Information on family structure was collected by instructing the participants to list the family members they were currently living with. It was assessed in the KCYPS with one question and nine corresponding options to reflect the household composition and parent/guardian characteristics of each respondent. These are listed below.

"What is the composition of 'this student' and the parents who are currently living together? Please circle the appropriate number below."

1. Biological mother and biological father
2. Biological father only
3. Biological mother only
4. Biological father and stepmother
5. Biological mother and stepfather
6. Stepmother and stepfather
7. Stepmother only
8. Stepfather only
9. No parents

This variable was recoded into five categories as follows (note: no participants in the analytical sample were in families with a stepmother and stepfather (response 6)):

1. Two-parent family (response 1)
2. Single-father family (response 2)
3. Single-mother family (response 3)
4. Restructured family (defined as families with stepmothers or stepfathers and could be currently living with one biological parent: responses 4, 5 and 7)
5. No parents (response 8)

Single-parent categories (single-father and single-mother families) were retained to examine their potentially independent associations with the main exposures (frequency of CSMU and PIC) and outcome (self-esteem). However, due to small sample sizes, they were combined into a single-parent category in the linear mixed-effects models.

To maintain consistency with the analyses of the UKHLS presented in Chapter 5, family structure was only assessed at baseline (wave 3) to avoid making assumptions about the directionality of changes in family structure over time. As such, changes can represent both positive and negative transitions.

Potential moderator: Parenting styles

Parental child-rearing attitudes refer to parents' behaviours, language and nonverbal communication exhibited as they rear their children, in order to promote their growth and development (118). The classifications of parenting styles set out below have been developed by TESPIA, a Korean psychological testing institution (174).

<u>Assessing parenting styles</u>

Parenting styles in the KCYPS (M1 Cohort) were assessed at waves 1, 4, 6 and 7, as shown in Table 4.4 in Chapter 4. The Parenting Styles scale is a 21-item scale consisting of six subscales. These are listed below.

- Supervision (3 items)
- Affection (4 items)
- Inconsistency (3 items)
- Unreasonable expectation (4 items)
- Over-involvement (4 items)
- Rational explanation (3 items)

This scale was adapted from Heo's parenting style scale (106, 175). Three subscales assess **positive parenting**: supervision, affection and rational explanation. Positive parenting is used to describe situations when parents express love and care towards their child(ren), communicate effectively and provide reasonable explanations for discipline. The other three subscales, inconsistency, unreasonable expectation and over-involvement assess **negative parenting**. Such behaviours may suggest that parents feel overly anxious about their child(ren), hold unreasonable demands and/or confuse their child(ren) through inconsistent behaviour.Table 6.2 lists the questions asked in each of these categories.

"Ask what the student thinks of their parents (or guardians if parents are not present). For each of the following questions, please answer the one that applies to you."

Table 6.2: Parenting styles

	Positive parenting
Supervision	My parents (guardians) know my whereabouts after school. My parents (guardians) know how I spend my time. My parents (guardians) know when I am coming back when I am out.
Affection	My parents (guardians) respect my opinion. My parents (guardians) express that they love me. My parents (guardians) try to cheer me up when I am feeling down. My parents (guardians) compliment me often.
Rational explanation	Rather than having me follow my parents' (guardians') decisions unconditionally, they explain why I should do things a certain way. When I have done something bad, my parents (guardians) tell me why it is bad before they scold me. If I make an unreasonable request, my parents (guardians) tell me why it cannot be done.
	Negative parenting
Inconsistency	My parents (guardians) can scold me or not scold me for the same thing. My parents (guardians) treat me however they want to. When guests come and go, the attitude of my parents (guardians) towards me is different from usual.
Unreasonable expectation	I feel burdened because my parents' (guardians') expectations are always above my ability. I wish my parents (guardians) did not worry or worried less about me. My parents (guardians) are passionate about my education more than anything else. My parents (guardians) emphasise that I must do better than others in every way.
Over-involvement	My parents (guardians) are usually worried about me doing what children can normally do and they would not let me do that. My parents (guardians) emphasise that I should always win/be successful no matter what I do. My parents (guardians) micromanage me. My parents (guardians) often do not let me do what I want.

Each item is rated on a four-point Likert scale, from "Strongly agree" (coded 1) to "Strongly disagree" (coded 4).

As set out in Table 6.2, examples of positive parenting items are (i) supervision*: "My parents (guardians) know how I spend my time"*, (ii) affection*: "My parents (guardians) compliment me often"* and (iii) rational explanation: *"If I make an unreasonable request, my parents (guardians) tell me why it can't be done"*. Examples of negative parenting items are (i) inconsistency: *"My parents (guardians) treat me however they want to"*, (ii) unreasonable expectation*: "I wish my parents (guardians) did not worry or worried less about me"* and (iii) over-involvement*: "My parents (guardians) micromanage me"*.

Among the 2,251 participants in the M1 Cohort at wave 1, Cronbach's alpha coefficient was estimated at α=0.83 for the whole scale (21 items). Cronbach's alpha for the six subscales set out in Table 6.2 ranged from α=0.64 (inconsistency) to α=0.83 (affection).

A single continuous variable for positive parenting was created based on the mean of the 10 items belonging to the three subscales of supervision, affection and rational explanation (range 1-4, α=0.88): higher scores indicated more positive parenting. A single continuous variable for negative parenting was created based on the mean of the 11 items belonging to the three subscales of inconsistency, unreasonable expectation and over-involvement (range 1-4, α=0.85): higher scores indicated more negative parenting.

For both scales, participants with missing values on *all* the items were assigned missing on the overall score and were imputed for the analyses, using MICE. The positive and negative parenting scores were moderately negatively correlated (Pearson's correlation: ρ = -0.27 at wave 1).

Similarly, the scores on the positive and negative parenting scales were computed at waves 4, 6 and 7. For descriptive analysis (where CSMU, PIC and self-esteem were assessed at wave 3), I grouped the continuous positive and negative parenting scores (assessed at wave 1) into tertiles for ease of interpretation.

Similar to previous studies (30), these subjective indicators of family life were treated as time-varying in the longitudinal models. As the parenting styles (waves 1, 4, 6 and 7) and self-esteem (waves 3, 5, 6 and 7) items were assessed at different waves, scores on positive and negative parenting at waves 1 and 4 were carried forward to waves 3 and 5, respectively. The scores were entered into the linear mixed-effects models as single continuous variables.

Confounders

To identify potential confounders in the associations between CSMU/PIC and self-esteem, I considered previous studies collated in Chapter 2, as well as variables that showed statistically significant p-values in the descriptive analyses.

Total annual household income in Won (₩) was chosen as a marker of socioeconomic position (SEP). According to the Korean Ministry of Health and Welfare (176), a 'low-income' family is defined by the minimum cost of living per family (i.e., the annual income is less than 120% of the minimum cost of living per family). For example, the minimum cost of living for a family of four is ₩1,668,329, and if the monthly income of this family is less than ₩2,001,994 (annual income is approximately ₩24,023,928 (US$20,419.83)), they are eligible for low-income family services. Household income in the KCYPS was assessed by an open-ended item in the parent/guardian survey which requested details about the annual household income from the parent/guardian per ₩10,000 after tax. Annual income (₩) was then grouped into four bands: <20 million, 20-40 million, 40-60 million and 60+ million.

I scored parents' highest educational qualification as a five-point categorical variable (below middle school, high school graduate, community college graduate, undergraduate and postgraduate). I used the highest qualification achieved by either parent or guardian. Lastly, the type of living area was classified as urban or rural. All confounders were treated as time-invariant in the longitudinal analyses (i.e. only assessed at wave 3).

6.3.3 Analytical strategy

Descriptive analyses

To answer the research questions set out in Section 6.2 (**RQ1**), I conducted two sets of bivariate analyses based on the analytical sample at wave 3.

First, I explored differences in mean levels of self-esteem at baseline by frequency (tertiles) of CSMU and PIC, gender, aspects of family life and potential confounders such as household income, place of residence and parental educational status. Statistical significance for the differences in mean self-esteem was examined using linear regression models and Wald tests.

Second, I explored differences in the frequency (tertiles) of CSMU and PIC by demographics, family variables and potential confounders. Statistical significance was examined using Pearson's chi-square test for the association between two variables.

All tests of statistical significance were based on two-tailed probability ($p<0.05$). Analyses were performed using Stata V17 (StataCorp, Texas, USA) and its *svy* commands, accounting for the complex survey design of the KYCPS by using the wave 3 cross-sectional weight (*weight1w3*) and the identifier of the school (*sclidw3*) as the clustering (PSU) variable.

Linear mixed-effects modelling

To answer the research questions set out in Section 6.2 (**RQ2-5**), I performed linear mixed-effects modelling in four stages. Linear mixed-effects models with time-since-baseline as timescale (expressed in years, coded as 0, 2, 3 and 4) were used to estimate the associations between CSMU/PIC and the change in self-esteem over the study period. A longitudinal study of a single birth cohort (i.e., M1 Cohort) does not allow us to investigate the effect of more than one timescale (e.g., separate calendar time and chronological age effects), as such, the chosen time metric was time-since-baseline. This method of analysis is described in detail in Section 4.4.6 of Chapter 4.

Moderation by gender

Any potential moderating effect of gender on the associations between CSMU/PIC and self-esteem was tested for by adding gender by CSMU/PIC interaction terms (**RQ2**).

First, three-way (CSMU/PIC × gender × time-since-baseline) and two-way (CSMU/PIC × gender) interaction terms were included to decide whether the subsequent regression models would be stratified by gender.

Once this was decided, I undertook the modelling in four stages.

Model building

Models 1-3 were estimated to examine **RQ3** (independent associations with self-esteem). Models were performed separately with CSMU and PIC as the main exposures of interest.

- **Model 1** included the main exposure (**frequency of CSMU/PIC** as a single continuous variable[47]) and year as independent variables (main effects) plus the interaction CSMU/PIC × time to allow the estimated 1-year rate of change in self-esteem to vary by frequency of CSMU/PIC, after adjusting for confounders.

- **Model 2** included the terms in Model 1 plus the objective family variable, **family structure** and its interaction with time to allow the estimated 1-year rate of change in self-esteem to vary by the categories of family structure.

- **Model 3** included the terms in Model 2 plus the subjective family variables, **parenting styles** (positive and negative parenting: entered as single continuous variables) and their interactions with time to allow the estimated 1-year rate of change in self-esteem to vary by parenting style scores. Moreover, the aim of my

[47] I also examined the statistical significance of a non-linear (quadratic) term for the frequency of CSMU/PIC to account for any potential U-shaped associations with self-esteem. The quadratic term was not statistically significant ($p>0.05$, data not shown); hence, I only included the linear term.

research questions (**RQ3** and **RQ4**) was to examine each subjective family variable while controlling for the other in the same model.

Models 4a and 4b were estimated to examine **RQ4** (moderation by family factors).

- **Model 4a** included the terms in Model 3 plus three-way interaction terms (family variables × CSMU/PIC × time) to allow the estimated change in self-esteem to vary by combinations of family variables and CSMU/PIC frequency.

- **Model 4b** included the terms in Model 3 plus two-way interaction terms (family variables × CSMU/PIC) to allow the baseline levels of self-esteem to vary by combinations of family variables and CSMU/PIC.

Estimation of mixed models in Stata was performed as described in Chapter 5. To maximise inclusion in the mixed-effects models (and so not use the provided longitudinal weights in the KCYPS [e.g. *weight2w7* at wave 7] which are only calculated for those who completed all waves, i.e., monotone attrition), the models were estimated using the cross-sectional weight at wave 3 using Stata's mixed command with the option *pweight*.

Supplementary analysis: adjustment for prior self-esteem

To address **RQ5**, I re-ran my analysis to statistically adjust for self-esteem scores at wave 1. This allowed me to estimate whether prior self-esteem played any role in confounding the associations between CSMU/PIC and self-esteem.

All models adjusted for confounders and their interactions with time-since-baseline.

6.3.4 Missing data

I used multiple imputation to avoid dropping cases with missing data (e.g., item non-response) on the exposure variables and potential confounders using chained equations (MICE). Details on multiple imputation and MICE were provided in Section 5.3.4 of Chapter 5 and so is not repeated here.

Linear regression was used in this study to fill in missing values for the scores on positive and negative parenting whilst multinomial logistic regression was used for family structure and highest parental educational qualification. I created 20 imputed datasets. Table 6.3 provides a summary of the number of missing observations for each imputed variable.

Table 6.3: Variables with missing values

Variables	Wave 3	Wave 5	Wave 6	Wave 7
	n (%)	**n (%)**	**n (%)**	**n (%)**
n (valid self-esteem)	2,251	2,072	2,036	1,865
Missing data:				
Positive parenting scale	1 (0.0%)	64 (3.1%)	0 (0.0%)	0 (0.0%)
Negative parenting scale	1 (0.0%)	64 (3.1%)	0 (0.0%)	0 (0.0%)
Family structure (wave 3)	62 (2.8%)	47 (2.3%)	45 (2.2%)	35 (1.9%)
Parents' highest educational qualification (wave 3)	66 (2.9%)	50 (2.4%)	48 (2.4%)	37 (2.0%)

Notes: Scores on positive and negative parenting at waves 1 and 4 were carried forward to waves 3 and 5, respectively.

Table B1 in the Appendices provides a summary of the variables used in the imputation models.

6.4 Results

6.4.1 Non-response and attrition

To examine representativeness, I compared baseline characteristics between participants that did and did not take part in the KCYPS at wave 3. The analytical sample at wave 3 was compared to participants at wave 1. Table 6.4 shows the unweighted retention rates of participants at wave 3 (the baseline for this study), among all participants at wave 1 (n = 2,351).

Table 6.4: Comparison of the characteristics of the analytical sample at wave 3 with those of participants at wave 1

	Wave 1 n (row %)	Wave 3 n (row %)	
Overall	2,351 (100)	Took part	Did not take part
		2,259 (96)	92 (4)
Gender:			
Male	1,176 (100)	1,140 (97)	36 (3)
Female	1,175 (100)	1,119 (95)	56 (5)

Response rates in the M1 cohort were 97% and 95% for males and females, respectively. Full retention rates for each cohort in the KCYPS are shown in the user guide (106) and matched those estimated using the supplied datasets. For example, retention rates decreased from 97% at wave 2 (98% males; 97% females) to 80% at wave 7 (79% males; 81% females) for the M1 cohort.

6.4.2 Participants

A breakdown of the baseline (wave 3) characteristics of the sample used in my main analysis (M1 Cohort) is given in Tables 6.5 and 6.6. As the 21 items on parenting styles set out in Table 6.2 were included in the KCYPS at wave 1 but not at wave 3, the tables show the associations between parenting styles as measured at wave 1 and average self-esteem and frequency (tertiles) of CSMU/PIC as measured at wave 3.

RQ1a: Baseline levels of self-esteem

Table 6.5 shows the means and standard deviations (SD) of self-esteem at baseline (wave 3) by frequency of computer social media use and phone-based interpersonal communication (grouped in tertiles), gender, family variables and confounders. This table includes the results of bivariate statistical tests outlined in the analytical strategy (Section 6.3.3).

Table 6.5: Mean self-esteem at wave 3 by frequency of CSMU and PIC, family variables, gender and confounders

Characteristics	Self-esteem		
	n (Column %)	Mean (SD)	P-value
All participants	2,251 (100)	28.2 (4.5)	-
Frequency of CSMU:			
Lowest tertile	866 (38)	28.7 (4.8)	0.009
Middle tertile	701 (31)	27.9 (4.3)	
Highest tertile	684 (31)	27.8 (4.4)	
Frequency of PIC:			
Lowest tertile	975 (44)	27.6 (4.2)	<0.001
Middle tertile	746 (32)	28.5 (4.8)	
Highest tertile	530 (23)	28.9 (4.7)	
Family structure:			
Two-parent family	1,890 (83)	28.3 (4.6)	0.086
Single-father family	107 (5)	27.7 (4.7)	
Single-mother family	140 (6)	27.6 (4.6)	
Restructured family*	27 (1)	26.2 (4.6)	
No parents	25 (1)	27.3 (4.0)	
Missing	62 (4)		
Positive parenting style (wave 1):			
Lowest tertile	826 (36)	26.9 (4.3)	<0.001
Middle tertile	694 (31)	28.3 (4.3)	
Highest tertile	730 (33)	29.5 (4.6)	
Missing	1 (0)		
Negative parenting style (wave 1):			
Lowest tertile	898 (39)	28.9 (4.8)	<0.001
Middle tertile	714 (31)	28.0 (4.3)	
Highest tertile	638 (30)	27.6 (4.3)	
Missing	1 (0)		
Gender:			
Males	1,137 (52)	28.5 (4.4)	0.028
Females	1,114 (48)	27.9 (4.6)	
Parents' highest educational qualification:			
Below middle school	80 (4)	27.6 (4.5)	<0.001
High school graduate	893 (37)	27.7 (4.5)	
Community college graduate	231 (10)	28.0 (4.4)	
Undergraduate	861 (39)	28.5 (4.6)	
Postgraduate	120 (6)	30.1 (4.4)	
Missing	66 (4)		
Annual household income (₩):			
<20 million	196 (8)	27.4 (4.8)	0.004
20-40 million	660 (28)	27.8 (4.6)	
40-60 million	895 (40)	28.2 (4.5)	
>60 million	500 (24)	28.9 (4.4)	
Type of living area:			
Urban	1,922 (88)	28.3 (4.5)	0.010
Rural	329 (12)	27.6 (4.6)	

Abbreviations: CSMU: computer social media use; PIC: phone-based interpersonal communication. *Notes:* Column percentages are weighted; sample sizes are unweighted. P-values were calculated using linear regression modelling and Wald tests of linear hypotheses, adjusting for the complex survey design. *Families with stepfathers or stepmothers and could be currently living with one or two biological parents.

The baseline analytical sample (M1 Cohort) comprised n = 2,251 participants who were 14 years old at wave 3 (2012) and who had a valid self-esteem score (Table 6.5). Males and females were roughly evenly split in this sample at baseline (52% and 48%, respectively). Mean self-esteem at wave 3 was 28.2 (SD 4.5).

Mean levels of self-esteem varied by frequency of computer social media use (p=0.009) and frequency of phone-based interpersonal communication (p<0.001): self-esteem being lowest on average for those with higher computer social media use frequency (28.7 versus 27.8 in the lowest and highest tertiles, respectively) and lowest for those with lower phone-based interpersonal communication frequency (27.6 versus 28.9 in the lowest and highest tertiles, respectively).

Mean levels of self-esteem varied by family structure (p=0.086): self-esteem was lowest on average for those living with a restructured family and was highest for those living with two biological parents (26.2 versus 28.3, respectively). The estimates for the former should be treated with caution due to the small sample size. Mean self-esteem also varied by parenting styles as assessed at wave 1 (p<0.001). Average self-esteem was lowest for those who ranked lowest on positive parenting (26.9 versus 29.5 in the lowest and highest tertiles, respectively) and was lowest for those who ranked highest on negative parenting (28.9 versus 27.6 in the lowest and highest tertiles, respectively).

With respect to the potential confounders or moderators, females had lower self-esteem on average than males (27.9 versus 28.5, respectively; p=0.028). Self-esteem also varied by parental educational status (p<0.001): being lowest for those whose parents' highest educational qualification was below middle school and highest for those whose parents' highest educational qualification was at postgraduate degree level (27.6 versus 30.1, respectively). A similar gradient in self-esteem was found by household income (27.4 versus 28.9 in the lowest and highest income bracket, respectively; p=0.004).

Those living in rural areas also had lower self-esteem on average than those living in urban areas (27.6 versus 28.3, respectively; p=0.010).

In summary, Hypothesis 1a was supported by the data as baseline self-esteem was significantly lower for more frequent computer social media users, females, participants not living in a household with two biological parents, and participants with lower scores on positive parenting and higher scores on negative parenting. Self-esteem was higher at higher levels of phone-based interpersonal communication.

RQ1b: Baseline levels of frequency of CSMU/PIC

Table 6.6 shows the frequency of CSMU and PIC by family variables, gender and potential confounders.

Table 6.6: Tertiles of CSMU and PIC frequency at wave 3 by family variables and confounders

		Frequency of CSMU (tertiles)					Frequency of PIC (tertiles)			
		Lowest	Middle	Highest			Lowest	Middle	Highest	
	Total n	n (row %)	n (row %)	n (row %)	P-value	Total n	n (row %)	n (row %)	n (row %)	P-value
All participants	2,251	866 (38)	701 (31)	684 (31)	-	2,251	975 (44)	746 (32)	530 (23)	-
Family structure:										
Two-parent	1,890	739 (39)	604 (32)	547 (29)	*0.041*	1,890	812 (44)	629 (33)	449 (23)	*0.454*
Single-father	107	37 (34)	28 (24)	42 (42)		107	49 (48)	38 (33)	20 (20)	
Single-mother	140	44 (28)	37 (29)	59 (43)		140	54 (39)	46 (33)	40 (28)	
Restructured*	27	10 (32)	6 (29)	11 (39)		27	15 (62)	7 (19)	5 (20)	
No parents	25	7 (32)	12 (50)	6 (18)		25	14 (60)	8 (23)	3 (17)	
Missing**	62	29 (45)	14 (24)	19 (32)		62	31 (48)	18 (29)	13 (23)	
Positive parenting (wave 1):										
Lowest	826	304 (36)	261 (31)	261 (33)	*0.161*	826	422 (52)	258 (30)	146 (18)	*<0.001*
Middle	694	255 (36)	224 (32)	215 (31)		694	306 (45)	223 (33)	165 (23)	
Highest	730	306 (41)	216 (31)	208 (28)		730	246 (35)	265 (35)	219 (30)	
Missing**	1	1 (1)	0 (0)	0 (0)		1	1 (1)	0 (0)	0 (0)	
Negative parenting (wave 1):										
Lowest	898	390 (43)	271 (30)	237 (26)	*<0.001*	898	366 (41)	321 (35)	211 (23)	*0.085*
Middle	714	246 (33)	248 (35)	220 (32)		714	305 (44)	242 (33)	167 (23)	
Highest	638	229 (36)	182 (29)	227 (35)		638	303 (49)	183 (28)	152 (23)	
Missing**	1	1 (1)	0 (0)	0 (0)		1	1 (1)	0 (0)	0 (0)	
Gender:										
Males	1,137	366 (33)	369 (32)	402 (35)	*<0.001*	1,137	547 (49)	340 (29)	250 (21)	*<0.001*
Females	1,114	500 (43)	332 (31)	282 (26)		1,114	428 (39)	406 (36)	280 (25)	
Parents' highest educational qualification:										
Below middle school	80	28 (32)	22 (25)	30 (42)	*0.021*	80	29 (32)	28 (37)	23 (30)	*0.114*
High school	893	296 (33)	302 (34)	295 (34)		893	388 (45)	304 (34)	201 (21)	
Community college	231	99 (42)	64 (29)	68 (29)		231	94 (42)	77 (31)	60 (28)	
Undergraduate	861	362 (41)	259 (31)	240 (29)		861	366 (43)	285 (33)	210 (24)	
Postgraduate	120	51 (46)	37 (31)	32 (23)		120	64 (58)	33 (23)	23 (19)	
Missing**	66	30 (45)	17 (25)	19 (30)		66	34 (49)	19 (29)	13 (22)	

Annual household income (₩):										
<20 million	196	67 (33)	63 (34)	66 (34)	*0.046*	196	94 (48)	59 (30)	43 (22)	*0.041*
20-40 million	660	235 (35)	201 (31)	224 (34)		660	276 (44)	235 (35)	149 (21)	
40-60 million	895	335 (37)	307 (34)	253 (29)		895	360 (41)	316 (35)	219 (24)	
>60 million	500	229 (44)	130 (27)	141 (29)		500	245 (49)	136 (27)	119 (24)	
Type of living area:										
Urban	1,922	754 (39)	593 (31)	575 (30)	0.298	1,922	823 (44)	652 (33)	447 (23)	0.283
Rural	329	112 (34)	108 (32)	109 (34)		329	152 (46)	94 (29)	83 (25)	

Notes: Row percentages are weighted: sample sizes are unweighted. Estimates may not sum to 100 due to rounding. P-values were calculated by Pearson's Chi-square test, adjusting for the complex survey design. *Families with stepfathers or stepmothers and could be currently living with one or two biological parents. **Excluded from test because of low frequencies or deemed not to be of substantive interest.

Frequency of computer social media use (CSMU)

In brief, a higher frequency of computer social media use was associated with being in a single-parent or restructured family, higher negative parenting, being male, lower educational status of parents and lower household income (Hypothesis 1b partially supported).

The frequency of computer social media use varied by family structure ($p=0.041$). 29% of participants in two (biological) parent households were classified in the highest tertile of use, compared with 42% of participants in single-father households and 43% of participants in single-mother households (these estimates should be treated with caution due to the small sample sizes).

The frequency of computer social media use also varied by tertiles of negative parenting ($p<0.001$). Higher levels of computer social media use were associated with higher negative parenting scores. For example, 35% of participants in the highest tertile of negative parenting were classified in the highest tertile of computer social media use, compared with 26% of participants in the lowest tertile of negative parenting. The frequency of computer social media use did not vary by tertiles of positive parenting ($p=0.161$).

With respect to the confounders or moderators, classification in the highest tertile of computer social media use did not vary by type of living area ($p=0.298$). Males were more likely than females to be classified in the highest tertile (35% versus 26%, respectively; $p<0.001$). The frequency of computer social media use varied by parental educational status ($p=0.021$): with the proportions in the highest tertile of use being 42% among those with below middle school qualifications and 23% among those with parent(s) with a postgraduate degree. The frequency of computer social media use also varied by annual income ($p=0.046$): with the proportions in the highest tertile being 34% among those with the lowest income and 29% among those with the highest income.

Frequency of phone-based interpersonal communication (PIC)

In brief, a higher frequency of phone-based interpersonal communication was associated with higher positive parenting, being female and with higher annual household income (Hypothesis 1b only supported for gender).

The frequency of phone-based interpersonal communication varied by scores on the positive parenting scale ($p<0.001$), but the pattern of association was different to that for computer social media use. Higher levels of PIC were associated with higher positive parenting scores. For example, 30% of participants in the highest tertile on positive parenting were classified in the highest tertile of PIC, compared with 18% of participants in the lowest tertile on positive parenting. The frequency of PIC did not vary significantly by tertiles of negative parenting ($p=0.085$).

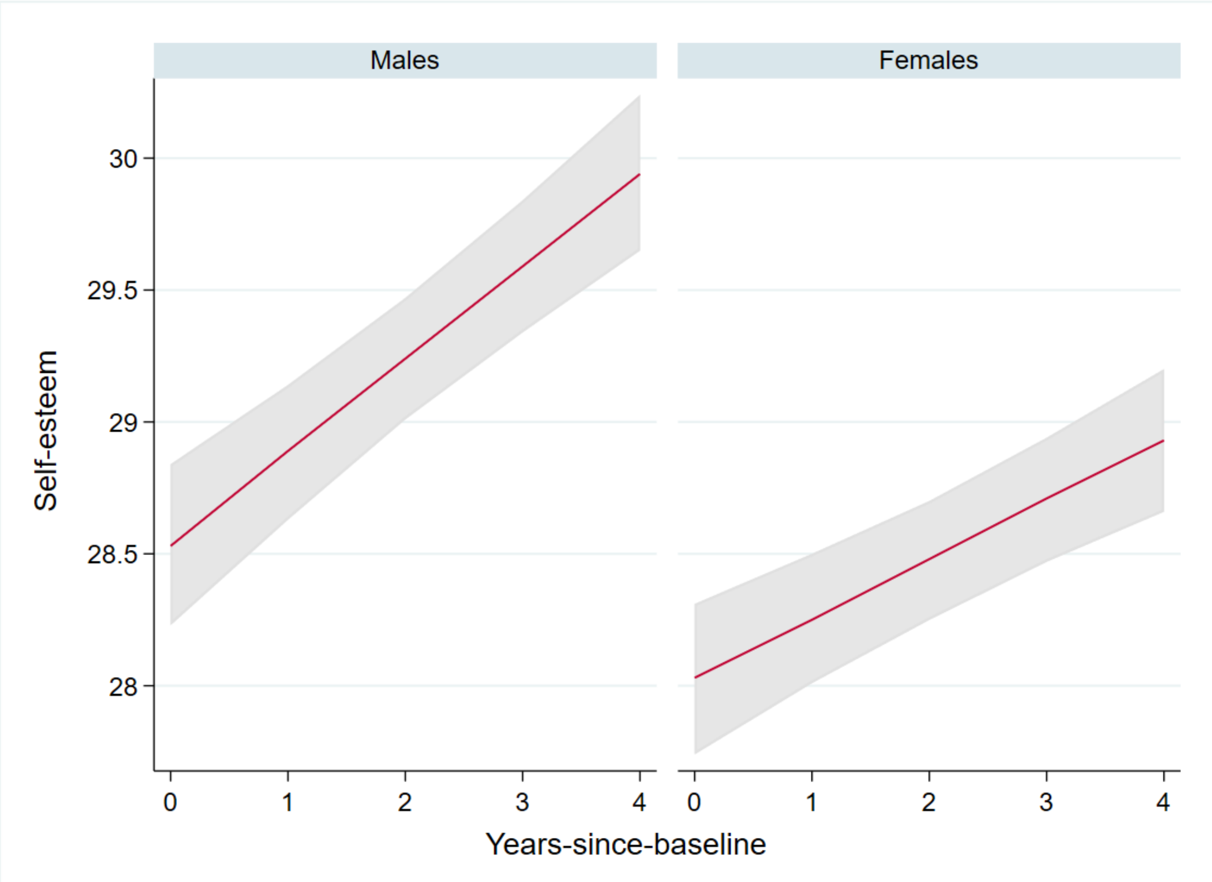
PIC frequency did not vary by family structure ($p=0.454$), parents' highest educational qualification ($p=0.114$) and type of living area ($p=0.283$). Frequency of PIC varied by gender ($p<0.001$), with the proportions in the highest tertile being 25% for females versus 21% for males. A higher proportion of males (49%) than females (39%) were classified in the lowest tertile of PIC. Frequency of PIC also varied by annual household income ($p=0.041$), with the proportions in the highest tertile being 24% among those with the highest income and 21% among those with the lowest income.

6.4.3 Trajectories of self-esteem by gender

A linear mixed-effects model containing just the main effects of time and gender showed that average levels of self-esteem increased over time (1-year rate of change $\beta = 0.29$: 95% CI: 0.23, 0.35; $p<0.001$) and that females on average had lower levels of self-esteem than males at each wave (β female = -0.77; 95% CI: -1.09, -0.45; $p<0.001$).

Based on a linear mixed-effects model that estimated the (linear) 1-year rate of change in self-esteem separately by gender (i.e., by including a two-way interaction term: gender × time), males and females showed some slight difference in the rate of change in self-esteem ($p=0.045$ for the two-way interaction). Figure 6.3 shows the estimated linear trajectories of self-esteem by gender, which portrays that males' self-esteem on average increased more sharply than females' self-esteem.

Figure 6.3: Self-esteem trajectories by gender



Notes: Predicted mean self-esteem from a linear mixed-effects model containing time, gender and the two-way interaction: gender-by-time.

6.4.4 Longitudinal analyses

RQ2: Moderation by gender

After testing for the three-way (CSMU/PIC x gender x time) and two-way interactions (CSMU/PIC x gender), the results showed no statistically significant moderating effects of gender in the linear mixed-effects models that assessed CSMU and PIC separately (estimates shown in Table B2 in the Appendices). Therefore, I did not stratify the subsequent models by gender.

RQ3: Main effects

Models with computer social media use as main exposure

Table 6.7 shows the results for the linear mixed-effect models that included the frequency of CSMU as the main exposure. The frequency of CSMU was entered into the models as a continuous variable, as such, the main effect represents the estimated difference in mean self-esteem at baseline (wave 3) for a one-unit increase in CSMU frequency. The CSMU-by-time two-way interaction term represents the estimated difference in the 1-year rate of change in self-esteem for a 1-unit increase in the frequency of computer social media use. Results for Models 1 to 3 (see Section 6.3.3 for details on the modelling strategy) are shown.

Table 6.7: Results from the linear mixed-effects models for the associations between frequency of computer social media use, family structure, positive and negative parenting, and self-esteem

Characteristics	Model 1			Model 2			Model 3		
	B	95% CI	P-value	B	95% CI	P-value	B	95% CI	P-value
Intercept	29.7	(29.0, 30.5)	<0.001	29.7	(29.0, 30.5)	<0.001	27.1	(25.4, 28.8)	<0.001
Time	0.23	(-0.01, 0.47)	0.058	0.23	(-0.01, 0.47)	0.060	0.13	(-0.47, 0.74)	0.664
CSMU	-0.44	(-0.67, -0.20)	<0.001	-0.44	(-0.67, -0.20)	<0.001	-0.48	(-0.71, -0.25)	<0.001
CSMU × time	0.04	(-0.05, 0.13)	0.401	0.04	(-0.05, 0.13)	0.393	0.07	(-0.02, 0.15)	0.124
Females	-0.59	(-1.00, -0.18)	0.005	-0.60	(-1.01, -0.19)	0.005	-0.70	(-1.11, -0.30)	0.001
Females × time	-0.13	(-0.25, 0.00)	0.046	-0.13	(-0.25, 0.00)	0.046	-0.13	(-0.25, -0.01)	0.033
Family structure (wave 3)									
2-parent family (ref)				-	-	-	-	-	-
Single-parent family				-0.03	(-0.76, 0.71)	0.938	0.08	(-0.65, 0.80)	0.839
Restructured family*				-1.57	(-3.51, 0.37)	0.113	-1.30	(-3.12, 0.51)	0.159
No parents				-0.45	(-2.19, 1.29)	0.615	-0.23	(-1.85, 1.40)	0.786
P-value						*0.417*			*0.521*
Family structure x time									
2-parent family (ref)				-	-	-	-	-	-
Single-parent family				-0.03	(-0.25, 0.18)	0.760	0.00	(-0.21, 0.21)	0.965
Restructured family*				0.18	(-0.37, 0.72)	0.521	0.12	(-0.38, 0.62)	0.638
No parents				-0.14	(-0.65, 0.37)	0.583	-0.12	(-0.63, 0.40)	0.651
P-value						*0.849*			*0.931*
Positive parenting							1.31	(0.96, 1.66)	<0.001
Pos. parenting x time							0.19	(0.06, 0.33)	0.005
Negative parenting							-0.48	(-0.82, -0.14)	0.006
Neg. parenting x time							-0.25	(-0.37, -0.13)	<0.001
Random effects (SD):									
Level-2 intercept	*3.3*	*(3.1, 3.5)*		3.3	(3.1, 3.5)		3.1	(2.9, 3.3)	
Level-2 slope	*0.7*	*(0.6, 0.8)*		0.7	(0.6, 0.8)		0.6	(0.5, 0.7)	
Correlation: int-slope	*-0.4*	*(-0.5, -0.3)*		-0.4	(-0.5, -0.3)		-0.5	(-0.6, -0.4)	
Level-1 residual	*3.1*	*(3.0, 3.2)*		3.1	(3, 3.2)		3.1	(3.0, 3.2)	

Abbreviations: CI: confidence interval; CSMU: computer social media use; ref: reference category; SD: standard deviation. Notes: Participants (n = 2,251); person-wave observations (8,224). **Model 1**: CSMU + confounders**; Model 2**: CSMU + family structure + confounders; **Model 3**: CSMU + family structure + parenting styles. *Families with stepfathers or stepmothers and could be currently living with one or two biological parents. Confounding variables included in each model were gender (reference: males), parental educational status (reference: undergraduate), annual household income (reference: 40-60 million **(₩)**) and type of living area (reference: urban).

Overall, a one-unit increase in the frequency of CSMU was significantly associated with lower baseline levels of self-esteem (Model 3: $\beta = -0.48$ (95% CI: -0.71, -0.25); $p<0.001$) but was not associated with the (linear) 1-year rate of change in self-esteem ($p=0.124$).

Family structure (treated as time-invariant, assessed at wave 3) was not significantly associated with baseline levels of self-esteem (Model 3: $p=0.521$) nor with the rate of change in self-esteem (Model 3: $p=0.931$).

A one-unit increase in positive parenting was associated with higher baseline self-esteem (Model 3: $\beta = 1.31$ (95% CI: 0.96, 1.66); $p<0.001$) and a faster (linear) rate of increase in self-esteem over time (Model 3: β positive parenting × time = 0.19 (95% CI: 0.06, 0.33); $p=0.005$).

A one-unit increase in negative parenting was associated with lower baseline self-esteem (Model 3: $\beta = -0.48$ (95% CI: -0.82, -0.14); $p=0.006$) and a slower (linear) rate of increase in self-esteem over time (Model 3: β negative parenting × time = -0.25 (95% CI: -0.37, -0.13); $p<0.001$).

Holding all variables constant, females had significantly lower baseline levels of self-esteem than males (Model 3: $\beta= -0.70$ (95% CI: -1.11, -0.30); $p=0.001$) and showed a slower (linear) rate of increase in self-esteem over time compared to an increasing trend among males (Model 3: β female × time = -0.13 (95% CI: -0.25, -0.01); $p=0.033$).

Models with phone-based interpersonal communication as main exposure

Table 6.8 shows the results for the models that included the frequency of PIC as the main exposure.

Table 6.8: Results from the linear mixed-effects models for the associations between frequency of phone-based interpersonal communication, family structure, positive and negative parenting, and self-esteem

	Model 1			Model 2			Model 3		
	B	**95% CI**	**P-value**	**B**	**95% CI**	**P-value**	**B**	**95% CI**	**P-value**
Intercept	27.4	(26.3, 28.4)	<0.001	27.4	(26.3, 28.4)	<0.001	25.1	(23.3, 26.9)	<0.001
Time	0.06	(-0.38, 0.51)	0.780	0.06	(-0.39, 0.51)	0.79	0.14	(-0.55, 0.83)	0.685
PIC	0.42	(0.14, 0.70)	0.003	0.42	(0.14, 0.70)	0.003	0.38	(0.09, 0.66)	0.009
PIC × time	0.08	(-0.04, 0.20)	0.190	0.08	(-0.04, 0.20)	0.187	0.04	(-0.09, 0.17)	0.540
Females	-0.55	(-0.96, -0.15)	0.008	-0.56	(-0.96, -0.15)	0.007	-0.66	(-1.06, -0.26)	0.001
Females × time	-0.14	(-0.26, -0.02)	0.023	-0.14	(-0.26, -0.02)	0.022	-0.15	(-0.27, -0.03)	0.018
Family structure (wave 3)									
2-parent family (ref)				-	-	-	-	-	-
Single-parent family				-0.07	(-0.81, 0.66)	0.843	0.02	(-0.71, 0.75)	0.953
Restructured family*				-1.51	(-3.45, 0.43)	0.128	-1.27	(-3.08, 0.54)	0.170
No parents				-0.25	(-1.96, 1.46)	0.776	-0.05	(-1.66, 1.56)	0.955
P-value						*0.479*			*0.573*
Family structure x time									
2-parent family (ref)				-	-	-	-	-	-
Single-parent family				0.00	(-0.22, 0.21)	0.968	0.02	(-0.19, 0.23)	0.853
Restructured family*				0.20	(-0.35, 0.75)	0.480	0.14	(-0.38, 0.66)	0.603
No parents				-0.22	(-0.75, 0.30)	0.403	-0.19	(-0.72, 0.33)	0.476
P-value						*0.743*			*0.830*
Positive parenting							1.27	(0.91, 1.63)	<0.001
Pos. parenting x time							0.18	(0.04, 0.32)	0.010
Negative parenting							-0.55	(-0.89, -0.20)	0.002
Neg. parenting x time							-0.23	(-0.35, -0.11)	<0.001
Random effects (SD):									
Level-2 intercept	3.3	(3.1, 3.5)		3.3	(3.1, 3.5)		3.1	(2.9, 3.3)	
Level-2 slope	0.7	(0.6, 0.8)		0.7	(0.6, 0.8)		0.6	(0.5, 0.7)	
Correlation: Int-slope	-0.4	(-0.5, -0.3)		-0.4	(-0.5, -0.3)		-0.5	(-0.6, -0.4)	
Level-1 residual	3.1	(3, 3.2)		3.1	(3.0, 3.2)		3.1	(3.0, 3.2)	

Abbreviation: CI: confidence interval; PIC: phone-based interpersonal communication; ref: reference category; SD: standard deviation. Notes: Participants (n = 2,251); person-wave observations (n = 8,224). **Model 1**: PIC + confounders**; Model 2**: PIC + family structure + confounders; **Model 3**: PIC + family structure + parenting styles. *Families with stepfathers or stepmothers and could be currently living with one or two biological parents. Confounding variables included in each model were gender (reference: males), parental educational status (reference: undergraduate), annual household income (reference: 40-60 million **(₩)**) and type of living area (reference: urban).

A one-unit increase in the frequency of PIC was significantly associated with baseline levels of self-esteem (Model 3: β = 0.38 (95% CI: 0.09, 0.66); $p=0.009$) but not with the rate of change in self-esteem (Model 3: $p=0.540$). Family structure was not significantly associated with baseline self-esteem (Model 3: $p=0.573$) nor with the rate of change in self-esteem (Model 3: $p=0.830$).

The parenting styles variables showed a similar pattern of association as for the models with computer social media use as the main exposure.

A one-unit increase in positive parenting was associated with higher baseline self-esteem (Model 3: β = 1.27 (95% CI: 0.91, 1.63); $p<0.001$) and a faster (linear) rate of increase in self-esteem over time (Model 3: β positive parenting × time = 0.18 (95% CI: 0.04, 0.32); $p=0.010$).

A one-unit increase in negative parenting was associated with lower baseline self-esteem (Model 3: β = -0.55 (95% CI: -0.89, -0.20); $p=0.002$) and a slower (linear) rate of increase in self-esteem over time (Model 3: β negative parenting × time = -0.23 (95% CI: -0.35, -0.11); $p<0.001$).

Holding all variables constant, females had significantly lower baseline self-esteem than males (Model 3: β female = -0.66 (95% CI: -1.06, -0.26); $p=0.001$) and showed a slower rate of increase in self-esteem over time compared to males (Model 3: β female × time = -0.15 (95% CI: -0.27, -0.03); $p=0.018$).

RQ4: Moderation by family factors

With regards to **RQ4**, additional models examined whether any of the family variables (family structure and parenting styles) moderated any associations between the frequency of CSMU/PIC and self-esteem. Adding to the terms in Model 3 (shown in Tables 6.9-6.10), the p-values for the relevant three-way and two-way interaction terms are shown in Table 6.9.

Table 6.9: Results from the linear mixed-effects models for the potential moderation by family variables on the associations between CSMU/PIC frequency and self-esteem

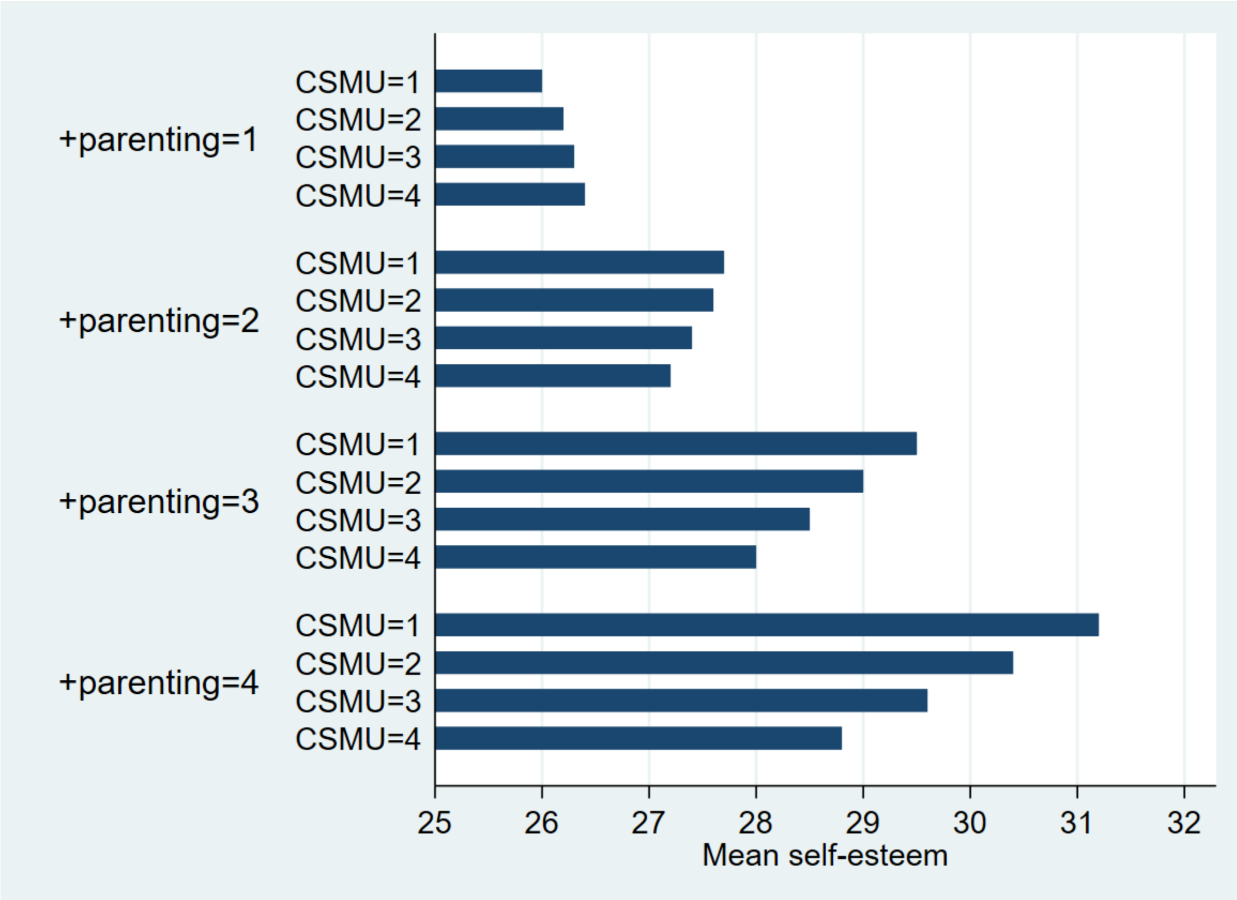
Interactions	CSMU as main exposure	PIC as main exposure
	P-value	**P-value**
Three-way interactions:		
Family structure × CSMU/PIC × time	0.832	0.580
Positive parenting × CSMU/PIC × time	0.521	0.261
Negative parenting × CSMU/PIC × time	0.406	0.948
Two-way interactions:		
Family structure × CSMU/PIC	0.352	0.248
Positive parenting × CSMU/PIC	0.045	0.018
Negative parenting × CSMU/PIC	0.051	0.540

Abbreviations: CSMU: computer social media use; PIC: phone-based interpersonal communication. *Notes:* Participants (n = 2,251); person-wave observations (n = 8,224). Three-way interaction terms investigate differences in the rate of change in self-esteem by combinations of family variables and CSMU/PIC frequency; two-way interaction terms investigate differences in baseline self-esteem by combinations of family variables and CSMU/PIC frequency. All three-way terms were included in the same model; all two-way terms were tested in the same model without the three-way terms.

Whilst most interaction terms did not reach statistical significance (p>0.05), the two-way interaction between positive parenting and CSMU (p=0.045) and positive parenting and PIC (p=0.018) showed statistical significance at the 5% level.

Figure 6.4 displays the predicted self-esteem values for different combinations of CSMU and positive parenting scores, as estimated by the model that included all two-way interaction terms. It shows that at higher levels of positive parenting, mean levels of self-esteem at baseline (wave 3) decreased with increasing frequency of CSMU.

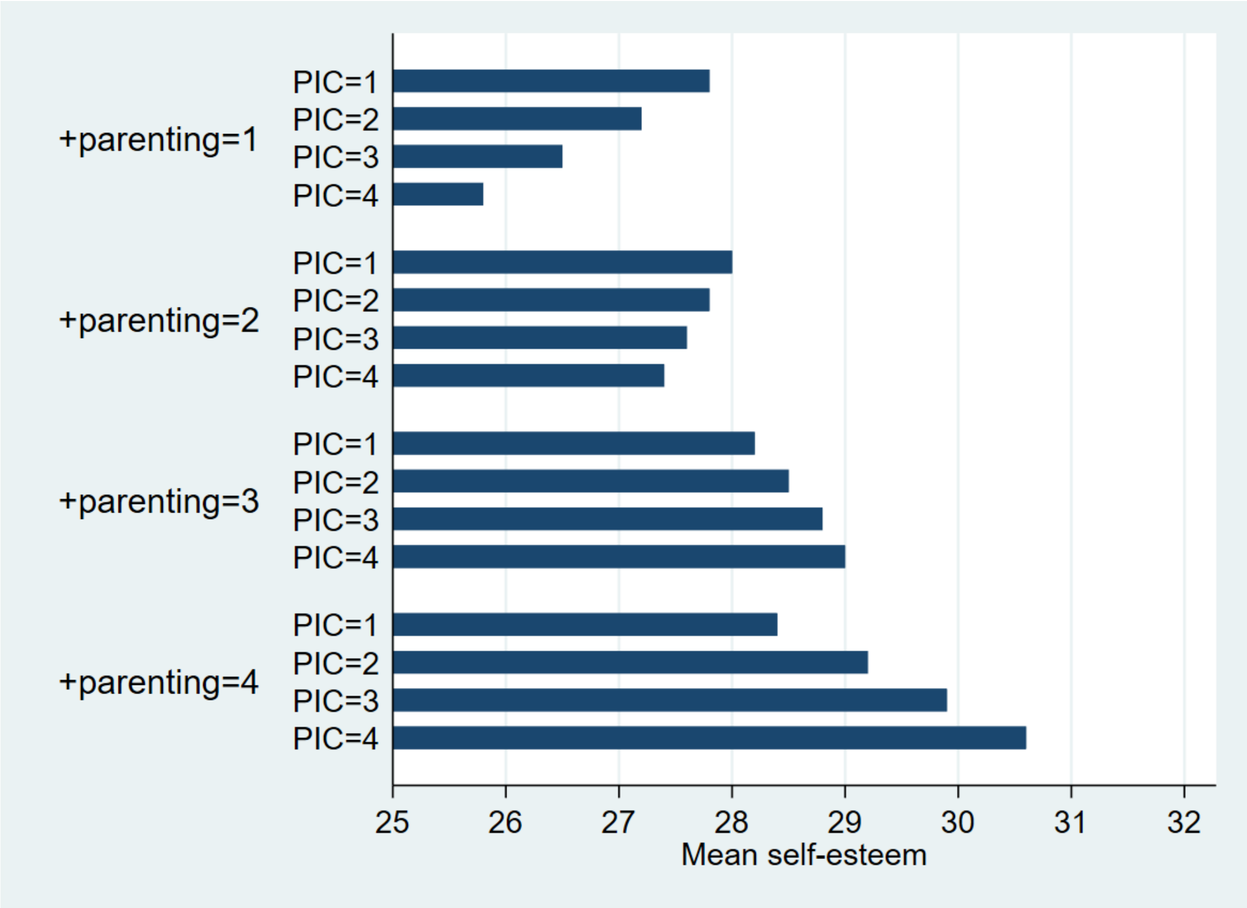
Figure 6.4: Self-esteem by CSMU frequency and positive parenting at baseline



Abbreviations: CSMU: Computer social media use; +parenting: Positive parenting.

Conversely, Figure 6.5 shows that at lower levels of positive parenting, mean levels of self-esteem at baseline decreased with increasing frequency of PIC, whereas at higher levels of positive parenting, mean self-esteem increased with increasing frequency of PIC.

Figure 6.5: Self-esteem by PIC frequency and positive parenting at baseline



6.4.5 Supplementary analysis

Similar to my analyses of the UKHLS data, I repeated my main analysis by statistically adjusting for prior levels of self-esteem (assessed at wave 1).

Table 6.10 shows the results for the fully-adjusted models that examined the associations between frequency of CSMU/PIC, family variables and self-esteem (over waves 3 to 7) after adjusting for prior self-esteem . The results of two models are shown: (i) **Model 1**: CSMU-only model and (ii) **Model 2**: PIC-only model.

Table 6.10: Results from the linear mixed-effect models for the associations between frequency of CSMU/PIC, family structure, positive and negative parenting, and self-esteem (after adjusting for prior levels of self-esteem and other confounders)

	Model 1 (CSMU)			Model 2 (PIC)		
	B	**95% CI**	**P-Value**	**B**	**95% CI**	**P-Value**
Intercept	19.6	(17.8, 21.4)	<0.001	17.6	(15.8, 19.5)	<0.001
Esteem at wave 1	0.28	(0.25, 0.31)	<0.001	0.28	(0.25, 0.31)	<0.001
Time	0.07	(-0.52, 0.67)	0.811	0.12	(-0.56, 0.79)	0.736
Computer SMU	-0.44	(-0.66, -0.21)	<0.001	-	-	
CSMU × time	0.07	(-0.01, 0.15)	0.107	-	-	
PIC	-	-	-	0.38	(0.12, 0.64)	0.004
PIC × time	-	-	-	0.03	(-0.09, 0.15)	0.648
Females	-0.45	(-0.82, -0.08)	0.018	-0.42	(-0.78, -0.05)	0.027
Females × time	-0.14	(-0.26, -0.02)	0.027	-0.15	(-0.27, -0.03)	0.015
Family structure (wave 3)						
2-parent family (ref)	-	-	-	-	-	
Single-parent family	0.27	(-0.38, 0.91)	0.418	0.21	(-0.43, 0.86)	0.516
Restructured family	-1.17	(-2.67, 0.32)	0.123	-1.13	(-2.62, 0.36)	0.136
No parents	0.23	(-1.29, 1.75)	0.768	0.40	(-1.13, 1.93)	0.607
P-value			*0.345*			*0.388*
Family structure x time						
2-parent family (ref)	-	-	-	-	-	
Single-parent family	0.01	(-0.20, 0.22)	0.948	0.03	(-0.18, 0.24)	0.780
Restructured family	0.16	(-0.38, 0.70)	0.569	0.17	(-0.38, 0.73)	0.543
No parents	-0.12	(-0.65, 0.41)	0.659	-0.19	(-0.73, 0.35)	0.498
P-value			*0.903*			*0.801*
Positive parenting	0.94	(0.60, 1.28)	<0.001	0.89	(0.55, 1.24)	<0.001
Pos. parent. x time	0.24	(0.11, 0.38)	<0.001	0.24	(0.10, 0.37)	0.001
Negative parenting	-0.31	(-0.64, 0.01)	0.059	-0.38	(-0.71, -0.05)	0.025
Neg. parent. x time	-0.29	(-0.41, -0.16)	<0.001	-0.27	(-0.39, -0.14)	<0.001
Random effects (SD):						
Level-2 Intercept	2.5	(2.3, 2.8)		2.5	(2.3, 2.8)	
Level-2 slope	0.6	(0.5, 0.7)		0.6	(0.5, 0.7)	
Correlation: Int-slope	-0.4	(-0.5, -0.3)		-0.4	(-0.5, -0.3)	
Level-1 residual	3.1	(3.0, 3.2)		3.1	(3.0, 3.2)	

Abbreviations: ref: reference category; SD: standard deviation; CSMU: Computer social media use; PIC: Phone-based interpersonal communication. *Notes:* Participants (n = 2,250); person-wave observations (n = 8,220). Confounding variables included in each model were gender (reference: males), parental educational status (reference: undergraduate), annual household income (reference: 40-60 million **(₩)**) and type of living area (reference: urban).

In both models, a one-unit increase in prior self-esteem was significantly associated with higher self-esteem at baseline (β = 0.28 (95% CI: 0.25, 0.31); $p<0.001$).

Adjusting for prior self-esteem and consistent with earlier results, a one-unit increase in the frequency of CSMU was significantly associated with lower self-esteem at baseline (Model 1: β = -0.44 (95% CI: -0.66, -0.21); $p<0.001$) but was not associated with the rate of change in self-esteem (Model 1: $p=0.107$). Also consistent with earlier results, a one-unit increase in the frequency of PIC was significantly associated with higher self-esteem at baseline (Model 2: β = 0.38 (95% CI: 0.12, 0.64); $p=0.004$) but was not associated with the rate of change in self-esteem ($p=0.648$).

In both models and consistent with earlier results, family structure was not significantly associated with baseline self-esteem (Model 1: $p=0.345$; Model 2: $p=0.388$) nor with its rate of change (Model 1: $p=0.903$; Model 2: $p=0.801$).

The parenting styles variables showed a similar pattern of association as described earlier. *A* one-unit increase in positive parenting was associated with higher baseline self-esteem (Model 1: β = 0.94 (95% CI: 0.60, 1.28); $p<0.001$; Model 2: β = 0.89 (95% CI: 0.55, 1.24); $p<0.001$) and a faster (linear) rate of increase in self-esteem over time (Model 1: β positive parenting × time = 0.24 (95% CI: 0.11, 0.38); $p<0.001$; Model 2: β positive parenting x time = 0.24 (95% CI: 0.10, 0.37); $p=0.001$). A one-unit increase in negative parenting was associated with lower baseline self-esteem (Model 1: β = -0.31 (95% CI: -0.64, 0.01); $p=0.059$; Model 2: β = -0.38 (95% CI: -0.71, -0.05); $p=0.025$) and a slower (linear) rate of increase in self-esteem over time (Model 1: β negative parenting × time = -0.29 (95% CI: -0.41, -0.16); $p<0.001$; Model 2: β negative parenting x time = -0.27 (95% CI: -0.39, -0.14); $p<0.001$).

In both models and consistent with earlier results, females had significantly lower self-esteem at baseline than males (Model 1: β female = -0.45 (95% CI: -0.82, -0.08); $p=0.018$; Model 2: β = -0.42 (95% CI: -0.78, -0.05); $p=0.027$) and females showed a slower rate of increase in self-esteem over time compared to an increasing trend among males (Model 1: β female × time = -0.14 (95% CI: -0.26, -0.02); $p=0.027$: Model 2: β = -0.15 (95% CI: -0.27, -0.03); $p=0.015$).

6.5 Discussion

In this section, I summarise the main findings and the strengths and limitations of the empirical work presented in this chapter. A lengthier discussion, including comparisons with other studies and a consideration of the policy implications of the findings, will be provided in the Discussion chapter (Chapter 8).

6.5.1 Main findings

My main findings from the descriptive analyses were that those with the lowest mean self-esteem scores at baseline were females, high-frequency computer social media users, low-frequency phone-based interpersonal communication users, participants in restructured families and those who ranked low on positive parenting and high on negative parenting. Males showed a higher frequency of computer social media use and higher self-esteem on average than females, whereas females showed a higher frequency of phone-based interpersonal communication.

Pertaining to the main analyses, my study produced three main findings: (1) the absence of effect modification by gender (**RQ2**), (2) the statistically significant independent main effects of CSMU, PIC and parenting styles on baseline self-esteem (**RQ3**) and (3) the statistically significant effect modification of positive parenting on the association between frequency of CSMU and PIC and self-esteem (**RQ4**).

Firstly, there was no effect modification by gender on the CSMU/PIC and self-esteem associations despite the model estimates showing that females had lower baseline self-esteem on average than males and showed a slower rate of increase in self-esteem over the study period. In Chapter 8, I will draw comparisons of this finding to other studies.

Secondly, more frequent computer social media users had lower baseline self-esteem whilst more frequent phone-based interpersonal communication users had higher baseline self-esteem, holding all other variables constant.

These differential associations with baseline self-esteem should be interpreted in relation to the questions' items chosen in my study to measure CSMU and PIC. The items used to measure CSMU captured involvement in gaming and entertainment, chatting or messaging, leaving comments, online community activities and personal social media pages (blog, Facebook, Twitter, MySpace/Minihompi, etc). In contrast, the PIC items captured involvement in calling/talking to family and friends, and texting family and friends (including on specified social networking sites such as KakaoTalk and Line).

The items used to measure CSMU were thus more specific to feeding one's interests through social websites, and the activities specified potentially involve a larger audience and more asynchronous interactions than the items used to measure PIC, which capture more practical means of directly communicating with family and friends in real-time. The PIC items *may* therefore capture aspects of positive social support via direct and one-on-one communication (and were observed to be positively associated with baseline self-esteem) that are not captured by the items on computer social media use.

With respect to parenting styles, higher scores in positive parenting were associated with higher baseline self-esteem, whilst higher scores in negative parenting were associated with lower baseline self-esteem, after controlling for all other variables.

Thirdly, there was a statistically significant moderation effect of positive parenting on the association between the frequency of CSMU and PIC and self-esteem. The results showed that mean self-esteem at baseline decreased with increasing CSMU at higher levels of positive parenting but increased with increasing PIC at higher levels of positive parenting.

These findings were similar after prior self-esteem was controlled for, suggesting the absence of bidirectional/cyclical effects and that the observed associations are most likely one-way (CSMU/PIC to self-esteem).

6.5.2 Strengths of this study

In the discussion section of Chapter 5, I highlighted the significance of exploring the associations between social media use and self-esteem, particularly in relation to subjective well-being. Additionally, examining gender and aspects of the family in this relationship can contribute to the existing literature and this was facilitated in this chapter by the study content of the KCYPS which was informed by Bronfenbrenner's ecological framework (3); thus allowing me to investigate the influence of the family and media environments on young people's well-being. Although the KCYPS had panel attrition like any other panel data, the retention rates were high (>80%) and showed no differences by gender, reflecting low attrition bias.

Additionally, previous studies that utilised the KCYPS in this area of research focused on mobile phone addiction (121) or internet use (123) to examine associations with mental health and behavioural outcomes. To my knowledge, this is the first study using the KCYPS to examine the associations between specific social media items (e.g., games and entertainment, text messages with friends and family on SNSs such as KakaoTalk and Line) and well-being (self-esteem).

6.5.3 Limitations of this study

Assessing the associations between computer social media use and phone-based interpersonal communication and self-esteem using the frequency of use measured in previous years may not be comparable to the present day due to the rapidly changing and evolving nature of social media. As further explored in Chapter 8, these changes pose significant challenges for current research on social media and its impact on self-esteem.

Moreover, whilst it would have been interesting to directly compare the impact of social media use through different devices (i.e., computer vs phone) had the questionnaire contained the same questions and items for computer and phone use, this distinction between computer and phone social media use may be less relevant nowadays. It is important to note that I do not attempt to make a direct comparison between computer social media use and phone-based interpersonal communication in my study as the items that measured each variable were different.

6.6 Conclusion

This study analysed five waves of KCYPS data and shed light on the associations between computer social media use, phone-based interpersonal communication and self-esteem in adolescents aged 14 to 18 years in South Korea. The findings revealed that the frequency of computer social media use was associated with lower self-esteem at baseline, whilst the frequency of phone-based interpersonal communication was linked to higher self-esteem. In order to expand on these findings, the next chapter will explore another outcome variable (depression) to assess similar associations using the KCYPS dataset.

Chapter 7: Computer social media use, phone-based interpersonal communication and depression in South Korea

Chapter 7 represents the third and final empirical investigation in my thesis, focusing on exploring the associations between the frequency of computer social media use and phone-based interpersonal communication and depression among young people (aged 14 years at baseline and followed up to the age of 18) in South Korea. The chapter also aims to examine whether gender and family factors play a moderating role in this association. To set the context, the chapter begins with a brief introduction, followed by a statement of research questions and hypotheses. An account of the methods is provided, which includes describing the participant demographics, measures used, analytical techniques employed, and how missing data were addressed. The chapter then presents the study's findings and offers a brief discussion of the results, highlighting specific strengths and limitations. A more comprehensive analysis of the results, as well as a broader discussion of the study's strengths and limitations, will be presented in the Discussion chapter (Chapter 8).

7.1 Introduction

In line with the aims and objectives of Chapter 3, I use the KCYPS in this study chapter to investigate the cross-sectional and longitudinal associations between the frequency of computer social media use (CSMU), phone-based interpersonal communication (PIC) and depression among adolescents, while also examining whether gender, family structure and parenting styles confound or modify these relationships. The aim is to expand our understanding of how CSMU/PIC may impact different aspects of mental health and well-being, such as self-esteem and depression, and contribute to the literature by analysing different outcomes using the same dataset. Neira and Barber's (2014) study of 13-21-year-olds in Western Australia found that heavy investment in social media use was associated with lower self-esteem and higher depressed mood, regardless of gender (47), highlighting the importance of examining the impact of social media use on mental health and well-being from multiple perspectives. Moreover, depression is a useful outcome to analyse as it has been linked with four domains of social media (discussed in Chapter 2): time spent, activity, investment and addiction, based on a systematic review conducted in 2018 (28).

7.2 Research questions and hypotheses

Five main research questions (**RQ**) and accompanying hypotheses (**H**) were considered in this chapter. These were set in light of the gaps in the literature as discussed in Chapter 2, that is, whether gender and aspects of family life influence (modify) any observed cross-sectional and longitudinal associations between social media use and mental health and well-being.

These research questions and accompanying hypotheses are set out below[48].

RQ1: Descriptive analyses of depression

> **RQ1: Do baseline levels of depression vary by the frequency of computer social media use (CSMU), the frequency of phone-based interpersonal communication (PIC), gender, family structure and parenting styles?**

H1: Descriptive analyses of depression

> **H1: Baseline levels of depression are higher on average for more frequent CSMU users, females, participants not living in a household with two biological parents, participants with lower scores on a positive parenting scale and higher scores on a negative parenting scale. Baseline levels of depression are lower on average for more frequent PIC users.**

[48] Research questions and hypotheses related to differences in levels of CSMU/PIC were explored in Chapter 6 and so are not repeated here. The analytical sample was also similar to that presented in Chapter 6, albeit with minor variations in numbers. Please refer to Table 6.6 in Chapter 6 for a comprehensive breakdown of the baseline levels of CSMU/PIC frequency by gender, family structure and parenting styles.

RQ2: Gender as a moderator of the CSMU, PIC and depression associations

RQ2: Does gender moderate any association between the frequency of CSMU/PIC and depression?

H2: Gender as a moderator of the CSMU, PIC and depression associations

H2: Gender moderates any association between the frequency of CSMU/PIC and depression, with a stronger association between CSMU/PIC and depression in females than males.

RQ3: Independent associations between key variables and depression

RQ3: Are levels of CSMU and PIC frequency, family structure and parenting styles independently associated with depression?

H3: Independent associations between key variables and depression

H3a: More frequent CSMU and less frequent PIC are significantly associated with higher levels of depression at baseline (main effects) and a slower rate of decline in depression (interaction with time-in-study) while holding various confounding variables and family variables constant.

H3b: Participants not living in a household with two biological parents, participants with lower scores on a positive parenting scale and higher scores on a negative parenting scale are associated with higher depression at baseline and a slower rate of decline in depression over the study period while holding all other variables constant.

RQ4: Family factors as moderator of the CSMU/PIC and depression associations

RQ4: Do family structure and parenting styles moderate any association between the frequency of CSMU/PIC and depression?

H4: Family factors as moderator of the CSMU/PIC and depression associations

H4: Family structure and parenting styles moderate the associations between the frequency of CSMU/PIC and depression. For example, more frequent computer social media use is hypothesised to be associated with a slower rate of decline in depression over the study period among participants who rank higher on negative parenting, holding all other variables constant.

RQ5: Supplementary analysis

RQ5: After controlling for prior (wave 2) depression, is the frequency of CSMU and/or PIC associated with depression?

H5: Supplementary analysis

H5: More frequent CSMU and/or less frequent PIC is significantly associated with higher levels of depression at baseline (wave 3; main effects) and a slower rate of decline in depression (interaction with time-in-study) while holding prior levels of depression and all other variables constant.

These hypotheses relate to a scenario of an expected decline in average levels of depression over time (in line with the observed increases in self-esteem on average as described in the previous chapter).

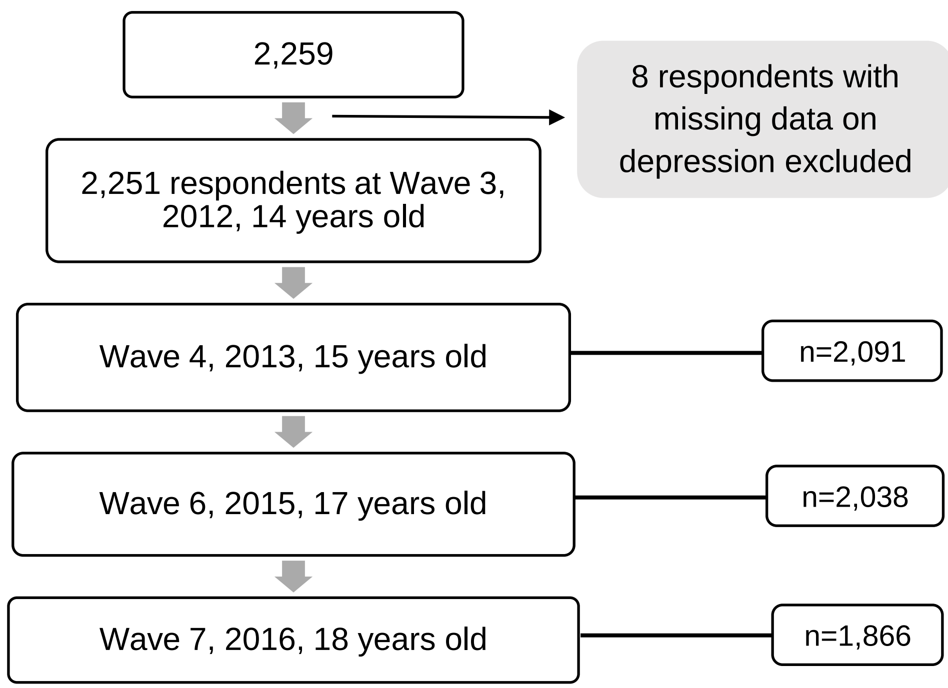
7.3 Methods

7.3.1 Analytical sample

The target sample was derived solely from the M1 cohort of the KCYPS (see Section 4.3.2 of Chapter 4). The M1 Cohort included 2,351 participants in wave 1 (2010). After a loss-to-follow-up of 92 participants and the exclusion of 8 participants with missing data on depression, the final sample for this study was 2,251 participants at wave 3, which was selected as the baseline wave for this analysis. The wave 3 sample consisted of Grade 9 students who were 14 years old. Those with a valid depression score at wave 3 (n = 2,251) were followed up to wave 7, the final year of data collection.

Of those 2,251 participants with a valid depression score at wave 3, 93% (2,091 participants) had a valid score at wave 4, 91% (2,038 participants) had a valid score at wave 6 and 83% (1,866 participants) had a valid score at wave 7 (the items on depression were not included in the study content at wave 5). Hence, the 2,251 participants with valid depression scores at wave 3 contributed a total of 8,246 person-wave observations. 1,759 participants (78%) had valid depression scores at each of the four waves (3, 4, 6 and 7). The process of deriving my analytical sample is illustrated in Figure 7.1.

Figure 7.1: Analytical sample of the KCYPS



7.3.2 Measures

Data for the KCYPS is collected annually. Wave 3 was selected as the baseline wave because it was the second wave to include depression in the study content, which allowed me to statistically adjust for prior levels of depression (wave 2) in a supplementary analysis. Table 4.3 provides a summary of when each variable of interest was assessed across waves 1 to 7. In the main analysis (waves 3 to 7), questions on depression were asked at waves 3, 4, 6 and 7, questions on computer social media use/phone-based interpersonal communication and family structure were asked at each wave and questions on parenting styles were asked at waves 1, 4, 6 and 7.

Outcome: Depression

The Center for Epidemiological Studies Depression Scale (CES-D) is a 20-item screening tool, initially developed by Radloff in 1977 to detect depression in general populations (178). Subsequently, several shorter versions have been developed, including Andresen's 10-item version (CES-D-10) (179). The scale is designed to gauge symptoms defined by the American Psychiatric Association's Diagnostic and Statistical Manual (DSM-V) for depressive disorder, which has been used to assess depression in adolescents (180, 181).

The KCYPS used an abridged version of the CES-D-10, henceforth referred to as the revised version of the CES-D-10 (CESD-R), which is a 10-item measure that captures depressive symptoms such as lack of energy and feeling lonely. Responses are rated on a four-point Likert scale, from "Strongly agree" (coded 1) to "Strongly disagree" (coded 4). This is presented in Table 7.1. Participants were asked the items on depression via a self-completion survey:

"This is a question about the student's usual behaviour. Please tick the appropriate box for each item below."

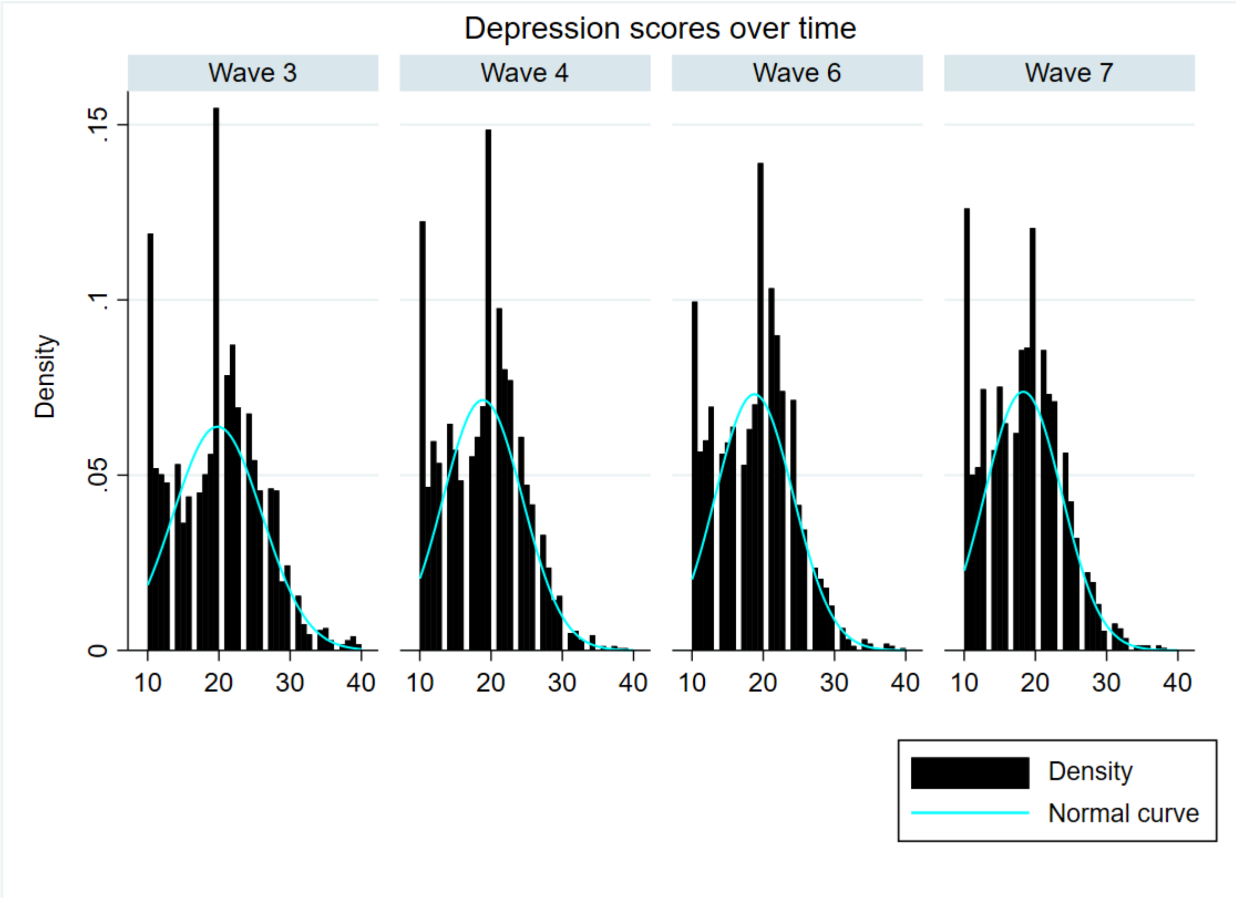
Table 7.1: Depression items from the CESD-R

Depression items	Strongly agree	Agree	Disagree	Strongly disagree
1. I do not have much energy.	1	2	3	4
2. I feel unhappy or sad and depressed.	1	2	3	4
3. I have a lot of worries.	1	2	3	4
4. I feel like dying.	1	2	3	4
5. I am good at crying.	1	2	3	4
6. When something goes wrong, I often think that it is my fault.	1	2	3	4
7. I feel lonely.	1	2	3	4
8. I have a lack of interest and excitement in everything.	1	2	3	4
9. The future is bleak.	1	2	3	4
10. Every day is hard.	1	2	3	4

The 10 items of the CESD-R were all negatively worded and hence reverse coded; higher scores on the scale indicate greater severity of depression. The internal reliability of the scale, as assessed by Cronbach's alpha, was high (α=0.91) for the 2,251 participants with valid responses to all 10 items at wave 3. To calculate the overall depression score at each wave, the responses to all 10 items were summed, resulting in a score range of 10 to 40.

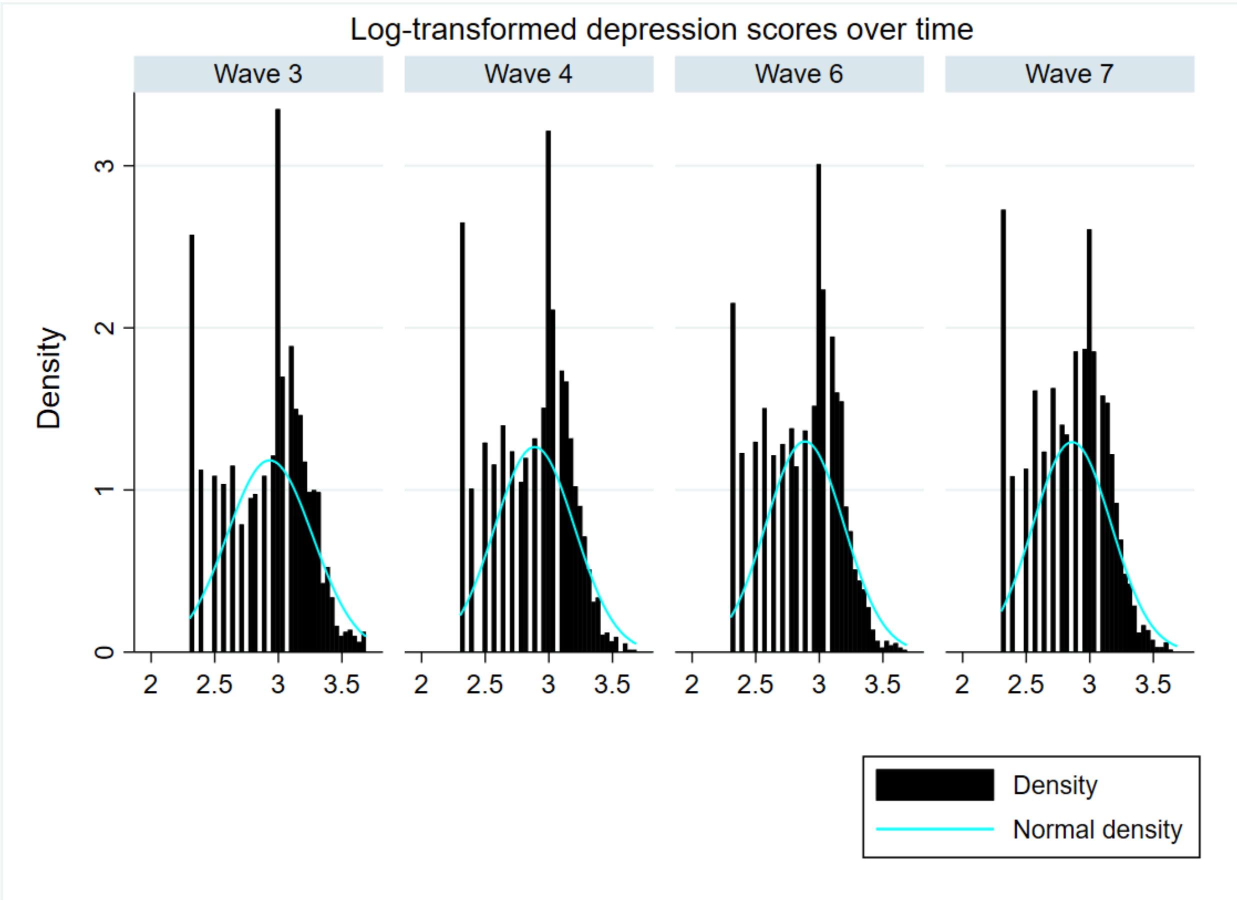
The histograms of the depression scores at each of the four waves displayed a right-tailed skewed distribution, as shown in Figure 7.2. In addition, the scores showed some evidence of a floor effect (e.g., 9% of participants at wave 3 had the lowest possible depression score [10 points]).

Figure 7.2: Distribution of depression (raw scores) at waves 3, 4, 6 and 7 (M1 Cohort)



To address the non-normal distribution, a natural logarithmic transformation of the depression scores was employed to achieve a more normal distribution, as demonstrated in Figure 7.3. This approach followed that of a previous study by Kim and Ahn (2016), which utilised the KCYPS data (M1 Cohort) to investigate the relationship between the amount of time spent on online video game play and depression (182).

Figure 7.3: Distribution of depression (log-transformed scores) at waves 3, 4, 6 and 7 (M1 Cohort)



Information on the key variables, including computer social media use, phone-based interpersonal communication, family structure, parenting styles and potential confounders, are described in Section 6.3.2 of Chapter 6 and are not repeated here.

7.3.3 Analytical strategy

Descriptive analyses

To answer the research questions set out in Section 7.2 (**RQ1**), I conducted two sets of bivariate analyses on the analytical sample at wave 3, using similar analytical techniques as outlined in Chapters 5 and 6.

Firstly, I investigated the differences in baseline levels of depression across the key variables, including the frequency (tertiles) of computer social media use and phone-based interpersonal communication, gender, aspects of family life and potential confounders such as household income, place of residence and parental educational status. To present these findings, the means of depression on the natural log scale were back-transformed using the exponential (anti-log) function and presented as geometric means along with their 95% confidence intervals. Using this method, the results are less likely to be distorted by the skewed distribution of the data compared to using arithmetic means. Linear regressions and Wald tests were used to assess the statistical significance of differences in mean (log) depression.

Secondly, I investigated the differences in the frequency (tertiles) of computer social media use and phone-based interpersonal communication by demographics, family variables and potential confounders. Statistical significance was examined using Pearson's chi-square test for the association between two variables. All tests of statistical significance were based on two-tailed probability ($p<0.05$). Analyses were performed using Stata's *svy* commands, accounting for the complex survey design of the KYCPS by using the wave 3 cross-sectional weight (*weight1w3*) and the identifier of the school (*sclidw3*) as the clustering (PSU) variable.

Linear mixed-effects modelling

To answer the research questions set out in Section 7.2 (**RQ2-5**), I performed linear mixed-effects modelling in four stages. Linear mixed-effects models with time-since-baseline as timescale (expressed in years, coded as 0, 1, 3 and 4) were used to estimate the associations between the frequency of CSMU/PIC and change in depression over the study period. This method of analysis is described in detail in Section 4.3.3 of Chapter 4.

As explained in the previous chapter, CSMU and PIC were treated separately in the modelling to avoid any misleading direct comparisons and masking of associations (as the items that measured each variable were different).

Modelling strategy

The modelling strategy (including the testing of any moderating effect by gender and family factors, and a supplementary analysis which adjusted for prior levels of depression) and estimation of the mixed models in Stata were similar to that described in the previous chapter (Section 6.3.3) and so is not repeated here.

7.3.4 Missing data

Participants with missing values on the outcome variable (depression) were excluded from the analytical sample. In contrast to Chapters 5 and 6, multiple imputation was not used in this chapter due to the relatively low frequency of participants with missing data on family structure assessed at wave 3 (n = 66) and parenting styles assessed at wave 1 (n = 1). To avoid a reduction in sample size, participants with missing data on family structure were included in the linear mixed-effects models by assigning them to a separate missing category. The results pertaining to this category are not included in the tables presenting the findings of the regression analyses, nor were they incorporated into the Wald test for model coefficients.

7.4 Results

7.4.1 Sample description

A breakdown of the baseline (wave 3) characteristics of the sample used in my main analysis is given in Table 7.2. As the 21 items on parenting styles were included in the KCYPS at wave 1 but not at wave 3, the table shows the associations between parenting styles as measured at wave 1 and average levels of depression as measured at wave 3.

RQ1: Baseline levels of depression (outcome)

Table 7.2 shows the geometric means and 95% confidence intervals (CI) of log-transformed depression at baseline (wave 3) by frequency of CSMU and PIC (grouped in tertiles), gender, family variables and confounders. 95% confidence intervals are presented rather than the standard deviation because the raw depression scores showed some departure from normality (183).

Table 7.2: Mean depression (geometric means and 95% CIs) at wave 3 by frequency of CSMU/PIC, family variables, gender and confounders

Characteristics	Log-transformed depression		
	n (Column %)	Geometric mean (95% CI)	P-value
All participants	2,251 (100)	18.7 (18.3-19.2)	-
Frequency of CSMU:			
Lowest tertile	867 (38)	18.1 (17.5-18.8)	0.059
Middle tertile	701 (31)	18.9 (18.3-19.6)	
Highest tertile	683 (31)	19.2 (18.4-20.1)	
Frequency of PIC:			
Lowest tertile	974 (44)	19.0 (18.4-19.7)	0.233
Middle tertile	749 (33)	18.6 (17.9-19.2)	
Highest tertile	528 (23)	18.3 (17.6-19.0)	
Family structure:			
Two-parent family	1,891 (83)	18.6 (18.1-19.1)	0.043
Single-father family	107 (5)	19.5 (18.2-20.9)	
Single-mother family	139 (6)	19.5 (18.2-20.9)	
Restructured family*	26 (1)	18.5 (15.6-21.8)	
No parents	26 (1)	21.3 (19.4-23.3)	
Missing**	62 (4)		
Positive parenting style (wave 1):			
Lowest tertile	824 (36)	20.1 (19.6-20.7)	<0.001
Middle tertile	694 (31)	18.7 (18.1-19.3)	
Highest tertile	732 (33)	17.3 (16.8-17.9)	
Missing**	1 (0)		
Negative parenting style (wave 1):			
Lowest tertile	898 (39)	18.0 (17.5-18.5)	<0.001
Middle tertile	718 (31)	19.2 (18.6-19.8)	
Highest tertile	634 (30)	19.1 (18.5-19.8)	
Missing**	1 (0)		
Gender:			
Males	1,137 (52)	17.7 (17.1-18.4)	<0.001
Females	1,114 (48)	19.8 (19.3-20.3)	
Parents' highest educational qualification:			
Below middle school	81 (4)	19.6 (18.2-21.2)	0.257
High school graduate	895 (37)	19.0 (18.3-19.8)	
Community college graduate	232 (10)	19.0 (18.1-19.9)	
Undergraduate	857 (39)	18.5 (17.9-19.0)	
Postgraduate	120 (6)	17.5 (15.8-19.3)	
Missing**	66 (4)		
Annual household income (₩):			
<20 million	196 (8)	20.1 (19.0-21.1)	0.056
20-40 million	658 (28)	19.1 (18.4-19.9)	
40-60 million	896 (40)	18.4 (17.7-19.1)	
>60 million	501 (24)	18.4 (17.7-19.1)	
Type of living area:			
Urban	1,923 (88)	18.6 (18.1-19.1)	0.007
Rural	328 (12)	19.6 (19.0-20.3)	

Abbreviations: CI: confidence interval*;* CSMU: computer social media use; PIC: phone-based interpersonal communication. *Notes:* Column percentages are weighted: sample sizes are unweighted. P-values were calculated using linear regression modelling (natural log-transformed scores as the dependent variable) and Wald tests, adjusted for the complex survey design. *Families with stepfathers or stepmothers and could be currently living with one or two biological parents*.* **Excluded from test because of low frequencies or deemed not to be of substantive interest.

The baseline analytical sample comprised n = 2,251 participants who were 14 years old at wave 3 (2012) and who had a valid depression score (Table 7.2). Males and females were roughly evenly split in this sample (52% and 48%, respectively).

The geometric mean for depression was 18.7 (95% CI: 18.3-19.2). The geometric means for depression did not vary by the frequency of computer social media use (p=0.059) and phone-based interpersonal communication (p=0.233).

The geometric means for depression varied by family structure (p=0.043): these were highest for those living with no parents and lowest for those living in a restructured family (21.3 versus 18.5, respectively): these two estimates should be treated with caution due to the small sample size. The geometric means for depression also varied by parenting styles as assessed at wave 1 (p<0.001). These were highest for those who ranked lowest on positive parenting (20.1 versus 17.3 for lowest and highest tertiles, respectively) and were highest for those in the middle tertile of negative parenting (19.2 in the middle tertile versus 18.0 and 19.1 in the lowest and highest tertiles, respectively).

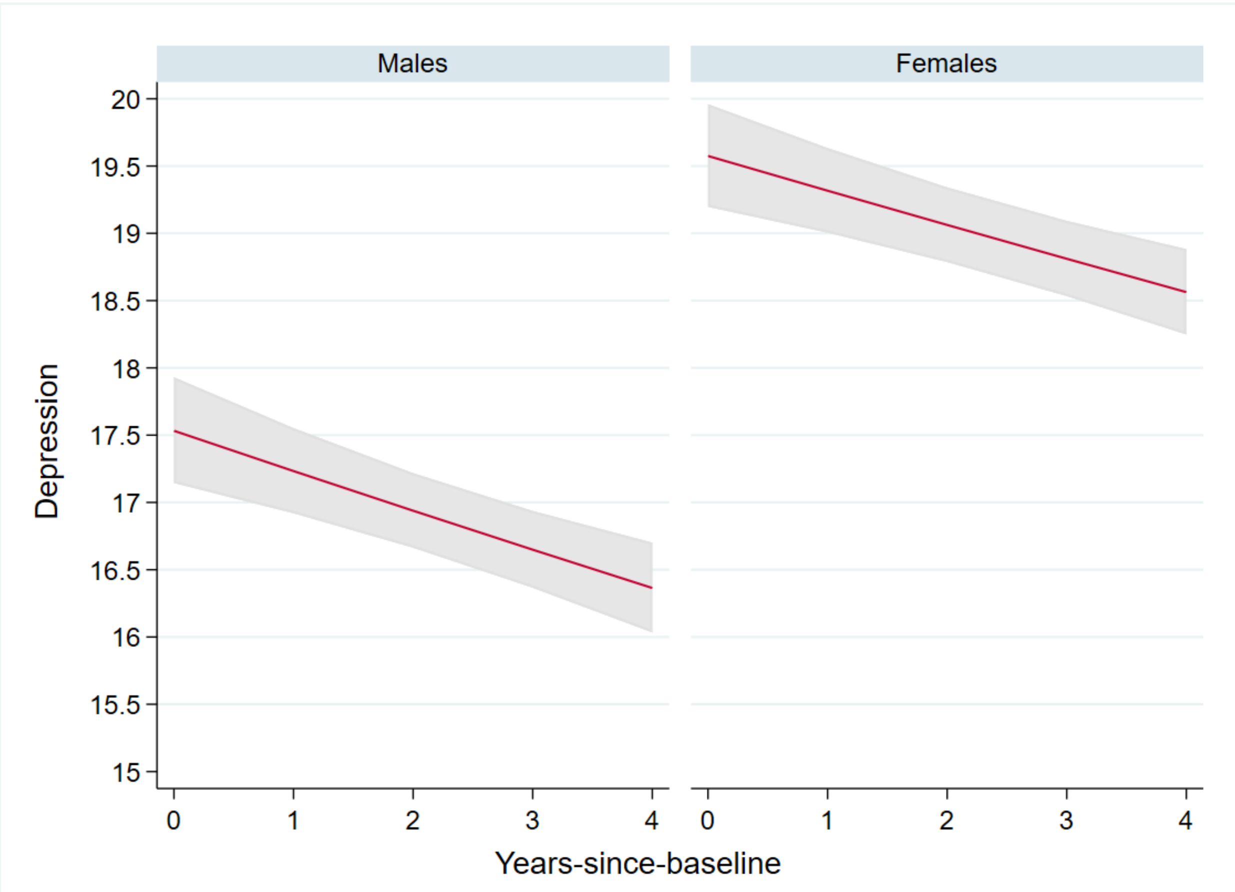
With respect to the potential confounders or moderators, the geometric mean for depression was higher for females than males (19.8 versus 17.7, respectively; p<0.001). The geometric means for depression did not vary by parental educational status (p=0.257) and household income (p=0.056). The geometric mean for depression was higher for those living in rural areas (19.6 in rural areas versus 18.6 in urban areas, p=0.007).

In summary, Hypothesis 1 was partially supported by the data as baseline depression was significantly higher for females, participants not living in a household with two biological parents, and participants with lower scores on positive parenting and higher scores on negative parenting.

7.4.2 Trajectories of depression by gender

Based on a linear mixed-effects model (depression scores at each wave transformed by the natural logarithm to meet linearity assumptions) that estimated the (linear) 1-year rate of change in the logged depression scores separately by gender (i.e. by including a two-way interaction term: gender × time), males and females showed no difference in the rate of change in depression over the four-wave study period (p=0.381 for the two-way interaction). After using the exponential (anti-log) function on the predicted scores from the model, Figure 7.4 shows the estimated trajectories of depression by gender (based on the model with gender × time), which portrays that the estimated depression scores at each wave were higher for females than males but the rate of decrease over the time period was similar.

Figure 7.4: Depression trajectories by gender



Notes: Predicted average levels of depression from a linear mixed-effects model containing time, gender and the two-way interaction: gender-by-time.

On average, females had significantly higher levels of depression at baseline (gender: $p<0.001$ for the model containing the main effects of gender and time). In terms of percentage difference, depression scores were approximately 11% higher for females than for males at baseline. This is calculated as 100 × ln(mean depression in females) – 100 × ln(mean depression in males) (184).

7.4.3 Longitudinal analyses

RQ2: Moderation by gender

After testing for the three-way (CSMU/PIC x gender x time) and two-way interactions (CSMU/PIC x gender), the results showed no statistically significant moderating effects of gender (estimates shown in Table C1 of the Appendices). Therefore, I did not stratify the subsequent models by gender.

Models with computer social media use as main exposure

Table 7.3 shows the results for the linear mixed-effects models that included the frequency of CSMU as the main exposure. The frequency of CSMU was entered into the models as a continuous variable, as such, the main effect represents the estimated difference in (log) depression at baseline (wave 3) for a one-unit increase in CSMU frequency. The CSMU-by-time two-way interaction term estimates the difference in the absolute 1-year rate of change in (log) depression for a 1-unit increase in CSMU frequency. Results for Model 1 (CSMU + confounders), Model 2 (+ family structure), and Model 3 (+ parenting styles) are shown.

Table 7.3: Results from the linear mixed-effects models for the associations between frequency of CSMU, family structure, positive and negative parenting, and log-transformed depression

Characteristics	Model 1			Model 2			Model 3		
	B	95% CI	P-value	B	95% CI	P-value	B	95% CI	P-value
Intercept	2.8	(2.7, 2.8)	<0.001	2.8	(2.7, 2.8)	<0.001	2.9	(2.8, 3.0)	<0.001
Time-since-baseline	-0.01	(-0.03, 0.00)	0.161	-0.01	(-0.03, 0.00)	0.156	0.04	(0.00, 0.08)	0.079
Computer SMU	0.03	(0.01, 0.04)	0.002	0.03	(0.01, 0.04)	0.002	0.02	(0.01, 0.04)	0.005
Computer SMU × time	0.00	(-0.01, 0.01)	0.759	0.00	(-0.01, 0.01)	0.780	0.00	(-0.01, 0.01)	0.836
Females	0.12	(0.09, 0.15)	<0.001	0.12	(0.09, 0.15)	<0.001	0.13	(0.10, 0.16)	<0.001
Females × time	0.00	(0.00, 0.01)	0.283	0.00	(0.00, 0.01)	0.279	0.00	(-0.01, 0.01)	0.537
Family structure (wave 3)									
Two-parent family (ref)				-	-	-	-	-	-
Single-parent family				0.00	(-0.05, 0.05)	0.950	-0.01	(-0.06, 0.04)	0.756
Restructured family				-0.02	(-0.16, 0.12)	0.806	-0.03	(-0.16, 0.11)	0.679
No parents				0.08	(-0.02, 0.17)	0.133	0.05	(-0.05, 0.16)	0.322
P-value						*0.483*			*0.700*
Family structure x time									
Two-parent family (ref)				-	-	-	-	-	-
Single-parent family				0.01	(-0.01, 0.02)	0.442	0.00	(-0.01, 0.02)	0.735
Restructured family				0.02	(-0.02, 0.06)	0.380	0.02	(-0.03, 0.07)	0.394
No parents				-0.01	(-0.04, 0.03)	0.720	-0.01	(-0.04, 0.02)	0.545
P-value						*0.681*			*0.735*
Positive parenting							-0.09	(-0.11, -0.06)	<0.001
Pos. parenting x time							-0.01	(-0.02, 0.00)	0.003
Negative parenting							0.07	(0.05, 0.09)	<0.001
Neg. parenting x time							0.00	(-0.01, 0.01)	0.746
Random effects:									
Level-2 intercept (SD)	0.2	(0.2, 0.3)					0.2	(0.2, 0.2)	
Level-2 slope (SD)	0.0	(0.0, 0.1)		0.2	(0.2, 0.3)		0.0	(0.0, 0.1)	
Correlation: int-slope	-0.6	(-0.7, -0.5)		0.0	(0.0, 0.1)		-0.7	(-0.7, -0.6)	
Level-1 residual (SD)	0.2	(0.2, 0.2)		-0.6	(-0.7, -0.5)		0.2	(0.2, 0.2)	

Abbreviations: CI: confidence interval; CSMU: computer social media use; ref: reference category; SD: standard deviation. *Notes:* Participants (n = 2,251); person-wave observations (Models 1 and 2: n = 8,246; Model 3: n = 8,245). Depression scores were log-transformed to better achieve normality. Coefficients are shown on the log scale. **Model 1**: CSMU + confounders**; Model 2**: CSMU + family structure + confounders; **Model 3**: CSMU + family structure + parenting styles. Confounding variables included in each model were annual household income (reference: 40-60 million ₩) and type of living area (reference: urban).

With regards to **RQ3** (independent associations), overall, a one-unit increase in the frequency of computer social media use was significantly associated with higher (log) depression at baseline (Model 3: $\beta = 0.02$ (95% CI: 0.01, 0.04); $p=0.005$) but was not associated with the (linear) 1-year rate of change in depression ($p=0.836$). Family structure was not significantly associated with baseline depression (Model 3: $p=0.700$) nor with the rate of change in depression (Model 3: $p=0.735$).

Positive parenting was significantly associated with baseline levels of (log) depression ($p<0.001$) and the 1-year rate of change in depression ($p=0.003$). A one-unit increase in positive parenting was associated with lower (log) depression at baseline (Model 3: $\beta = -0.09$ (95% CI: -0.11, -0.06); $p<0.001$) and with a slower rate of increase in depression over time (Model 3: β positive parenting × time = -0.01 (95% CI: -0.02, 0.00); $p=0.003$).

Negative parenting was also significantly associated with baseline levels of (log) depression ($p<0.001$) but not with the 1-year rate of change in depression ($p=0.746$). A one-unit increase in negative parenting was associated with higher (log) depression at baseline (Model 3: $\beta = 0.07$ (95% CI: 0.05, 0.09); $p<0.001$).

Holding all variables constant, females had significantly higher baseline levels of (log) depression than males (Model 3: $\beta = 0.13$ (95% CI: 0.10, 0.16); $p<0.001$) but, in line with the earlier descriptive analysis, the estimated 1-year rate of change in depression did not vary significantly by gender (Model 3: β gender × time; $p=0.537$).

Model with phone-based interpersonal communication as main exposure

Table 7.4 shows the results for the models that included the frequency of phone-based interpersonal communication as the main exposure.

Table 7.4: Results from the linear mixed-effects models for the associations between frequency of PIC, family structure, positive and negative parenting, and log-transformed depression

	Model 1			Model 2			Model 3		
	B	**95% CI**	**P-value**	**B**	**95% CI**	**P-value**	**B**	**95% CI**	**P-value**
Intercept	2.9	(2.8, 2.9)	<0.001	2.9	(2.8, 2.9)	<0.001	2.9	(2.8, 3.0)	<0.001
Time-since-baseline	0.02	(-0.01, 0.05)	0.302	0.02	(-0.02, 0.05)	0.328	0.05	(0.01, 0.10)	0.024
PIC	-0.01	(-0.03, 0.01)	0.463	-0.01	(-0.03, 0.01)	0.450	0.00	(-0.02, 0.02)	0.764
PIC × time	-0.01	(-0.02, 0.00)	0.047	-0.01	(-0.02, 0.00)	0.051	0.00	(-0.01, 0.00)	0.253
Females	0.11	(0.08, 0.14)	<0.001	0.11	(0.08, 0.14)	<0.001	0.12	(0.09, 0.15)	<0.001
Females × time	0.01	(0.00, 0.01)	0.203	0.01	(0.00, 0.01)	0.199	0.00	(-0.01, 0.01)	0.495
Family structure (wave 3)									
Two-parent family (ref)				-	-	-	-	-	-
Single-parent family				0.00	(-0.05, 0.05)	0.928	0.00	(-0.05, 0.05)	0.861
Restructured family				-0.02	(-0.16, 0.12)	0.769	-0.03	(-0.16, 0.10)	0.662
No parents				0.07	(-0.02, 0.17)	0.125	0.05	(-0.05, 0.16)	0.319
P-value						*0.472*			*0.718*
Family structure x time									
Two-parent family (ref)				-	-	-	-	-	-
Single-parent family				0.00	(-0.01, 0.02)	0.573	0.00	(-0.01, 0.02)	0.825
Restructured family				0.02	(-0.02, 0.06)	0.389	0.02	(-0.03, 0.07)	0.389
No parents				0.00	(-0.04, 0.03)	0.783	-0.01	(-0.04, 0.02)	0.606
P-value						*0.769*			*0.778*
Positive parenting							-0.08	(-0.11, -0.06)	<0.001
Pos. parenting x time							-0.01	(-0.02, 0.00)	0.005
Negative parenting							0.07	(0.05, 0.09)	<0.001
Neg. parenting x time							0.00	(-0.01, 0.01)	0.560
Random effects									
Level-2 intercept (SD)	0.2	(0.2, 0.3)		0.2	(0.2, 0.3)		0.2	(0.2, 0.2)	
Level-2 slope (SD)	0.0	(0.0, 0.1)		0.0	(0.0, 0.1)		0.0	(0.0, 0.1)	
Correlation: Int-slope	-0.6	(-0.7, -0.5)		-0.6	(-0.7, -0.5)		-0.7	(-0.7, -0.6)	
Level-1 residual (SD)	0.2	(0.2, 0.2)		0.2	(0.2, 0.2)		0.2	(0.2, 0.2)	

Abbreviations: CI: confidence interval; PIC: phone-based interpersonal communication; ref: reference category; SD: standard deviation. *Notes:* participants (n = 2,251); person-wave observations (Models 1 and 2: n = 8,246; Model 3: n = 8,245). Depression scores were log-transformed to better achieve normality. Coefficients are shown on the log scale. **Model 1**: PIC + confounders**;** **Model 2**: PIC + family structure + confounders; **Model 3**: PIC + family structure + parenting styles. Confounding variables included in each model were annual household income (reference: 40-60 million ₩) and type of living area (reference: urban).

With regards to **RQ3** (independent associations), a one-unit increase in the frequency of PIC was not significantly associated with baseline levels of (log) depression (Model 3: $p=0.764$) nor with the rate of change in depression (Model 3: $p=0.253$). Family structure was not significantly associated with baseline (log) depression (Model 3: $p=0.718$) nor with the rate of change in depression (Model 3: $p=0.778$).

The parenting styles variables showed a similar pattern of association as for the models with the frequency of computer social media use as the main exposure. Positive parenting was significantly associated with baseline (log) depression (Model 3: $p<0.001$) and the rate of change (Model 3: $p=0.005$). A one-unit increase in positive parenting was associated with lower (log) depression at baseline (Model 3: $\beta = -0.08$ (95% CI: -0.11, -0.06); $p<0.001$) and a slower rate of increase in depression over time (Model 3: β positive parenting × time = -0.01 (95% CI: -0.02, 0.00); $p=0.005$).

Negative parenting was also significantly associated with baseline levels of (log) depression ($p<0.001$) but not with the 1-year rate of change in depression ($p=0.560$). A one-unit increase in negative parenting was associated with higher (log) depression at baseline (Model 3: $\beta = 0.07$ (95% CI: 0.05, 0.09); $p<0.001$).

Holding all variables constant, females had significantly higher baseline (log) depression than males (Model 3: β female = 0.12 (95% CI: 0.09, 0.15); $p<0.001$) but gender was not associated with the 1-year rate of change in depression ($p=0.495$).

With regards to **RQ4** (moderation by family factors), additional models examined whether any of the family variables (family structure and parenting styles) moderated any associations between the frequency of CSMU/PIC and (log) depression. Adding to the terms in Model 3 (shown in Tables 7.3 and 7.4), the p-values for the relevant three-way and two-way interaction terms used to answer **RQ4** are shown in Table C2 of the Appendices. In all models, none of the interactions were statistically significant at the 5% level ($p>0.05$).

7.4.4 Supplementary analysis

With regards to **RQ5**, I repeated my main analysis by statistically adjusting for prior scores on the depression scale (assessed at wave 2). This allowed me to estimate whether prior depression played any role in confounding the associations between the frequency of CSMU/PIC and depression.

Table 7.5 shows the results for the fully-adjusted models that examined the associations between frequency of CSMU/PIC, family variables (family structure and positive/negative parenting) and depression (over waves 3 to 7) after adjusting for prior levels of depression (assessed at wave 2).

Table 7.5: Results from the linear mixed effect models for the associations between frequency of CSMU/PIC, family structure, positive and negative parenting, and log-transformed depression (after adjusting for prior levels of depression and other confounders)

	Model 1 (CSMU)			Model 2 (PIC)		
	B	**95% CI**	**P-value**	**B**	**95% CI**	**P-value**
Intercept	2.0	(1.9, 2.1)	<0.001	2.0	(1.9, 2.2)	<0.001
(ln) depress (wave 2)	0.30	(0.27, 0.33)	<0.001	0.30	(0.27, 0.33)	<0.001
Time-since-baseline	0.04	(0.00, 0.08)	0.083	0.05	(0.01, 0.10)	0.029
CSMU	0.02	(0.01, 0.04)	0.009			
CSMU × time	0.00	(-0.01, 0.01)	0.965			
PIC				0.00	(-0.02, 0.02)	0.931
PIC × time				0.00	(-0.01, 0.00)	0.251
Females	0.09	(0.07, 0.12)	<0.001	0.09	(0.06, 0.12)	<0.001
Females × time	0.00	(-0.01, 0.01)	0.487	0.00	(-0.01, 0.01)	0.427
Family structure (wave 3)						
Two-parent family (ref)	-	-	-	-	-	-
Single-parent family	-0.02	(-0.07, 0.03)	0.462	-0.02	(-0.06, 0.03)	0.537
Restructured family	0.00	(-0.10, 0.11)	0.963	0.00	(-0.10, 0.11)	0.992
No parents	0.05	(-0.03, 0.13)	0.228	0.05	(-0.03, 0.13)	0.243
P-value			*0.477*			*0.539*
Two-parent family (ref)	-	-	-	-	-	-
Single-parent family	0.00	(-0.01, 0.02)	0.860	0.00	(-0.01, 0.02)	0.951
Restructured family	0.00	(-0.03, 0.04)	0.796	0.01	(-0.03, 0.04)	0.792
No parents	-0.02	(-0.05, 0.01)	0.286	-0.02	(-0.05, 0.02)	0.335
P-value			*0.718*			*0.786*
Positive parenting	-0.07	(-0.09, -0.04)	<0.001	-0.07	(-0.09, -0.04)	<0.001
Pos. parenting x time	-0.01	(-0.02, 0.00)	0.004	-0.01	(-0.02, 0.00)	0.007
Negative parenting	0.06	(0.04, 0.08)	<0.001	0.06	(0.04, 0.09)	<0.001
Neg. parenting x time	0.00	(-0.01, 0.01)	0.672	0.00	(-0.01, 0.01)	0.507
Random effects						
Level-2 Intercept (SD)	0.2	(0.2, 0.2)		0.2	(0.2, 0.2)	
Level-2 slope (SD)	0.0	(0.0, 0.1)		0.0	(0.0, 0.1)	
Correlation: Int-slope	-0.6	(-0.7, -0.5)		-0.6	(-0.7, -0.5)	
Level-1 residual (SD)	0.2	(0.2, 0.2)		0.2	(0.2, 0.2)	

Abbreviations: CSMU: Computer social media use; PIC: Phone-based interpersonal communication; ref: reference category; SD: standard deviation. *Notes:* Participants (n = 2,220); person-wave observations (n = 8,145). Depression scores were log-transformed to achieve normality. Coefficients are shown on the log scale. Confounding variables included in each model were gender (reference: males), annual household income (reference: 40-60 million ₩) and type of living area (reference: urban).

In both models, higher prior (log) depression scores were significantly associated with higher (log) depression at baseline (β = 0.30 (95% CI: 0.27, 0.33); p<0.001).

Adjusting for prior depression and consistent with earlier results, a one-unit increase in the frequency of CSMU was significantly associated with higher (log) depression at baseline (Model 1: β =0.02 (95% CI: 0.01, 0.04); p=0.009) but CSMU frequency was not significantly associated with the rate of change in depression over time (Model 1: β CSMU × time; p=0.965). Also consistent with earlier results, a one-unit increase in the frequency of PIC was not significantly associated with (log) baseline depression (Model 2: p=0.931) nor with its rate of change (Model 2: p=0.251).

In both models and consistent with earlier results, females had higher (log) depression at baseline than males (e.g., Model 1 [CSMU]: β female = 0.09 (95% CI: 0.07, 0.12); p<0.001) and the 1-year estimated rate of change in depression did not vary by gender (e.g., Model 1 [CSMU]: β gender × time; p=0.487).

In both models and consistent with earlier results, family structure (assessed at wave 3) was not significantly associated with baseline (log) depression (e.g., Model 1 [CSMU]: p=0.477) nor with the rate of change (Model 1 [CSMU]: β family structure × time; p=0.718).

The parenting styles variables showed a similar pattern of association as described earlier. After adjusting for prior depression and frequency of CSMU/PIC*,* positive parenting was significantly associated with baseline (log) depression (p<0.001) and with the rate of change in depression over time (Model 1: p=0.004; Model 2: p=0.007). A one-unit increase in the positive parenting scale was associated with lower (log) depression at baseline (e.g., Model 1: β = -0.07 (95% CI: -0.09, -0.04); p<0.001) and a slower rate of increase in depression over time (e.g., Model 1: β positive parenting × time = -0.01 (95% CI: -0.02, 0.00); p=0.004).

Negative parenting was also significantly associated with baseline levels of (log) depression (p<0.001) but not with the 1-year rate of change in depression (Model 1: p=0.672; Model 2: p=0.507). A one-unit increase in the negative parenting scale was associated with higher (log) depression at baseline (e.g., Model 1: β = 0.06 (95% CI: 0.04, 0.08; p<0.001).

7.5 Discussion

In this section, I summarise the main findings and the strengths and limitations of the empirical work presented in this chapter. A lengthier discussion, including comparisons with other studies and a consideration of the policy implications of the findings, will be provided in the Discussion chapter.

7.5.1 Main findings

Using five waves of KCYPS data collected from participants aged 14 years at baseline (wave 3: 2012) and who were followed up to the age of 18, I examined the bivariate associations of depression, frequency of computer social media use and phone-based interpersonal communication, family variables (family structure and both positive and negative parenting styles) and covariates (e.g., measures of socioeconomic position) (**RQ1**). My main findings from the descriptive analyses were that those with the highest geometric mean depression scores at baseline were females, participants who lived with no parents (the small sample size meant that this finding should be treated with caution), participants who ranked lowest (bottom third) on positive parenting and those who ranked in the middle tertile on negative parenting, and participants living in rural areas.

My regression analyses using linear mixed-effects models produced two main findings: (1) the absence of effect modification by gender (**RQ2**) and (2) the statistically significant independent main effects of CSMU frequency and parenting styles on depression (**RQ3**).

Firstly, although females had significantly higher baseline depression scores than males, there was no significant moderation of the CSMU/PIC and depression associations by gender.

Secondly, pertaining to the independent associations, more frequent computer social media users had higher depression scores at baseline, whereas frequency of phone-based interpersonal communication was not significantly associated with depression. There are several explanations for why a greater frequency of CSMU may be associated with higher depression scores in this cohort: these include the displacement effect, negative social comparison, active versus passive use and neurocognitive processes. I will elaborate on these potential explanations in the concluding chapter.

Next, with respect to parenting styles, higher scores in positive parenting were associated with lower baseline (log) depression, whilst higher scores in negative parenting were associated with higher baseline (log) depression, after controlling for all covariates, frequency of CSMU/PIC and family structure. In addition, a one-unit increase in positive parenting was associated with a more favourable trajectory of depression (a slower rate of increase). In Chapter 8, I will delve into how these findings align with the research presented in my systematic review (Chapter 2).

These findings were similar after prior levels of depression were statistically controlled for (**RQ5**), suggesting the absence of bidirectional/cyclical effects in this cohort of Korean young people between 2012 and 2016 and that the observed cross-sectional association is most likely one-way (CSMU to depression).

7.5.2 Strengths of this study

As mentioned in Section 6.5.1 of Chapter 6, I considered how the questionnaire items used in the KCYPS to measure the frequency of computer social media use and phone-based interpersonal communication allowed me to investigate how different ways of utilising social media may relate to self-esteem (and in this chapter, depression) in the Korean cohort. This analysis expands upon the existing literature beyond solely assessing the amount of time users spend on social media such as social networking sites in general. Additionally, as previously mentioned, this study enhances previous research based on nationally representative longitudinal data from the KCYPS by examining specific items of social media use, rather than more general items on mobile phone use or internet use. These strengths were previously discussed in Chapter 6 and are also applicable to the analyses shown in the present chapter.

7.5.3 Limitations of this study

As mentioned in Section 6.5.2 of Chapter 6, I noted that comparing my findings to other epidemiological studies is challenging as no previous study based on this data has explored specific CSMU/PIC items. Additionally, as mentioned earlier, social media usage trends are constantly evolving, and data collected several years ago may no longer reflect current usage patterns. A direct comparison of social media use through different devices (i.e., computer vs phone) was also not possible, albeit the distinction between computer and phone social media use may no longer be relevant nowadays.

7.6 Conclusion

This study analysed five waves of KCYPS data spanning five years (2012-16) and supplemented our understanding of computer social media use/phone-based interpersonal communication and levels of depression in adolescents aged 14 to 18 years in South Korea. The findings revealed that frequency of computer social media use was associated cross-sectionally with lower depression, whereas no significant association between phone-based interpersonal communication and depression was observed. Furthermore, this study has highlighted that gender and aspects of family life (family structure and parenting styles) did not significantly modify the associations between the frequency of computer social media use/phone-based interpersonal communication and depression in the study sample.

The final chapter of my thesis will summarise the work done thus far, including an outline of the strengths and limitations of my research, potential policy implications and future research avenues.

Chapter 8: Discussion

This final chapter represents the culmination of my PhD research. Firstly, it provides a summary of the work that has been undertaken in the previous chapters. This includes a critical analysis and discussion of the key findings from the three empirical chapters, followed by a discussion of the strengths and limitations of my empirical studies, while also highlighting future research avenues that could build upon my work. Following that, this chapter provides an outline of the potential policy implications of my research. Additionally, I explore the emerging concept of digital wellness, which has become increasingly important as digital technologies become ever-present in our daily lives. After that, I summarise the avenues for future research. Finally, this chapter concludes my thesis with a summary of the key contributions presented in this work.

8.1 Critical analysis of main findings

My aim was to undertake empirical research among young people to:

1. Describe differences in levels of SMU/SNS use and mental health/well-being.
2. Quantify the cross-sectional and longitudinal associations between SMU/SNS use and mental health/well-being.
3. Identify any differences (moderation) in this association by gender and aspects of family life.
4. Identify any differences in key findings across different populations of young people by comparing my findings across different countries.

In this section, I provide a summary of the main findings from each chapter, organised into six themes and corresponding sub-sections. These themes are as follows: (i) gender differences, (ii) cultural differences, (iii) independent associations of social media use, (iv) independent associations of family variables, (v) moderation by family variables and (vi) supplementary analyses. Next, I compare my results between the two datasets analysed (UKHLS versus KCYPS), as well as previous studies, to provide a deeper understanding of my findings. These comparisons are presented within each of the aforementioned themes. Additionally, I critically analyse my main findings and suggest possible avenues for future research. These discussions provide insight into how my work can be expanded and developed further, which may be of interest to other researchers in the field.

8.1.1 Gender differences

My analyses of the UKHLS (participants aged 10-21 years at baseline) showed that females were more likely than males to be heavier users of social networking sites (SNSs) (4+ hours/weekday) and had significantly lower levels of self-esteem on average as the duration of SNS use increased from light to heavy use (unadjusted model, Figure 5.4). In the fully-adjusted model, duration of SNS use remained significantly associated with baseline levels of self-esteem in females: compared to light users, non-users had higher self-esteem at baseline, whilst moderate and heavy users had lower self-esteem at baseline (Table 5.7). However, this association was not observed in males, neither at baseline nor with the rate of change in self-esteem (Table 5.6).

The results from the KCYPS (participants aged 14 years at baseline and followed up to the age of 18) indicated that males were more likely than females to be in the highest tertile of computer social media use (CSMU) frequency, whilst females were more likely than males to be in the highest tertile of phone-based interpersonal communication (PIC) frequency (Table 6.6). Gender did not modify the associations between the frequency of CSMU/PIC and self-esteem (See Appendices: Table B2) or depression (See Appendices: Table C1).

Collectively, these findings imply that prolonged usage of SNSs may have an adverse impact on the self-esteem of young females in the UK. However, in the birth cohort analysed in South Korea (M1 Cohort in the KCYPS), the links between CSMU/PIC and self-esteem and depression did not significantly differ between adolescent males and females.

A strength of my studies was that the UKHLS and KCYPS measured self-esteem using a similar (Rosenberg) scale. The different findings regarding the relationship between duration of SNS use (UKHLS)/frequency of CSMU/PIC (KCYPS) and self-esteem may be partly explained by differences in the measurement of the exposure. In the UKHLS, participants were asked a single question about the number of hours they spent chatting or interacting with friends on social websites (e.g., Bebo, Facebook, MySpace) on a normal school day ('youth' questionnaire) or weekday ('young adult' questionnaire), whilst in the KCYPS, participants were asked about the frequency of various social media or communication-based activities on computer and phone platforms. Frequency of computer social media use was assessed using items that measured participation in (i) online games and entertainment, (ii) chatting or messaging with others, (iii) engagement in online community activities, (iv) use of personal social media pages (e.g., blogs, Facebook, Twitter, MySpace/Minihompi) and (v) leaving comments. Phone-based interpersonal communication, on the other hand, was assessed using items that measured communication with friends and family, including, but not limited to, text messages through messaging platforms (e.g., KakaoTalk, Line).

The UKHLS measurement of chatting or interacting with friends on social websites may be more indicative of female-dominated activities on social networking sites, potentially leaving females more vulnerable to low self-esteem. On the other hand, males may engage in different types of social media activities that do not leave them as vulnerable as females. For example, research from CHILDWISE, a leading specialist in research with children and young people in the UK, showed that boys tend to spend more time on intense gaming activities than girls (185). Research on UKHLS data by Booker, Skew, Kelly, et al. (2015) has also shown that the number of hours spent playing computer games was not associated with socioemotional difficulties among participants aged 10 to 15 years, whereas chatting or interacting with friends on social websites for 4+ hours per weekday was associated with higher odds for developing socioemotional difficulties (140). Additionally, research suggests that adolescent girls seek more intimate relationships than boys, especially in friendships and romantic relationships (186). Men's sense of self is typically founded upon independence, whereas women's sense of self is often founded on interdependence and relatedness (187), which could make the latter more susceptible to the negative impact of heavy SNS use on self-esteem in the UK.

The gender differences found in my studies are consistent with the contrasting findings reported in the literature reviewed in Chapter 2. For instance, Booker, Kelly and Sacker (2018), using data from the UKHLS conducted from 2009-11 to 2013-15, found that among participants aged 10 to 15 years, longer duration of SNS use at age 10 was associated with subsequent decreases in well-being in females but not in males (10). In contrast, Neira and Barber (2014), using data from the Youth Activity Participation Study (survey year unknown), found that among young people aged 13 to 21 years in Western Australia, the associations between investment in SNS use (e.g., perceived as being an integral part of daily life) and self-esteem and depression were not moderated by gender (47). Similarly, Primack, Shensa, Sidani, et al. (2021) found that among young people aged 18 to 30 years in the USA, the association between social media use and the development of depression did not differ among males and females, based on data from a longitudinal study conducted in 2018 (39). These findings highlight the complexity of the relationship between social media use and mental health and well-being, which is often influenced by country, context, how social media is measured, the age group under investigation and the outcome(s) being examined. Pertaining to Bronfenbrenner's ecological framework (3), the interaction between individual factors (e.g., gender and age) and social media use might be influenced by the relationships and connections between various microsystems in the lives of individuals (including various aspects of family life), but the research findings could also be influenced by the macrosystem, for example varying cultural norms and societal expectations related to gender roles and social media use in different countries. Further research is needed to better understand how young males and females use social media in different countries, for what purposes they use social media and how they relate to mental health and well-being outcomes cross-sectionally and longitudinally.

My empirical studies found that females had lower levels of self-esteem than males across all waves of the study period in the UKHLS and KCYPS. Additionally, in an unadjusted model, females in the UKHLS showed a significant decline in self-esteem over time, whilst males had a comparatively slower rate of decline (Figure 5.3). In contrast, in an unadjusted model, both males and females in the M1 Cohort in the

KCYPS had increasing self-esteem over time, with males showing a more marked increase than females (Figure 6.3).

These gender differences are in line with the ABC (Affective-Biological-Cognitive) model, which posits a complex interplay between affective, biological and cognitive factors in explaining gender disparities in depression (188). For example, females may experience higher levels of stress and negative emotions (affective factors) when forming deep connections on social media, which can interact with hormonal changes (biological factors) to increase their risk of developing depression. This links to the Stress-Vulnerability Theory discussed in Section 1.3.2 of Chapter 1, which posits that the more stress one experiences, the more likely one could manifest a symptom or a diagnosable mental illness that one has a predisposition towards (e.g., depression, anxiety disorders, etc.) (100).

8.1.2 Cultural differences

Apart from gender differences, my studies revealed notable cross-national differences in the estimated trajectories of self-esteem in the UKHLS and KCYPS (M1 Cohort). Specifically, the estimated 1-year rate of change in self-esteem showed a decline over time in the UKHLS (Figure 5.3), whilst in the KCYPS, the estimated 1-year rate of change in self-esteem showed an increase over time (Figure 6.3). These findings suggest that trends in self-esteem differ between these two specific study populations. However, this finding must be interpreted in light of the age heterogeneity in the study populations (discussed in Section 8.2.2).

Extending these findings to the Social Comparison Theory discussed in Section 1.3.2 of Chapter 1, it is plausible that social comparison in Western cultures is more individualistic and contrasting. This could result in social media users comparing themselves to others based on personal achievements and traits, leading to reduced self-esteem (i.e., contrasting upward social comparison; Table 1.2), as outlined in the Identification-Contrast Model (88). On the other hand, social comparison in Asian cultures may be more collectivistic and assimilative, with individuals comparing themselves to others for motivation and in socially harmonious ways (i.e., assimilative social comparison; Table 1.2). This could explain potential differences in mental health and well-being trends between Western and Asian cultures, as collectivism and assimilation, particularly on social media, may lead to higher self-esteem and better mental health and well-being outcomes.

8.1.3 Independent associations of social media use

Based on the fully adjusted models, results from the UKHLS showed that the duration of SNS use was not associated with baseline self-esteem nor with the rate of change in self-esteem in males (Table 5.6). However, as mentioned above in the discussion of gender differences, the duration of SNS use was significantly associated with baseline self-esteem in females (Table 5.7). Compared to light users of social networking sites (reference: <1 hour/weekday), non-users had higher self-esteem at baseline, whilst moderate users (1-3 hours/weekday) and heavy users (4+ hours/weekday) had lower self-esteem at baseline.

Analyses of the M1 Cohort in the KCYPS showed that more frequent computer social media use was associated with (i) lower baseline self-esteem (Table 6.7) and (ii) higher baseline depression (Table 7.3) for both genders, holding all else constant. In contrast, more frequent phone-based interpersonal communication was associated with higher baseline self-esteem (Table 6.8), but it was not associated with depression at baseline nor with its rate of change (Table 7.4).

As in all survey-based research, these findings suggest that the associations observed may partly depend on how the exposure variables are measured in a specific study. Given the questionnaire wording in the KCYPS, I could not consider the two sets of items (computer and phone) as simply being different ways to access social media. The phone-based items may capture aspects of positive social support potentially available by SNSs that are very different in nature to those aspects of social media use captured by the computer use items and this difference (rather than a difference in mode use per se) may to some extent explain the divergent associations.

In the following paragraphs, I will explain how several theories and concepts, some of which were introduced in the background presented in Chapter 1, shed light on these findings.

The negative associations observed in my study between SNSs (UKHLS)/CSMU (KCYPS) and self-esteem may be explained by **negative social comparison**, as reflected in a study conducted by Reer, Tang and Quandt (2019) on German internet users aged 14 to 39 years. The study measured social comparison using the shortened (6-item) version of the Iowa-Netherlands Comparison Orientation Measure. Example items are “I often compare how I am doing socially (e.g., social skills, popularity) with other people” and “I often try to find out what others think who face similar problems as I face”. The study found that participants high in depression were also high in social comparison orientation, which was associated with greater social media engagement (42). Furthermore, the study found that self-esteem negatively correlated with social comparison after controlling for social media duration and type of use (active versus passive use). This is particularly relevant during adolescence, a critical period for developing one’s sense of self, where exposure to unrealistic images on social media can cultivate feelings of depression (191).

In the KCYPS, the items used to measure computer social media use could explain why computer social media use has a greater tendency to foster negative social comparisons than phone-based interpersonal communication. As described in Section 6.3.2 of Chapter 6, the items that measured computer social media use included gaming and entertainment, chatting or messaging, leaving comments, online community activities and personal social media pages (e.g., blog, Facebook, Twitter, MySpace/Minihompi). Items that measured phone-based interpersonal communication included calling/talking to family and friends, and texting family and friends (e.g., KakaoTalk, Line).

Computer social media activities offer fewer interpersonal cues and are more focused on general, asynchronous activities such as browsing through social media sites, which can lead to passive consumption and comparison of images and content, whereas phone-based interpersonal communication involves direct communication with family and friends through texting on social networking sites and calling. The lack of interpersonal cues and the presence of more asynchronous interactions allow users to carefully choose the information they wish to present in order to create a favourable impression (192). As a result, computer social media use could lead to a higher likelihood of engaging in negative social comparison and, in turn, lower levels of self-esteem and higher levels of depression. Conversely, phone-based interpersonal communication is more conducive to direct and one-on-one communication online, which may have a protective effect on the self-esteem of users, as tentatively suggested by the results of my study.

Next, my findings could be linked to the **displacement effect** discussed in Section 1.3.2 of Chapter 1. Longer duration in SNS use and high-frequency computer social media use can take up a significant amount of time, which may displace more beneficial activities, such as forming one-on-one relationships, achieving true goals, or reflecting on oneself (193). Consequently, this displacement of more valuable activities could erode one's mood, leading to lower levels of self-esteem or higher levels of depression.

Conversely, the items that captured phone-based interpersonal communication in the KCYPS, such as calling or texting friends or family members, could reflect more beneficial activities through developing one-on-one relationships. This implies that individuals who engage in high-frequency phone-based interpersonal communication may be less vulnerable to the displacement effect compared to those who engage in high-frequency computer social media use. With regards to my research findings using the KCYPS, this could partly explain why the frequency of computer social media use was associated with lower self-esteem (Table 6.7) and with higher depression scores (Table 7.3) at baseline, whereas the frequency of phone-based interpersonal communication was associated with higher baseline self-esteem (Table 6.8). Furthermore, the mobile nature of phone-based interpersonal communication implies that it can occur while on the go, which further reinforces the idea that higher levels of phone-based interpersonal communication may be less susceptible to the displacement effect. On the other hand, computer social media use tends to be more sedentary and therefore more likely to displace other activities.

The nature of **active versus passive use** may also shed light on why the frequency of computer social media use and phone-based interpersonal communication had different associations with self-esteem/depression in the M1 Cohort of the KCYPS over the study period. The former involves more asynchronous and possibly passive interactions, whereas the latter involves more direct and active forms of communication. Research has shown that passive social media use is linked to poorer mental health outcomes, such as depressed mood. For example, Thorisdottir, Sigurvinsdottir, Asgeirsdottir, et al. (2019) found that passive social media use was associated with depressed mood among teenagers aged 14 to 16 years in Iceland, even after controlling for the duration of social media use (45). It is possible that the items included in the KCYPS that measured computer social media use captured passive aspects of social media use, whilst the items that measured phone-based interpersonal communication included active aspects of social networking site use, which could, to some extent, further explain the differences in their empirical associations with self-esteem/depression. However, further research using the KCYPS and other datasets is required to elucidate this hypothesis and provide more insights into the potentially nuanced associations between different measurements of social media use (including differences in the devices used to access social media) and mental health and well-being.

Finally, it is important to consider that continual exposure to social media may potentially disrupt **normal developmental neurocognitive processes** (194-196). This disruption could stem from the design of social media, as discussed in Section 1.3.1 of Chapter 1, which features rapid cycling of reward and cognitive processes. This could in turn increase the likelihood of mental health and well-being issues. However, research in this area is still in its preliminary stages, and further studies are needed to fully assess the sociobiological mechanisms involved in these processes.

Findings from previous studies may also provide a useful context to the observed positive association between phone-based interpersonal communication and baseline self-esteem found in my study of the KCYPS. A cross-national study by Boer, van den Eijnden, Boniel-Nissim, et al. (2020) conducted in 2017-18 among teenagers aged 11, 13, and 15 years reported that in countries with a high prevalence of intense social media use, intense social media use was weakly associated with psychological complaints, but it was positively associated with family support and life satisfaction (151). This study also found that intense social media users across all countries reported higher levels of friend support than non-intense users. Drawing a parallel to my study using the KCYPS, positive parenting could extend beyond in-person interactions and encompass positive communication with parents via phone or social media, including calling and texting family members. Similarly, friend support could mean a higher frequency of phone-based interpersonal communication, as the items chosen in my study to measure the frequency of phone-based interpersonal communication also included calling and texting friends. Hence, intense social media use in the aforementioned cross-national study could be potentially analogous to high-frequency phone-based interpersonal communication in the KCYPS, which could reflect social engagement, participation, inclusion and positive communication, possibly leading to a positive association with self-esteem. Nevertheless, it is important to note that a constraint of this speculation is that I could not distinguish between positive and negative phone-based interpersonal communication (e.g., positive versus negative calls or texts).

Overall, these findings and discussions relating to social media use and phone-based interpersonal communication within the context of Bronfenbrenner's ecological framework (3) highlight the interconnectedness between individual characteristics (e.g., gender and age), individual behaviour, technology use and the various ecological systems (including the family microsystem) that shape and influence the personal development, mental health and well-being of young people. It emphasises that social media use is not isolated but is embedded within a complex web of interactions and influences across multiple levels.

8.1.4 Independent associations of family variables

Descriptive analyses of the UKHLS data showed that participants who hardly ever talked to their mothers and fathers and those who quarrelled on most days with their mothers were more likely to be heavy users of social networking sites (4+ hours/weekday). Participants living with no parents were more likely to be heavy users than those living with at least one parent (Table 5.5).

With regards to self-esteem, females who talked less often and quarrelled more often with their mothers had significantly lower baseline self-esteem (Table 5.7), whereas males who quarrelled more often with their mothers had significantly lower baseline self-esteem (Table 5.6). Furthermore, family structure (number of parents the participant was living with) at baseline was not significantly associated with baseline self-esteem nor with the rate of change in self-esteem, even after adjusting for parent-child relationship quality in both genders (Tables 5.6 and 5.7).

Descriptive analyses of the KCYPS data showed that participants living in a single-parent family and those ranking higher on the negative parenting scale were more likely to be in the highest tertile of CSMU frequency (Table 6.6). Those ranking higher on the positive parenting scale were more likely to be in the highest tertile of PIC frequency.

With regards to self-esteem, my results from the fully adjusted models showed that higher scores in positive parenting were associated with higher baseline self-esteem and a faster rate of increase in self-esteem over the study period, whereas higher scores in negative parenting were associated with lower baseline self-esteem and a slower rate of increase in self-esteem (Tables 6.7 and 6.8). Family structure showed no association with self-esteem.

With regards to depression, my results from the fully adjusted models showed that higher scores in positive parenting were associated with lower baseline depression and a slower rate of increase in depression over time, whereas higher scores in negative parenting were associated with higher baseline depression, but not with the rate of change in depression (Tables 7.3 and 7.4). Family structure showed no association with depression.

In Section 8.1.1, I discussed and referenced the greater intimacy and relatedness of female relationships compared to male relationships. This could mean that talking and quarrelling with mothers may have a stronger impact on the self-esteem of females rather than males among 10-21-year-olds in the UKHLS. Additionally, having supportive family relationships can serve as a form of protection against the negative impact of stress, while also promoting resilience and self-confidence (173). This is supported by a study on 13-17-year-old adolescents in Singapore which found that positive relationships with both parents were associated with lower levels of depression (135). Similarly, another study conducted on 'youth' aged 10 to 15 years in the UKHLS found that being in a supportive family significantly increased life satisfaction scores between two time points (138). These findings emphasise the importance of the microsystem of Bronfenbrenner's ecological framework (3), that having supportive family relationships, as opposed to unhelpful ones may improve mental health and well-being, especially among females.

8.1.5 Moderation by family variables

My analyses of the UKHLS suggested some evidence that the association between the duration of SNS use and self-esteem at baseline was moderated by family structure in females (Table 5.8; Figure 5.5). For females living with at least one parent, the average self-esteem score at baseline decreased slightly with greater duration of SNS use. In contrast, for females living with no parents, moderate SNS use was associated with higher self-esteem at baseline compared with light SNS use. However, this finding could be explained by unobserved confounding since the females living with no parents were likely to be older and living independently.

My analyses of the KCYPS suggested a statistically significant moderation effect of positive parenting on the fully-adjusted association between the frequency of CSMU and self-esteem; the same association was observed between the frequency of PIC and self-esteem (Table 6.9; Figures 6.4 and 6.5). Mean levels of self-esteem at baseline decreased with increasing CSMU at higher levels of positive parenting but increased with increasing PIC at higher levels of positive parenting. These findings suggest that positive parenting practices may have a protective effect on the self-esteem of users more frequently engaged in phone-based interpersonal communication (which could include enhancing communication with their family) but less so for frequent users of computer social media use (which, as mentioned earlier, involves more asynchronous and possibly passive interactions). The results also showed that at lower levels of positive parenting, mean self-esteem decreased with increasing PIC, highlighting that the reverse could also be true: low positive parenting could mean poor or unhealthy phone-based interpersonal communication with family members and therefore lower self-esteem of these users.

The potential influence of the broader cultural and societal context on the relationships between social media use/phone-based interpersonal communication and self-esteem, which form the macrosystem of Bronfenbrenner's ecological framework (3), may help to explain these findings. For example, these findings might be attributed to Confucianism, a philosophical and ethical belief system that emphasises self-cultivation and moral education (190). Confucianism has had a significant impact on many Asian cultures, including those in China, Japan and Korea (190). Parents in Asian cultures may emphasise humility and modesty over self-promotion, which could influence how adolescents view themselves and their self-worth. Participants in the KCYPS who had high positive parenting scores (regardless of the frequency of computer social media use or phone-based interpersonal communication, see Figures 6.4 and 6.5) may have had higher self-esteem levels due to this cultural emphasis. However, further research is needed to explore the potential influence of culturalism on adolescent self-esteem.

Furthermore, whilst my results are tentative and need to be interpreted in light of the limitations of the study (these are set out below), my findings may have potential implications for parents, educators and mental health professionals, as they suggest that positive parenting may promote healthy self-esteem in young people and that reducing computer social media use frequency alone may not be sufficient to improve self-esteem without considering the role of parenting. This supports the study conducted by Lee, Ho and Lwin (2017) among adolescents aged 13 to 17 years in Singapore which found that positive parent-child relationships reduced the occurrence of psychosocial problems and an unhealthy reliance on social networking sites (135). In another study, Boniel-Nissim, Tabak, Mazur et al. (2015) found that cross-nationally, the inverse relationship between life satisfaction and frequent electronic media communication was the strongest in adolescents who perceived their communication with both parents as difficult (44). This suggests that supportive parent-child communication potentially buffers against the negative effects of electronic media communication with friends on life satisfaction.

Given that multiple contexts and environments influence child development (3), it is also important to examine the way in which parents perceive and use media themselves, as they are likely influencing the media experiences of their children by setting rules or modelling behaviours and mindsets about media use (197). For example, if parents use phone-based interpersonal communication regularly and value its role, it is likely that children will not only observe their parents engaging in increased phone-based interpersonal communication, but also be in an environment in which it is encouraged or supported, or at minimum less penalised. This could explain why, cross-sectionally, average levels of self-esteem in the KCYPS were highest for those with higher levels of phone-based interpersonal communication and higher levels of positive parenting (Figure 6.5), as this would in theory create a very different microsystem for those young people, compared to the group for which self-esteem decreased as computer social media use and positive parenting increased, suggesting that computer social media use is less valued or possibly worrying for parents. Thus, it is important to consider parent media attitudes and rules, as well as their own use of social media, in order to understand in more detail the influence of the family microsystem on the association between social media use and mental health and well-being among young people.

8.1.6 Supplementary analyses

Previous studies have identified the potentially bidirectional/cyclical associations between social media use and mental health and well-being (e.g., poor mental health leading to greater use of social media, which in turn leads to poorer mental health). A number of studies have attempted to account for this potentially cyclical association by statistically controlling for prior measures of mental health and well-being.

My analyses of the UKHLS suggested that the main findings remained consistent after controlling for prior self-esteem (Table 5.9).

Likewise, my analyses of the KCYPS suggested that the main findings remained consistent after controlling for prior self-esteem (Table 6.10) and prior depression (Table 7.5).

The findings from the supplementary analyses suggested that the relationship between social media use and the outcomes of self-esteem and depression was likely to be unidirectional in both the UKHLS and KCYPS study samples over the time period studied. This conclusion is also supported by a study conducted by Riehm, Feder, Tormohlen, et al. (2019) in the USA, which found that a longer duration of social media use was associated with internalising and externalising problems in adolescents aged 12 to 17 years, even after controlling for prior mental health problems (41). Recent research among 14-17-year-olds using the UK Millennium Cohort Study also found little support for the existence of cyclical relationships between social media use and mental health (198).

The concept of persuasive design (53) (described in Section 1.3.1 of Chapter 1) aims to maximise the time and attention users devote to a particular application to the exclusion of other online or offline activities. This suggests that users need not necessarily experience poor mental health to spend more time on social media. In this context, the design of social media platforms can be seen as factors within the microsystem of Bronfenbrenner’s ecological framework (3) that could influence young people's mental health and well-being.

The algorithms behind social media have gained significant attention in recent times, as highlighted in the Netflix documentary-drama The Social Dilemma (2). The show features tech experts from Silicon Valley who discuss how the design of social media nurtures addiction to maximise profit, manipulate users' thoughts, feelings, and behaviours, and spread conspiracy theories and disinformation. Future research could explore how various social media features impact the amount of time spent on social media, the way users feel and the purposes of using social media. This could provide more insights into the direct impact of social media on the mental health and well-being of young people.

8.2 Strengths and limitations

In this section, I discuss the broad strengths and limitations of my thesis. Each empirical chapter (Chapters 4-6) had specific strengths and limitations, which were discussed in their respective Discussion sections. In Section 8.5, I highlight potential avenues for future research that may help to address some of the limitations of my work or expand on its findings.

8.2.1 Strengths

My PhD has made three contributions to the research on associations between social media use and mental health and well-being outcomes in young people. Firstly, there is a dearth of studies that have examined the role of family factors in the relationship between social media use and self-esteem/depression. Secondly, there is a lack of research that has stratified analyses by gender and that have conducted analyses by statistically adjusting for the outcome measure prior to assessing levels of social media use, to account for any potential cyclical associations between social media use and mental health/well-being. These gaps were identified in an extensive literature review on social media research (124) as well as in several papers included in my literature review (43, 138, 148, 152). Thirdly, my PhD has utilised data from large-scale, multi-topic and nationally representative longitudinal surveys in the UK and South Korea, providing an added benefit by examining data across different countries.

Utilising the UKHLS and KCYPS, which included the most recent data available at the time of analysis, provided the opportunity to examine changes in the rate of self-esteem (UKHLS and KCYPS) and depression (KCYPS) over five or more time points. A strength of my studies was that the UKHLS and KCYPS measured self-esteem using a similar scale (i.e., Rosenberg Self-Esteem Scale). The questionnaires in both surveys were also empirically supported with highly reliable and well-validated measures.

Deciphering the direction of the association between social media use and mental health and well-being can be challenging when working with cross-sectional data. Heavy social media use may undermine future levels of mental health and well-being, as discussed in Section 1.3.2 of Chapter 1, through the displacement effect and social comparison. Simultaneously, poor mental health may lead to heavy use of social media as a coping mechanism, or to seek the rewards provided by social media, as described in the Hook Model in Section 1.3.1 of Chapter 1. In Chapters 5 to 7, I aimed to account for any potential bidirectional/cyclical associations by using longitudinal data from seven waves of the UKHLS and five waves of the KCYPS: this enabled me in supplementary analyses to control for prior measures of self-esteem and depression in order to avoid or mitigate any under- or over-estimations of the exposure and outcome associations.

The use of multiple items to measure the frequency of computer social media use and phone-based interpersonal communication in the KCYPS enabled an examination that went beyond assessing the amount of time spent only on social networking sites. As highlighted in Section 1.3.1 (Attention Economy), screen time is a complex and multifaceted activity, which can include various factors such as the type of screen, the way it is used, the duration of use and the activities engaged in (52). By using different items to measure computer social media use and phone-based interpersonal communication (which included SNS use via platforms such as KakaoTalk and Line), my research was able to investigate these separately and find divergent associations: the frequency of CSMU was associated with lower self-esteem and higher depression at baseline, whereas the frequency of PIC was associated with higher baseline self-esteem.

In contrast, the data collected by the UKHLS at the time of analysis (up to wave 10) only provided data on the amount of time that participants spent chatting or interacting on social websites, which to some extent limited our understanding of the potential associations between social media use and mental health and well-being (45). Future waves of the UKHLS are including questions on more specific aspects of social media use, including a distinction between weekday and weekend use, and frequency of using the internet for specific reasons (e.g., looking at content on social media or posting content on social media websites).

To address missing data in both datasets (e.g., item non-response) and avoid reductions in sample size and statistical precision, I utilised multiple imputation. Multiple imputation is a flexible and powerful technique that can handle data that is missing at random (MAR), that is, where any systematic difference between the missing values and the observed values can be explained by differences in observed data (199).

Multiple imputation can produce unbiased estimates and standard errors if the imputation models are correctly specified, and it can also increase statistical power and reduce bias compared to other methods for handling missing data, such as complete case analysis or single imputation (199). Lastly, multiple imputation allows for uncertainty to be properly accounted for in the estimation of missing values by introducing additional error variance to each imputation (200), resulting in more realistic estimates of variability.

8.2.2 Limitations

Caution must be taken when drawing comparisons between the findings from the UKHLS and KCYPS due to age heterogeneity in the study populations. Specifically, the age range of participants in the UKHLS was 10 to 21 years as questions on self-esteem were asked only of participants in this age range. This broad age range was used to increase sample sizes, especially as the modelling was performed separately by gender. In contrast, the participants in the M1 Cohort of the KCYPS were aged 14 years at the baseline wave in my study and were followed up to age 18.

Adolescence is a critical developmental stage marked by increasing autonomy and significant changes in social and emotional development (7).Younger children may not yet have fully developed social comparison abilities, for example. Mental health and well-being issues also tend to emerge more frequently during adolescence (25). For example, in the UKHLS data, self-esteem declined on average at a faster rate for younger versus older females both in the main and supplementary analyses (age x time $p<0.05$). Studies that involve different age ranges in young people (i.e., defined, for statistical purposes, by the WHO as those aged 10 to 24 years (159)) may exhibit differences in developmental factors, such as cognitive development, which could potentially influence the association between social media use and self-esteem or depression. Additionally, different age groups may have different social contexts and support structures, which can interact with social media use to produce varying effects on mental health and well-being, as supported by Bronfenbrenner's Ecological Systems Theory discussed in Chapter 1. As such, going beyond my present study which only examined age as an independent predictor, my future research could additionally consider the moderating effects of age in the association between social media use and mental health and well-being, possibly including age-gender stratified analyses where sample sizes allow.

The ever-evolving nature of social media and its functionalities is a significant limitation of my research. The relationship between social media use and self-esteem/depression may have changed since the data was collected, highlighting the need for ongoing research to reflect the latest trends in social media use.

It is recognised that the specific ways in which social media is accessed by young people may be important in any comprehensive assessment of its impacts on mental health and well-being outcomes. On one hand, a key limitation of my analyses of data collected by the KCYPS was that I could not consider the computer and phone use items as simply capturing different ways of accessing social media. Due to the questionnaire wording for the items on phone use (set out in Chapter 6), I could not specifically separate interpersonal communication via social media (such as texting on SNSs) from more traditional communications (such as calling a friend or family member with a SIM card). On the other hand, by treating CSMU and PIC separately, I was able to reveal the aforementioned divergent associations with self-esteem and depression.

The new panel study of the KCYPS, which began in 2018 and is planned to continue until 2025, has updated the questions assessing frequency of mobile phone use to reflect changes in internet use, including social media use (177). The distinction between computer and phone use, as measured in KCYPS 2010-16, has become less relevant due to the increasing prevalence of internet use (including social media use) on mobile devices for all purposes. Consequently, the KCYPS 2018-25 now only includes a single variable on mobile phone use (177).

Both the UKHLS and KCYPS only focused on one dimension of self-esteem, as measured by the Rosenberg Self-Esteem Scale, which assessed self-esteem in relation to the personal self (Tables 5.1 and 6.1). Personal self-esteem refers to deriving a sense of self-worth from personal attributes such as abilities and talents (13). According to social identity theory, self-esteem can also stem from the social self (in addition to the personal self) (201, 202). The social self is composed of both relational and collective self-concepts (203, 204). The relational self is based on interpersonal attachments and shared aspects with significant others (205, 206), whilst the collective self is derived from membership in social groups such as ethnic communities (207, 208). Research has demonstrated that these three types of self-concepts are distinct and can have unique influences on various psychological phenomena (204, 209). Given that my research examined relational and collective characteristics, such as social media use, family structure, parent-child relationship quality and parenting styles, self-esteem scores pertaining to the relational and collective selves may differ from what was measured in the UKHLS and KCYPS, which only assessed self-esteem in relation to the personal self. Hence, future research should consider examining these other dimensions of self-esteem to gain a more comprehensive understanding of self-esteem.

Furthermore, whilst some of the measures are widely used and validated, information on the key variables was collected by self-report in both the UKHLS and KCYPS, which are potentially subjected to potential recall and social desirability bias, particularly for sensitive questions such as those related to parent–child relationship quality or parenting styles. As a result, there could be inaccuracies of under- or over-reporting. Regarding the social media measures in the UKHLS and KCYPS, future research could use device applications to measure the actual time spent on social media sites (210), providing a more accurate representation of social media use, as there could be potential under-reporting of social media use via self-report. Additionally, it would be valuable to include questions in future surveys that gather data on social media usage per platform. Research has shown that young people use different social media platforms for different purposes (211), which could potentially affect their mental health and well-being in diverse ways. Additionally, Primack, Shensa, Escobar-Viera, et al. (2017) found that the use of multiple social media platforms had stronger associations with symptoms of depression and anxiety than the duration of social media use among young people aged 19 to 32 years in the USA, using data from the Growth from Knowledge panel (146). By collecting this information, researchers could gain a deeper understanding of the relationship between social media use and mental health and well-being outcomes among young people.

My research employed linear mixed-effects modelling in each empirical chapter. Whilst mixed models have their strengths, such as accounting for within-subject variability, allowing non-monotone patterns of response and handling missing data (under the assumption that data are missing at random), this analytical technique also has its limitations. For example, linear mixed-effects models rely on observed variables rather than latent ones, as such, they do not allow for formal mediation analysis. Mediation analysis can be used to separate the direct and indirect effects of an exposure on an outcome by examining the role of a mediator variable (postulated to lie on the causal pathway between the exposure and the outcome). For instance, family factors such as parenting styles could potentially mediate (rather than moderate or confound) the relationships between social media use and mental health or well-being. Hence, my future research could investigate potential mediators using more complex formal mediation analysis to gain a more comprehensive understanding of the pathways involved in these relationships.

A further limitation of my study is that the large number of statistical tests performed due to fitting gender-specific models (Chapter 5) and modelling the CSMU/PIC exposures separately (Chapters 6 and 7) inevitably increased the risk of Type 1 error. However, I reported only the findings relevant to the research questions and where relevant focused my interpretations on the results of the joint-test (using Stata's *testparm* command for multi-category variables such as family structure) rather than reporting pairwise comparisons. Nonetheless, my future research could consider using multiple comparison tests, such as the Bonferroni correction.

As in most studies, missing data was an unavoidable limitation. In my PhD, a major contributor to missing data in both datasets was the key variables not being collected at every wave of the study. Self-esteem in the UKHLS was only included in the study content at the even-numbered waves, whilst the parent-child relationship quality variables were only included at the odd-numbered waves. In the KCYPS, self-esteem was included in all study waves, but the variables on parenting styles were not included in some waves. For the purposes of estimation, for example in the UKHLS, scores on the parent-child relationship quality variables were carried forward to the following wave (e.g., in the longitudinal dataset, a row for a participant contained the self-esteem score assessed at wave 4 and the scores of talking/quarrelling with mothers assessed at wave 3). As a result, missing data on the key independent variables reflected both item non-response (e.g., refusals) and survey non-response (e.g., a participant with a valid self-esteem score at wave 4 of the UKHLS returning to the study after non-participation at wave 3).

As mentioned above, I used multiple imputation to maximise sample sizes. Nonetheless, multiple imputation has several limitations (199). Using correctly specified multiple imputation models to include cases with missing data can achieve unbiased estimates only if the data are missing at random. Although I used several variables in the imputation models, including the baseline score on the outcome variable, there remains the possibility that other variables useful for predicting the missing values were not included.

Attrition is a perennial problem in longitudinal studies. In my study, response rates were higher for the KCYPS than for the UKHLS (but bearing in mind the aforementioned age heterogeneity in the study populations). I used the cross-sectional weights in both descriptive and longitudinal analyses to account for differences in selection probabilities and propensity for non-response. In contrast to the longitudinal weights created at the final wave in the analysis (developed only for monotone attrition, i.e., participants who have taken part at all relevant waves), these weights were available for the majority of participants in the analytical sample. However, notwithstanding the use of weights, my analysis of response to the UKHLS between waves 3 and 4 showed possible excess attrition among 17-to-20-year-olds, which might have been a source of bias.

Finally, as in all observational studies, our findings could have been influenced by additional confounders that were not available. Although my longitudinal research allowed me to shed some light on the direction of associations, it does not establish causality. Future research could explore more complex methods such as Instrumental Variables (IV) estimation, which can help identify causal effects by generating only exogenous variation in the exposure of interest.

8.3 Policy implications

Whilst my results are tentative and need to be interpreted in light of the aforementioned study limitations, some of the findings connect to public- and policy-debate (68, 212, 213).

Technology companies and regulators responsible for social media platforms should consider how these platforms can be designed to minimise the risk of mental health and well-being issues. The social media industry is under increasing pressure to do more to reduce the harms of social media use, for example, incorporating a pop-up heavy usage warning to prevent excessive use of social media (214). However, this has only recently been implemented in Apple. A similar function for Android does not exist yet. Meta has developed a Bullying Prevention Hub which aims to help parents, teens and educators deal with issues related to bullying and conflict (215). On Instagram, there is a “You’re All Caught Up” message to let users know that they have seen all posts from the last two or three days. This potentially reduces heavy usage of social media. Another recent development is the option to not display the number of “likes” on Instagram posts, which could potentially prevent negative social comparisons.

In the UK, initiatives to enable users to safely navigate their lives online have ranged from digital literacy training to technological solutions (86, 212). An example of the latter is “Instagram Together”, a tool which provides well-being support for parents and their children on the app’s safety features (216). In addition, the Online Safety Bill, which was first proposed as legislation in the UK in 2021, aims to improve online safety for users, especially children (32). It requires social media companies to take greater responsibility for user-generated content and to remove harmful content promptly. The UK Department for Education has also recently issued statutory guidance on online safety (217), including a case study for schools in dealing with cyberbullying (218). Personal, Social, Health and Economic (PSHE) lessons have also been introduced in schools to help pupils navigate social media safely (156).

UK Chief Medical Officers’ have shared advice for parents to set boundaries for screen time and screen use with their children in order to strike a healthy balance between offline and online activities (219). In addition, the Children’s Commissioner for England has established a “Digital 5 A Day” framework to have a safe and fulfilling time online (220). “Connect” is about having open communication between parents (or carers) and children in navigating the online world and having an avenue for them to share their concerns while recognising the importance of maintaining relationships online. “Be Active” stresses the need for non-sedentary activities that does not involve screentime, such as playing a sport, going to a dance class, or going out together with family. “Get Creative” encourages internet users to be active rather than passive users, such as creating video content or learning how to code. “Give To Others” involves supporting and encouraging friends both online and offline through positive messages and refraining from spreading hate content by reporting them and blocking trolls. “Be Mindful” is a reminder to parents and carers that being online can be addictive, as such, setting rules to manage social media use could be helpful, for example by restricting bedtime use of smartphones or other electronics.

The Making Sense of Media (MSOM) programme, which has been ongoing since 2019, is an initiative by Ofcom, the UK's communications regulator, to promote media literacy among children and young people (32). It provides resources and guidance to help children and young people understand and critically evaluate media content, including online content. The programme aims to empower them to make informed choices about the media they consume and to develop the skills to navigate online risks.

In the USA, the American Academy of Pediatrics (AAP) has identified ways to guide parents on their teenager(s) use of media both smartly and safely (221). Educating teenagers about digitally distorted reality, such as the portrayal of unrealistic body images and that people may not always be who they say they are online, can help prevent them from forming unrealistic expectations about themselves and others they meet online. Furthermore, promoting media literacy in teenagers involves educating them about the permanent nature of their digital footprint, even when utilising an app's privacy settings to share images and texts online. For example, images on social networking sites such as Snapchat and Instagram might disappear after viewing, but they can always be screenshotted and stored by viewers. The AAP has also devised a Family Media Plan (222) to regulate media use at home. It allows families to create goals and rules of media use with respect to hours and purposes of use that fit in line with their family values. In addition, parents could ensure that the age restriction on social networking sites (set as 13 years by Congress in the Children's Online Privacy Protection Act) is adhered to (68).

In South Korea, the Media Literacy Plus programme has been developed to improve digital literacy and media education among young people (223). The programme is part of the government's broader efforts to promote the safe and responsible use of technology, protect young people from online risks, and enhance their digital citizenship. It was launched in 2016 and is overseen by the Korea Communications Commission (KCC), a government agency responsible for regulating and promoting the communications industry in South Korea. The programme has been praised for its comprehensive approach to digital media literacy education and its efforts to engage multiple stakeholders (e.g., teachers and educators, young people, libraries, and community centres) in promoting safe and responsible use of technology (223).

Additionally, digital detox camps have become increasingly popular in South Korea. These camps offer programmes aimed at reducing social media and technology use and promoting mental health and well-being. The camps provide opportunities for participants to engage in outdoor activities, meditation and mindfulness practices, and encourage participants to reflect on their digital habits and develop healthier relationships with technology. One digital detox camp in South Korea is the Healing Forest Centre, located on Jeju Island (224). The Healing Forest Centre offers a variety of programmes designed to help people disconnect from technology and reconnect with nature and themselves, including retreats, workshops and individual counselling sessions (224).

8.4 Redefining technology: Digital wellness

The COVID-19 pandemic has radically shifted the public conversation about technology. Given that so many people are now working remotely and will be doing so indefinitely if not permanently, public discourse about the effects of technology has shifted from negating technology to exploring how people can most effectively manage their relationship with technology themselves. Young people's social lives have also had to move solely or mainly online. This could potentially create a disparity between experienced and non-experienced users and depending on the context, some groups could benefit more from online social interaction than others.

Digital wellness has emerged as a new concept reflecting the increasing need for more balance in the way that digital technologies are integrated into every aspect of human life. Digital wellness is the optimum state of health, personal fulfilment and interpersonal satisfaction that each individual using technology can achieve (102). Digital wellness incorporates strategies and solutions to achieve a state of digital well-being and reflects a way of life while using technology that involves balancing physical, mental and emotional health to live life to the fullest both online and offline.

Digital wellness can be thought of as a spectrum that encompasses a continuum of behaviours, from complete digital detoxes to digital addiction (102). In the middle of the spectrum lies digital flourishing, defined as a mindful approach to digital technology use that supports our thriving in different areas of life (102). This approach empowers us to take advantage of the benefits of technology while avoiding associated harms.

Much of the research on social media has used instruments that measure negative perceptions of social media use, for example, problematic social media use (225) and the fear of missing out (35). Meanwhile, research on positive perceptions of adolescents' social media use is scarce. Recently, however, the Digital Flourishing Scale for adolescents has been developed and scientifically validated in 2022 to better understand positive digital experiences and behaviours in adolescence, including aspects of social media use (226). This scale is designed to measure behaviours that reflect positive digital communication in adolescents aged 11 to 20 years, using various devices, applications, and channels of communication. Future research could explore developing a similar scale specifically for social media use and measuring adolescents' positive experiences on social media and its associations with indicators of mental health and well-being, possibly also testing whether positive social media experiences or communications could be a mediator in the relationship between the duration or frequency of social media use and mental health and well-being outcomes. The added advantage to this is that measuring positive communication on social media is shared across devices, applications and functions (227, 228) rather than only measuring social media use tied to a function (e.g., chatting or interacting on social networking sites, as in the UKHLS) or a device (e.g., computer and phone, as in the KCYPS).

8.5 Avenues for future research

The empirical associations between social media use and mental health and well-being among young people are complex and influenced by various factors such as country, context and outcome measures. I provided details on potential future research avenues in Sections 8.1 to 8.4. These are summarised below.

- Research on how young males and females use social media in different countries and for what purposes.
- Research on whether the social media items in the KCYPS could be associated with active and passive uses.
- Cross-national research on personality traits and mental health and well-being to elucidate cultural differences (e.g., Confucianism).
- Research on the sociobiological mechanisms involved in any potentially negative associations between social media use and mental health and well-being, particularly among young people.
- Research on whether cultural values play a role in protecting against any negative associations between social media use and self-esteem.
- Research on the impact of specific social media features on indicators of mental health and well-being.
- Research on the relational and collective dimensions of self-esteem to gain a more comprehensive understanding of any associations between social media use and self-esteem.
- Replication of findings using more recent data, for example, the KCYPS 2018.
- Research on using device applications to accurately measure time spent on social media and gather data on social media usage per platform to gain deeper insights into relationships between social media use and mental health and well-being.
- Research on the moderating role of age in the associations between social media use and mental health and well-being.
- Formal mediation analyses and causal analyses to elucidate the pathways involved in relationships between social media use and mental health and well-being.
- Developing a questionnaire to measure positive social media use and researching its associations with indicators of mental health and well-being.

By considering these areas for improvement and further investigation, we can continue to advance our understanding of the complex relationships between social media use and mental health and well-being outcomes in young people.

8.6 Conclusions

My PhD thesis examined the cross-sectional and longitudinal associations between social media use/phone-based interpersonal communication and self-esteem among young people in the UK and South Korea, and between social media use/phone-based interpersonal communication and depression among young people in South Korea. My thesis also explored whether gender and family factors modified these associations.

The literature review and empirical chapters presented in my PhD highlighted the complex associations between social media use and outcomes of mental health and well-being in young people. My findings emphasised the importance of thinking carefully about the measurement of social media use and the significance of gender- and family-specific factors in modifying the associations between social media use and mental health/well-being.

My PhD has implications both within and outside of academia. My research findings can inform university curricula, for example by providing insights into how sociological factors such as parenting styles modify the associations between social media use and self-esteem among young people.

My research also has the potential to inform public and non-profit organisations and raise awareness of the complexities around social media's influence on mental health and well-being, including the role of gender. My research revealed that among young people in the UK, chatting and interacting with friends on social networking sites was negatively associated with self-esteem in females but not in males. However, when evaluating social media use more holistically among young people in South Korea, no gender differences were observed.

Additionally, my research findings can aid in the development of policies and interventions aimed at regulating social media use to maximise its benefits while minimising its harms. Policymakers should focus on comprehending the motivations driving social media usage among young people in different countries, while also examining how these factors vary by gender, family environment and culture. My research may also signal social media companies to enhance the design of social media that entails protecting users' welfare and shifting the focus away from engagement-based revenue.

Effective policies and interventions aimed at strengthening both online and offline relationships can foster resilience, promote positive interactions and enhance mental health and well-being. It is imperative to prioritise the development of research and interventions in this area to address the growing concerns about the effects of social media use on young people's mental health and well-being.

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Appendices

Table A1: Multiple imputation models and number of cases with missing data in the UKHLS (Chapter 5)

Variables with missing data	Imputation model used	Variables used in the imputation	Analytical sample	Number of missing cases (unweighted %)
SNS use (wave 4)	Multinomial logistic regression	Gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure	7,412	13 (0.2)
SNS use (wave 6)	Multinomial logistic regression	SNS use at Wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure	3,795	32 (0.8)
SNS use (wave 8)	Multinomial logistic regression	SNS use at waves 4 & 6, gender, age, self-esteem (Wave 4), household income, cross-sectional weight, family structure	2,617	6 (0.2)
SNS use (wave 10)	Multinomial logistic regression	SNS use at waves 4, 6 & 8, gender, age, self-esteem (Wave 4), household income, cross-sectional weight, family structure	1,688	22 (1.3)
Ethnicity	Multinomial logistic regression	Gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure	7,412	8 (0.1)
Residential area	Logistic regression	Gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure	7,412	1 (0.0)
Parents' highest educational qualification	Multinomial logistic regression	Gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure	7,412	644 (8.7)
Talking to mother about things that matter (wave 4)	Multinomial logistic regression	SNS use at Wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area	7,412	2,077 (28.0)
Quarrelling with mother (wave 4)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area, talking to mother	7,412	1,977 (26.7)
Talking to father about things that matter (wave 4)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional	7,412	2,196 (29.6)

		weight, family structure, ethnicity, residential area, talking to mother, quarrelling with mother		
Quarrelling with father (wave 4)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area, talking to mother, quarrelling with mother, talking to father	7,412	1,988 (26.8)
Talking to mother about things that matter (wave 6)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area	3,795	630 (16.6)
Quarrelling with mother (wave 6)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area, talking to mother	3,795	614 (16.2)
Talking to father about things that matter (wave 6)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area, talking to mother, quarrelling with mother	3,795	736 (19.4)
Quarrelling with father (wave 6)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area, talking to mother, quarrelling with mother, talking to father	3,795	615 (16.2)
Talking to mother about things that matter (wave 8)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area	2,617	473 (18.1)
Quarrelling with mother (wave 8)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area, talking to mother	2,617	458 (17.5)
Talking to father about things that matter (wave 8)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area, talking to mother, quarrelling with mother	2,617	554 (21.2)

Quarrelling with father (wave 8)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area, talking to mother, quarrelling with mother, talking to father	2,617	464 (17.7)
Talking to mother about things that matter (wave 10)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area	1,688	287 (17.0)
,Quarrelling with mother (wave 10)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area, talking to mother	1,688	277 (16.4)
Talking to father about things that matter (wave 10)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area, talking to mother, quarrelling with mother	1,688	366 (21.7)
Quarrelling with father (wave 10)	Multinomial logistic regression	SNS use at wave 4, gender, age, self-esteem (wave 4), household income, cross-sectional weight, family structure, ethnicity, residential area, talking to mother, quarrelling with mother, talking to father	1,688	280 (16.6)

Table B1: Multiple imputation models and number of cases with missing data in the KCYPS (Chapter 6)

Variables with missing data	Imputation model used	Variables used in the imputation	Analytical sample	Number of missing cases (unweighted %)
Positive parenting at wave 3	Linear regression	Gender, self-esteem (wave 3), household income, cross-sectional weight, type of living area	2,251	1 (0.0)
Positive parenting at wave 5	Linear regression	Positive parenting at wave 3, gender, self-esteem (wave 3), household income, cross-sectional weight, type of living area	2,072	64 (3.1)
Positive parenting at wave 6	Linear regression	Positive parenting at waves 3 and 5, gender, self-esteem (wave 3), household income, cross-sectional weight, type of living area	2,036	0 (0.0)
Positive parenting at wave 7	Linear regression	Positive parenting at waves 3, 5 and 6, gender, self-esteem (wave 3), household income, cross-sectional weight, type of living area	1,865	0 (0.0)
Negative parenting at wave 3	Linear regression	Gender, self-esteem (wave 3), household income, cross-sectional weight, type of living area	2,251	1 (0.0)
Negative parenting at wave 5	Linear regression	Negative parenting at wave 3, gender, self-esteem (wave 3), household income, cross-sectional weight, type of living area	2,072	64 (3.1)
Negative parenting at wave 6	Linear regression	Negative parenting at waves 3 and 5, gender, self-esteem (wave 3), household income, cross-sectional weight, type of living area	2,036	0 (0.0)
Negative parenting at wave 7	Linear regression	Negative parenting at waves 3, 5 and 6, gender, self-esteem (wave 3), household income, cross-sectional weight, type of living area	1,865	0 (0.0)
Family structure at wave 3	Multinomial logistic regression	Self-esteem at wave 3, gender, cross-sectional weight, household income, type of living area	2,251	62 (2.8)
Parents' highest educational qualification at wave 3	Multinomial logistic regression	Self-esteem at wave 3, gender, cross-sectional weight, household income, type of living area	2,251	66 (2.9)

Table B2: Results from the linear mixed-effects models for the potential moderation by gender on the associations between CSMU/PIC frequency and self-esteem (Chapter 6)

Interaction terms	CSMU as main exposure	PIC as main exposure
	P-value	P-value
Gender x SMU x time	0.526	0.922
Gender x SMU	0.792	0.553

Abbreviations: CSMU: computer social media use; PIC: phone-based interpersonal communication. Notes: Participants (n = 2,251); person-wave observations (8,224). Three-way interaction terms investigated differences in the 1-year rate of change in self-esteem by combinations of CSMU/PIC frequency and gender; two-way interaction terms assessed differences in baseline self-esteem by combinations of CSMU/PIC frequency and gender.

Table C1: Results from the linear mixed-effects models for the potential moderation by gender on the associations between CSMU/PIC frequency and log depression (Chapter 7)

Interaction terms	CSMU as main exposure	PIC as main exposure
	P-value	P-value
Gender x CSMU/PIC x time	0.968	0.876
Gender x CSMU/PIC	0.408	0.163

Abbreviations: CSMU: computer social media use; PIC: phone-based interpersonal communication. *Notes*: Participants (n = 2,251); person-wave observations (n = 8,245). Three-way interaction terms investigated differences in the 1-year rate of change in (log) depression by combinations of CSMU/PIC frequency and gender; two-way interaction terms assessed differences in baseline (log) depression by combinations of CSMU/PIC frequency and gender.

Table C2: Results from the linear mixed-effects models for the potential moderation by family variables on the associations between CSMU/PIC frequency and log depression (Chapter 7)

Interaction terms	CSMU as main exposure	PIC as main exposure
	P-value	P-value
Three-way interactions:		
Family structure × CSMU/PIC × time	0.136	0.223
Positive parenting × CSMU/PIC × time	0.069	0.139
Negative parenting × CSMU/PIC × time	0.470	0.135
Two-way interactions:		
Family structure × CSMU/PIC	0.173	0.750
Positive parenting × CSMU/PIC	0.108	0.685
Negative parenting × CSMU/PIC	0.229	0.772

Abbreviations: CSMU: computer social media use; PICSMU: phone-based interpersonal communication. Notes: Participants (n = 2,251); person-wave observations (n = 8,245). Three-way interaction terms investigated differences in the rate of change in depression by combinations of family variables and CSMU/PIC frequency; two-way interaction terms investigated differences in baseline depression by combinations of family variables and CSMU/PIC frequency. All three-way terms were included in the same model; all two-way terms were tested in the same model without the three-way terms.