

The role of the social environment in adolescent adiposity and physical activity



**UNIVERSITY OF
CAMBRIDGE**

Campbell Foubister

Jesus College

MRC Epidemiology Unit

University of Cambridge

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Declaration

This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration except where specifically indicated in the text.

It has not been previously submitted, in part or whole, to any university or institution for any degree, diploma, or other qualification at the University of Cambridge or any other University.

All of the research presented in this dissertation was conducted at the Centre for Diet and Activity Research (CEDAR), MRC Epidemiology Unit, under the supervision of Esther M.F. van Sluijs and Russell Jago (University of Bristol)

This dissertation does not exceed 60,000 words excluding references, tables, figures, and appendixes, as prescribed by the Degree Committee of the Faculty of Clinical Medicine.

Campbell Foubister

MRC Epidemiology Unit, Centre for Diet and Activity Research

Jesus College, University of Cambridge

January, 2023

Abstract

Obesity and physical inactivity during adolescence are associated with an increased risk of mental and physical health outcomes including heart disease, and depression. There are widely accepted benefits of intervening to address excess adiposity and insufficient physical activity. It is important to address the settings that are most pertinent in shaping these. Given adolescents' social reorienting towards friends and away from parents, the social environment, and in particular, the school, and digital social environment are key focusses of this thesis. This thesis is organised into two linked parts.

In the first part of this thesis, I focus on the school social environment. I used data from GoActive, a large-scale physical activity intervention of adolescents living in the East of England (n=1,765). I explored associations between the school policy, social and physical environment and change in adolescent accelerometer-assessed physical activity. I tested many potential predictors of change as a hypotheses-generating exercise (Chapter 3). I found that friendship support for physical activity was predictive of change in physical activity, and that sex and socioeconomic status modified these relationships.

In the second part of this thesis, I explored the association between social media use and adiposity using data from the Millennium Cohort Study, a large population-based cohort of young people in the UK. I first investigated these associations cross-sectionally, showing that social media use and measured BMI z-score at age 14 years was associated in girls at the ≥ 5 hours/day level (vs. 0 to <1 hours/day, no associations for boys) (n=10,798). This association was partially explained by sleep duration, depressive symptoms, body weight satisfaction, and wellbeing (Chapter 5). I then explored the prospective association between social media use at age 14 years and change in BMI z-score from age 14 to 17 years in boys and girls (n=8,024). I showed that greater social media use was associated with a lower change in BMI z-score at the 3 to <5 hours/day range (vs. 0 to <1) for boys, and at the 1 to <3 hours/day range for girls (Chapter 6).

Overall, the results from my thesis suggests two key findings. First, friendship support for physical activity may be particularly important for increasing physical activity during adolescence. Second, although a negative association was found between social media use and change in BMI z-score at the population level, this finding must be interpreted cautiously given that associations were small, and are not consistent with the few studies completed to date which used self-reported BMI. However, associations differed by sex and there may be specific sub-populations at greater risk (e.g. extreme users, adolescents living with mental health challenges). The overall findings of this thesis highlight a need for further research to understand the potential influence of friendship support for physical activity, and to better understand and harness adolescents' high engagement with social media use for combatting adolescent obesity.

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Table of Contents

Declaration.....	2
Abstract.....	3
Acknowledgements.....	5
List of Tables	11
List of Figures	13
List of Abbreviations and Acronyms	15
List of Appendices	17
1 Chapter 1: General Introduction - Environmental influences on adolescent obesity and physical activity.....	18
1.1 The global burden of obesity	18
1.2 Defining adolescence	18
1.3 Adolescent obesity measurement	21
1.3.1 Defining obesity	21
1.3.2 Obesity measurement methods	21
1.3.3 BMI.....	23
1.3.4 BMI z-score.....	23
1.4 The burden of obesity during adolescence.....	24
1.4.1 Adolescent obesity and physical health.....	25
1.4.2 Adolescent obesity and mental health	25
1.4.3 Obesity and economic costs	26
1.5 Descriptive epidemiology of adolescent obesity.....	27
1.5.1 Global prevalence of adolescent obesity.....	27
1.5.2 Adolescent obesity in the United Kingdom	29
1.6 Prevention of adolescent obesity	32
1.6.1 Obesity as a complex systems problem.....	33
1.6.2 Individual factors relating to adolescent obesity.....	35
1.7 Physical activity and adolescent obesity.....	37
1.7.1 Defining physical activity.....	37
1.7.2 Physical activity measurement	37
1.7.3 Physical activity guidelines.....	39
1.7.4 Physical inactivity is a global problem	39
1.7.5 Physical inactivity and adolescent health	41
1.8 The “obesogenic” environment, adolescent physical activity and adiposity	43
1.9 Environmental influences on adolescent obesity and physical activity	46

1.9.1	Home environmental influences.....	46
1.9.2	Neighbourhood environmental influences.....	47
1.9.3	School environmental influences.....	48
1.9.4	Digital environmental influences.....	51
1.10	Thesis Part One - The school environment.....	53
1.10.1	Defining the school environment.....	53
1.10.2	The secondary school system as a setting for health promotion.....	53
1.10.3	Obesity prevention within the school setting.....	53
1.10.4	Physical activity promotion within the school setting.....	55
1.11	Thesis Part Two - The digital environment.....	59
1.11.1	Defining social media use.....	59
1.11.2	Adolescent social media use is highly prevalent.....	59
1.11.3	Social media use and adolescent health.....	60
1.12	Chapter 1 Summary.....	61
2	Chapter 2 Thesis objectives and aims.....	62
2.1	The behavioural epidemiology framework.....	62
2.2	PhD Aim and Objectives.....	63
3	Chapter 3: The school policy, social, and physical environment and change in adolescent physical activity: An exploratory analysis using the LASSO.....	64
3.1	Abstract.....	65
3.2	Background.....	66
3.3	Methods.....	68
3.3.1	Study sample.....	68
3.3.2	Recruitment and Ethics.....	68
3.3.3	Outcome measure.....	68
3.3.4	Exposures.....	69
3.3.5	Descriptive data and covariates.....	71
3.3.6	Statistical analyses.....	71
3.4	Results.....	74
3.4.1	Main analyses.....	76
3.4.2	Stratified analyses by sex.....	78
3.4.3	Stratified analyses by SES.....	78
3.4.4	Post hoc analyses.....	78
3.5	Discussion.....	81
3.5.1	Main analyses findings.....	81
3.5.2	Longitudinal post hoc findings.....	84

3.5.3	Strengths and Limitations	85
3.6	Conclusion.....	87
4	Chapter 4: The online social environment and adolescent adiposity.....	88
4.1	Introduction to Thesis Part Two.....	88
4.2	Defining the social environment.....	89
4.3	Adolescents are particularly open to influence from the social environment	89
4.4	Social environments can consist of offline friendships, online friendships, or both	90
4.5	Friendships and adolescent obesity.....	93
4.5.1	Potential mechanisms underpinning friendships’ influence	96
4.5.2	Friendship’s influence on obesity and obesogenic behaviours	98
4.6	Adolescent social media use	101
4.6.1	Social media use: Definitions and terminology	101
4.6.2	Social media use and adolescent friendships	102
4.6.3	Social media measurement.....	103
4.7	Descriptive epidemiology of social media use during adolescence	104
4.7.1	Smartphone ownership.....	104
4.7.2	Social media use frequency	106
4.7.3	Social media use platform preferences	109
4.7.4	Social media use demographic differences	112
4.8	Mechanisms underpinning the potential influence of social media use on adolescent adiposity.....	112
4.8.1	The displacement hypothesis	116
4.8.2	The “rich get richer”, social compensation, and “Goldilocks” hypothesis.....	116
4.8.3	Goffman’s theory of strategic self-presentation	116
4.8.4	Cultivation theory	117
4.8.5	Advertising	118
4.9	Narrative review of social media use and adolescent health	119
4.9.1	Historical concerns surrounding new technologies.....	119
4.9.2	Methods of narrative review on social media use and health outcomes.....	119
4.9.3	Results of narrative review on social media use and health outcomes	120
4.10	Chapter 4 Conclusions	126
5	Chapter 5: Social media use and BMI z-score: a cross-sectional explanatory pathway analysis of 10,798 14-year-old boys and girls.....	127
5.1	Abstract.....	128
5.2	Background	129
5.3	Materials and Methods.....	132

5.3.1	Study sample.....	132
5.3.2	Outcome measure: BMI z-score.....	132
5.3.3	Exposure: Social media use.....	132
5.3.4	Descriptive data and covariates.....	133
5.3.5	Potential explanatory pathways.....	135
5.3.6	Statistical analysis.....	138
5.4	Results.....	140
5.4.1	Primary objective: Association between social media use and BMI z-score.....	143
5.4.2	Secondary objective: Analyses of Potential Explanatory Pathways with SEM.....	145
5.5	Discussion.....	149
5.5.1	Strengths and Limitations.....	151
5.6	Conclusions.....	154
6	Chapter 6: Social media use and BMI z-score: a longitudinal propensity score matching analysis of 8,024 14 to 17 year olds.....	155
6.1	Abstract.....	156
6.2	Background.....	157
6.3	Methods.....	158
6.3.1	Study design and participants.....	158
6.3.2	Data sources/measurement.....	158
6.3.3	Statistical methods.....	161
6.4	Results.....	162
6.4.1	Descriptive data.....	162
6.4.2	Association between social media use and change in BMI z-score.....	166
6.5	Discussion.....	168
6.5.1	Main findings.....	168
6.5.2	Strengths and Limitations.....	168
6.5.3	Interpretation.....	169
6.5.4	Policy and research implications.....	171
6.6	Conclusions.....	172
7	Chapter 7: Discussion.....	173
7.1	Introduction.....	173
7.2	Summary of main findings.....	174
7.2.1	Chapter 3: “The school policy, social, and physical environment and change in adolescent physical activity: An exploratory analysis using the LASSO”.....	174
7.2.2	Chapter 5: “Social media use and BMI z-score: a cross-sectional explanatory pathway analysis of 10,798 14-year-old boys and girls”.....	176

7.2.3	Chapter 6: “Social media use and BMI z-score: a longitudinal propensity score matching analysis of 8,024 14 to 17 year olds”	176
7.2.4	Summary of main findings overview.....	177
7.3	Methodological considerations	178
7.3.1	Internal validity	178
7.3.2	External validity.....	188
7.4	Implications for public health policy and practice	190
7.4.1	Encouraging harnessing of friendship support for physical activity in policy, and practice 190	
7.4.2	The potentially limited impact of social media use on BMI z-score may provide opportunities for harnessing high adolescent engagement for health improvement	190
7.4.3	Need for transparent collaborations with industry researchers for increased social media use data access	191
7.5	Recommendations for future research.....	191
7.5.1	Network-based physical activity interventions.....	192
7.5.2	Social environmental moderation of physical activity intervention effectiveness.....	193
7.5.3	The potential of population health improvement via adolescent engagement with social media	193
7.5.4	Social media use cases	194
7.6	PhD Reflections	195
7.6.1	Learnings	195
7.6.2	What I would do differently.....	195
7.6.3	How my thinking has progressed.....	196
7.7	Conclusion.....	198
8	References	199
	Appendices.....	217
	Appendix 1: Learning and skill development.....	218
	Peer reviewed first-author publications	218
	Conference presentations.....	218
	Awards	218
	Co-authorship	218
	Internship in NHS	220
	Writing group.....	220
	Journal club.....	221
	Public Engagement/Dissemination Activities	221
	Courses.....	222
	Appendix 2: Supplementary Materials	223

S1: NHS Internship blog post: “Public Health in practice – our fellowship at NHS England and Improvement 265

S4: School environment paper: GoActive School Environment Survey (presented overleaf).... 271

List of Tables

Table 1: Key advantages and limitations of adolescent adiposity assessment methods **Table 2:** Baseline descriptive characteristics: GoActive school environment study

Table 3: Estimated effects of the variables selected by the LASSO on change in MVPA during adolescence: GoActive school environment study

Table 4: Estimate effects of change in the variables selected by the LASSO and change in MVPA: GoActive school environment study

Table 5: Potential mechanisms underpinning friendship influences on adolescent adiposity

Table 6: Potential mechanisms explaining the influence of social media use on health, and adiposity

Table 7: Studies included in narrative review of social media use and mental, and physical health

Table 8: Strength of evidence of the potential association between social media use and mental health outcomes

Table 9: Descriptive characteristics of the analysis sample: Millennium Cohort cross-sectional study

Table 10: Potential explanatory pathway variables of the analysis sample: Millennium Cohort cross-sectional study

Table 11: Association of social media use with BMI z-score, stratified by sex: Millennium Cohort cross-sectional study

Table 12: Association of social media use with BMI z-score after adjustment for potential explanatory variables in girls: Millennium Cohort cross-sectional study

Table 13: Associations between ≥ 5 hours of social media use (vs 0 to < 1 hours/day) and BMI z-score via potential explanatory pathways for girls only (N=5,332): Millennium Cohort cross-sectional study

Table 14: Descriptive statistics of the analysis sample (n=8,024): Millennium Cohort longitudinal study

Table 15: Descriptive statistics of participants excluded from the analysis sample (n=2,674): Millennium Cohort longitudinal study

Table 16: Association of change in BMI Z-score with daily social media use, stratified by sex: Millennium Cohort longitudinal study

Table 17: Extent of agreement with Bradford Hill's criteria for causation for each analytical chapter

List of Figures

Figure 1: World population by age and sex, 2022

Figure 2: Age-standardised prevalence of obesity by sex and country in 2016 in children, aged 5 to 19 years

Figure 3: BMI category prevalence for 10 and 11 year old children in England, by sex

Figure 4: Prevalence of children living with obesity in Year 6 by IMD decile (based on postcode of child)

Figure 5: The Foresight obesity system map

Figure 6: Global trends in insufficient physical activity among 1.6 million boys and girls

Figure 7: A socioecological model for understanding individual and environmental factors influencing adolescent obesity

Figure 8: Forest plot of standardized mean difference of change in physical activity between intervention and control groups of school-based physical activity interventions

Figure 9: Social network structure

Figure 10: Social media and the potential for friendship influence

Figure 11: Smartphone ownership in the UK, by age

Figure 12: USA-based adolescent social media use (aged 13-17 years)

Figure 13: USA-based adolescents switching social media platform preferences

Figure 14: UK-based children switching social media platform preferences, 2017 to 2022

Figure 15: Directed Acyclic Graph for the study of the association between social media use and BMI z-score with the covariates family structure, family income, and ethnicity: Millennium Cohort cross-sectional study

Figure 16: Associations between ≥ 5 hours/day (vs 0 to < 1 hours/day) of social media use and BMI z-score via potential explanatory pathways in girls: Millennium Cohort cross-sectional study

List of Abbreviations and Acronyms

\$	United States Dollar
%	Percentage
£	Great Britain Pound
<	Less than
>	Greater than
≤	Less than or equal to
≥	Greater than or equal to
BMI	Body Mass Index
B	Billion
c.	Circa
CI	Confidence Interval
Cm	Centimetres
DALY	Disability adjusted life years
DAG	Directed acyclic graphs
DEXA	Dual x-ray absorptiometry
E.g.	Exempli gratia or “for example”
I.e.	Id est or “that is”
Kg	Kilogram
M	Million
MCS	Millennium Cohort Study
Mins	Minutes
MVPA	Moderate-to-vigorous physical activity
N	Number (used to indicate number of participants in a study)

NCDs Noncommunicable diseases

NCMP National Child Measurement Programme

OR Odds ratio

RCT Randomized controlled trial

SD Standard Deviation

SEM Structural equation modelling

SES Socioeconomic status

UN United Nations

USD United States Dollar

WHO World Health Organisation

List of Appendices

Appendix 1: Learning and skill development

Appendix 2: Supplementary Materials

1 Chapter 1: General Introduction - Environmental influences on adolescent obesity and physical activity

1.1 The global burden of obesity

Obesity is a growing global health problem across the life course, with a rising prevalence of obesity worldwide [1]. Rates of obesity across the globe are increasing across all ages, sexes, ethnic groups, socioeconomic statuses, and geographies [2]. It is estimated that 1 in 3 people worldwide are living with overweight or obesity [2]. Simultaneously, the number of deaths and DALYs (Disability adjusted life years) attributed to high body mass index (BMI) between 1990 and 2017 have more than doubled [3]. There is therefore an urgent need to reverse and prevent obesity at all ages. In this thesis, I focus on preventing obesity during the life period of adolescence.

1.2 Defining adolescence

The World Health Organization (WHO) suggests adolescence can be considered the stage of life between 10 and 19 years [4]. This is the definition of adolescence I use during my thesis. Figure 1 shows that in 2022, there were an estimated 1.9 billion adolescents worldwide (24% of the global population) [5]. However, the age range spanning adolescence is not unanimously agreed on and can also be identified in a sociocultural context by the achievement of certain life milestones. For example, adolescence can be considered the life period between the beginning of puberty and gaining relative self-sufficiency (e.g. employment, and financial independence), [6] although these life events occur at different ages worldwide [7]. During this age range (10-19 years) most adolescents undergo puberty, develop an understanding of their personal and sexual identity, and begin to establish autonomy and financial, emotional, and personal independence from their parents. A large number of changes occur biologically, psychologically, and socially during each phase (e.g. menarche, voice breaks, development of abstract thinking skills, and vocational capabilities) [8]. Coinciding with these changes are associated changes in physical, psychological and social health [7] including decreased physical activity [9] and increased adiposity (e.g. excessive accumulation of adipose tissue, also known as fat)

[10]. The first step in obesity prevention is population level monitoring which requires an understanding of how obesity is measured.

Figure 1: World population by age and sex, 2022

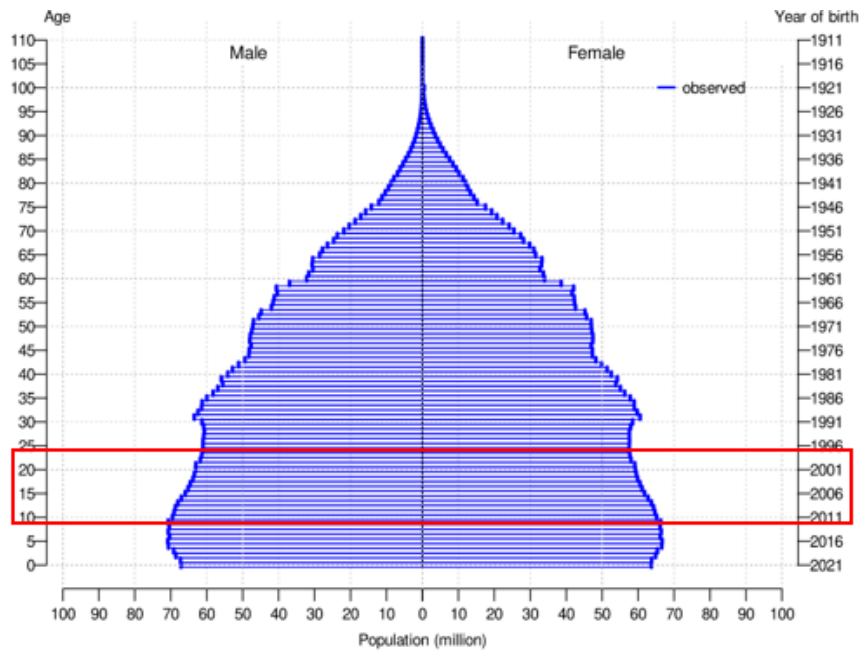


Figure taken from: 2022 United Nations. DESA, Population Division. Licensed under Creative Commons license CC BY 2.0 IGO. United Nations, DESA, Population Division. World Population Prospects 2022. <http://population.un.org/wpp/> (red box added to highlight period of adolescence, 10-24 years)

1.3 Adolescent obesity measurement

1.3.1 Defining obesity

The WHO defines overweight and obesity as “an abnormal or excessive fat accumulation that presents a risk to health” [11]. Obesity is widely recognised as one of the biggest public health crises facing health systems.

1.3.2 Obesity measurement methods

In epidemiology, anthropometric measures (e.g. measurements relating to the human body including height, weight, and body circumference) are used to screen adolescents for risk of obesity. Adolescent obesity is measured most frequently via BMI and compared to population growth estimates adjusted for sex and age [12]. Other methods available to directly measure adiposity are presented in Table 1 (e.g. self-reported, body fat calliper, bioelectrical impedance, and Dual-energy X-ray Absorptiometry [DEXA]). However, these methods have limited applicability to the study of large populations because they are either prone to bias, expensive, require specialist training, and/or are not routinely calculated in clinical and research settings to facilitate population level comparison [12].

Table 1: Key advantages and limitations of adolescent adiposity assessment methods [12]

Method	Advantages	Limitations
Self-reported height and weight (upon which BMI is derived)	<ul style="list-style-type: none"> • Inexpensive • Accessible 	<ul style="list-style-type: none"> • Low accuracy and reliability • Prone to self-report bias
Body fat measurement (with calliper)	<ul style="list-style-type: none"> • Inexpensive 	<ul style="list-style-type: none"> • Requires specialist training • Medium time cost • Participant acceptability
Bioelectrical impedance	<ul style="list-style-type: none"> • Low time cost 	<ul style="list-style-type: none"> • Medium expense • Requires conversion • Dependent on hydration status
Dual-energy X-ray Absorptiometry (DEXA)	<ul style="list-style-type: none"> • Gold standard measure 	<ul style="list-style-type: none"> • Expensive • Requires specialist training • High time cost • Not routinely collected
Measured height and weight upon which BMI, and BMI z-score can be derived	<ul style="list-style-type: none"> • Low time cost • Accessible • High specificity and sensitivity • Facilitates comparison at the population level 	<ul style="list-style-type: none"> • May misidentify adolescents with high lean mass, or shorter in height • Requires conversion with equations

1.3.3 BMI

BMI is derived from weight in kilograms divided by height in metres squared (kg/m^2). An adult who has a BMI less than $18.5\text{kg}/\text{m}^2$ is considered to be living with underweight, 18.5 to $<25\text{kg}/\text{m}^2$ is living with healthy weight, 25 to $<30\text{kg}/\text{m}^2$ is living with overweight, and an individual with a BMI $30\text{kg}/\text{m}^2$ or higher is considered to be living with obesity. BMI is commonly used in research settings because the measure is relatively easily obtained. However, there are a number of limitations of BMI. Most notably, the measure does not differentiate between lean body mass and adipose tissue. As shown in Table 1, this means BMI as a measure of adiposity performs more poorly in individuals who are shorter in height. This leads to adolescents living with higher lean mass, and shorter height having a higher BMI [13]. However, most adolescents living with obesity will be identified through reviewing their BMI with few misclassifications [14]. BMI has high sensitivity (81.9%) and specificity (96.5%) in diagnosing adolescents living with obesity with slightly poorer performance in diagnosing adolescents living with overweight (sensitivity = 76.3%, and specificity = 92.1%) [14]. In epidemiology, sensitivity and specificity are important metrics for determining accuracy of having a condition or not having a condition (e.g. adolescents living with obesity). A test with high sensitivity means that there are few false negative results (e.g. an adolescent is diagnosed with not living with obesity when they are living with obesity). A test with high specificity means an adolescent living with obesity will be identified as living with obesity. For comparison, although self-reported height and weight (with which BMI is calculated) is valuable in conditions where no other data exist, self-reported measurement of adiposity may substantially underestimate true adiposity levels due to weight often being underestimated (particularly common in girls) and height being overestimated (most common in boys) [15]. A reported 25-45% (vs. around 8%) of adolescents living with overweight may be missed if self-reported data were relied on alone instead of BMI derived from measured height and weight [15].

1.3.4 BMI z-score

At the population level, BMI z-scores (standard deviation scores) are the most widely used measure to classify young people as BMI z-scores allow for the comparison of young people to a reference

population [12]. BMI z-scores show the number of standard deviations (SD) below or above the reference mean or median value by age and sex [16]. The key benefit of this approach is that it allows for age and sex differences in BMI distribution to be identified. The WHO Global database on Child Growth and Malnutrition consider a BMI z-score of $>+2$ SD as high weight-for-height, or overweight in adolescents [16]. While other measures of adiposity exist (e.g. cut-points defined by rounded percentiles where BMI $>95^{\text{th}}$ percentile is equivalent to living with obesity [12]), BMI z-scores are recommended for research settings due to misclassifications in percentile-based classifications which limit consistency and comparability between studies [17]. The WHO 2007 Growth References are recommended for adolescents. Adolescents living with overweight are identified by a BMI 1 to 1.99 SD (e.g. BMI z-score = 1 to 1.99 SD), and obesity as BMI ≥ 2 SD (e.g. BMI z-score = 2 SD and higher) of the median for age and sex [18]. This is the definition of overweight and obesity used throughout this thesis unless specified. For example, earlier growth references (e.g. 1997) suggested BMI of 1 to 1.99 SD equated to a risk of living with overweight, and BMI ≥ 3 SD denoted obesity which shows that our understanding of obesity risk has increased. These criteria are important to quantify the prevalence of adolescent obesity across different geographies, for population level surveillance over time, and to test the effectiveness of interventions [12].

1.4 The burden of obesity during adolescence

Hundreds of millions of adolescents worldwide live with obesity (approximately 19.9% of boys, and 23.6% girls worldwide, aged 5-17 years) [19]. Once obesity during adolescence is established it is challenging to reverse [20]. Adolescent overweight and obesity is associated with overweight and obesity in adulthood, with adolescents living with obesity being around five times more likely to live with obesity during adulthood (vs. adolescents living with normal weight) [21]. Around 80% of adolescents living with obesity will also live with obesity in adulthood [21]. Development of obesity is therefore best prevented as early as possible because of the associations with a range of immediate and compounding physical and mental health outcomes and high economic burden throughout the life course.

1.4.1 Adolescent obesity and physical health

Adolescent obesity is a risk factor for often preventable non-communicable diseases including diabetes, heart disease [22, 23], and cancer in adulthood [24]. For example, 23 year follow-up data from 4 studies of 6,328 children living with overweight or obesity identified an increased risk of diabetes, hypertension, dyslipidemia, and atherosclerosis compared to those with normal weight [25]. In this study, meta-analysis of 500 participants who lived with obesity during adolescence, and also in adulthood was performed. For diabetes, relative risk (95% CI) (vs. individuals living with normal BMI during adolescence, and living free from obesity as adults) was 5.4 (3.4-8.5), while for hypertension relative risk was 2.7 (2.2-3.3) [25]. A consistent association has also been identified between overweight and obesity and higher all-cause mortality in 10,625,411 adults in Asia, Australia and New Zealand, Europe, and North America (across 239 prospective studies) [26]. Comorbidities of adolescent obesity are common and can include menstrual irregularities, metabolic syndrome, sleep disorder [27], and non-alcoholic fatty liver disease [28]. Obesity during adolescence is also related to a number of mental, and psycho-social health outcomes.

1.4.2 Adolescent obesity and mental health

Obesity during adolescence may be a risk factor for mental health challenges. Depression and impaired quality of life as a result of bullying are more prevalent in adolescents living with overweight or obesity compared to adolescents living with normal weight; although most evidence is cross-sectional which precludes causal inference [29, 30]. Obesity during adolescence may also bring rise to adverse psycho-social outcomes (e.g. bullying, social isolation, and body image dissatisfaction) [31]. Adolescents with overweight and obesity have increased school absenteeism compared to their peers living with normal weight. For example, in meta-analysis findings, the odds of being absent from school was 27% and 54% higher for adolescents living with overweight and obesity respectively (vs. adolescents living with normal weight) [32]. Obesity can also bring rise to substantial economic costs [33].

1.4.3 Obesity and economic costs

The economic burden of obesity is large. Economic costs of obesity include direct healthcare costs such as treatment for non-communicable disease but can also include further economic costs borne by society including productivity loss through presenteeism (e.g. reduced productivity because of illness while at work), income penalty and workdays lost (e.g. absenteeism) [34]. Although health economists have estimated costs to society for treatment of overweight and obesity to be in the tens of billions (USD), most analyses are imperfect due to not accounting for the additional costs society would bear if obesity was reversed and premature mortality was prevented where individuals would live with normal weight for longer and bring rise to further healthcare costs from diseases of older age (e.g. dementia, Parkinson's disease) [35]. However, it is accepted globally that obesity during adolescence is problematic and should be prevented.

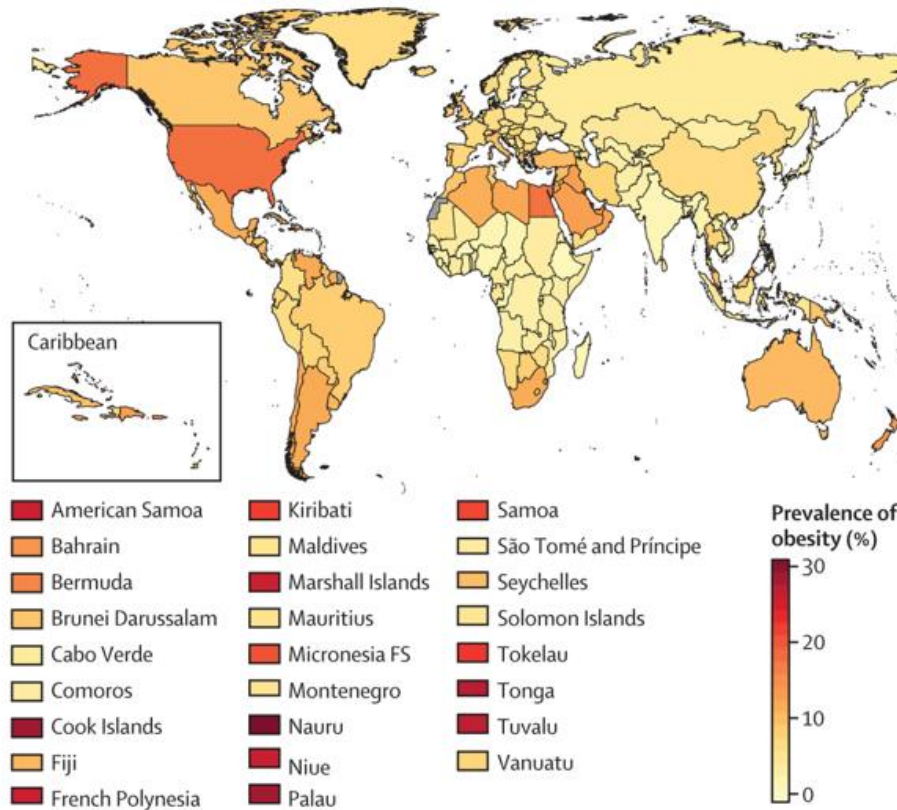
1.5 Descriptive epidemiology of adolescent obesity

1.5.1 Global prevalence of adolescent obesity

In 2016, around one in five (circa [c.] 324 million) adolescents (10-24 years) worldwide were living with overweight or obesity [36]. Figure 2 shows age-standardised prevalence of obesity by sex and country in 2016 in children and adolescents [10]. The figures shows a high prevalence of obesity in boys and girls worldwide. The highest prevalence of obesity (more than 30% in girls and boys), was in the Oceania-based island territories of Nauru, the Cook Islands, and Palau, compared to about 20% or more in several countries in the Middle East, North Africa, and USA [10]. Key strengths of this data is the pooling of 2,416 population-based studies with data from 31.9M children aged 5-19 years restricted to measured height and weight. Simulations – based on the current levels of childhood (2-19 years) obesity in the United States have projected that almost 60% of children today will be obese at age 35 [37]. It is particularly important to intervene to prevent adolescent obesity in the wake of the COVID-19 pandemic because increased weight gain has been reported among adolescents living in Europe and the USA (vs. pre-pandemic levels) [38, 39].

Figure 2: Age-standardised prevalence of obesity by sex and country in 2016 in children, aged 5 to 19 years

C Obesity prevalence in girls



D Obesity prevalence in boys

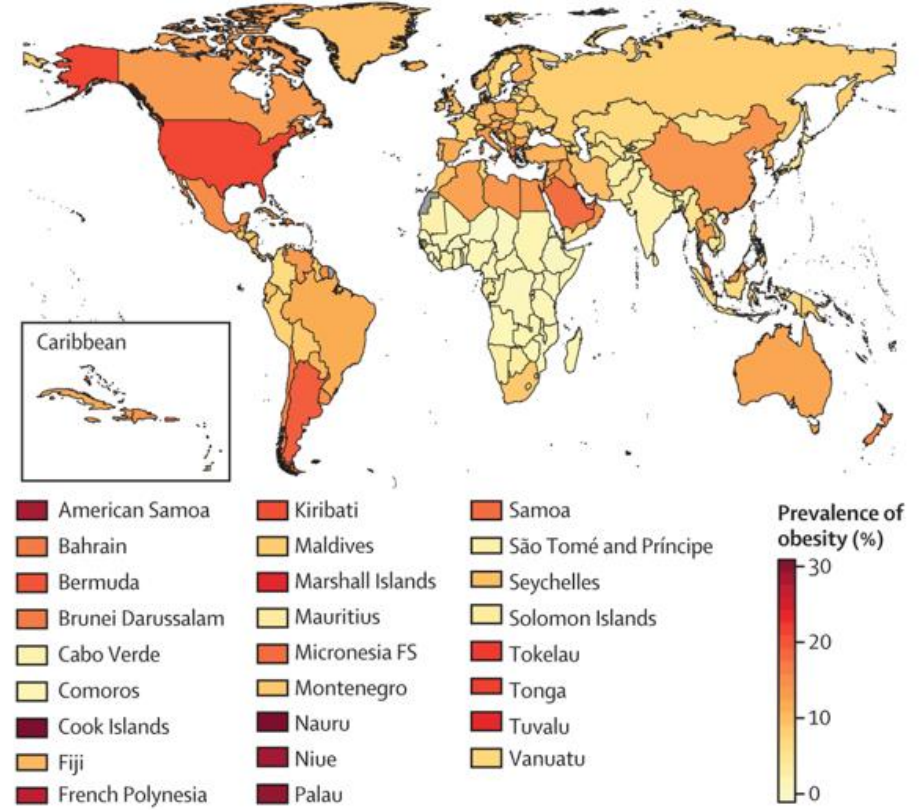


Figure taken from: NCD-RisC (2017). "Worldwide trends in body-mass index, underweight, overweight, and obesity from 1975 to 2016: a pooled analysis of 2416 population-based measurement studies in 128.9 million children, adolescents, and adults." Figure focusses on 31.9M children, aged 5-19 years only.

Figure cut to focus on obesity prevalence only (full figure also shows mean BMI, and prevalence of underweight)

1.5.2 Adolescent obesity in the United Kingdom

Adolescent obesity is highly prevalent in the United Kingdom (UK). The following data, unless stated comes from the National Child Measurement Programme (NCMP), 2022 data collection phase. The NCMP is a UK Government mandated annual programme delivered by local authorities which involves measuring the height and weight of all school children in Reception (aged 4 to 5 years) and Year 6 (10 to 11 years). The data source is considered a “world class source of public health intelligence and holds UK National Statistics status” due to proposed national representativeness [40]. However, availability of population health data relating to adolescent obesity differs by region of the UK with fewer data available to facilitate disaggregation by sex and deprivation for Northern Ireland, Wales, and Scotland compared to England. This suggests that data out with England may not be representative of other regions in the UK.

1.5.2.1 England

In 2022, 40.9% of adolescents aged 10 and 11 years were living with overweight or obesity with an increase of around 4.5 percentage points versus 2019-2020, possibly contributed to by measures to control the COVID-19 pandemic (e.g. school closures, national lockdowns) [40]. Figure 3 shows BMI category prevalence for 10 and 11 year old children in England, by sex. Boys are more likely to be living with obesity than girls (26.4% boys vs. 20.4% girls, 23.4% overall obesity prevalence). The difference in the prevalence of children living with obesity between boys and girls is larger at age 10 to 11 years compared to at age 4 to 5 years (10.3% boys vs. 9.9% girls) [41]. Figure 4 shows the prevalence of children living with obesity in Year 6 by Index of Multiple Deprivation (IMD) decile (based on postcode of child). Adolescents living in the most deprived areas are substantially more likely to live with obesity (vs. adolescents living in the least deprived areas) (31.3% most deprived vs. 13.5% least deprived) [41]. The deprivation gap between children living in the most and least deprived areas increased by 4.9 percentage points between 2013/14 and 2021/22 due to an increase in prevalence of children living with obesity in the most deprived areas [41].

1.5.2.2 Scotland

In Scotland, National Child Measurement Programme data show that 1 in 3 adolescents (aged 10-15 years) are living with obesity with boys being more likely to live with obesity than girls (2019) [41]. No other population level data are currently available in Scotland to allow disaggregation by sex and socioeconomic status.

1.5.2.3 Wales

From National Child Measurement Programme data, the rates of childhood obesity in Wales is the highest in the UK with around 35% of children under 16 years classified to be living with overweight or obesity in 2019 (19% living with obesity; no distinction was made by age, e.g. children vs. adolescents) [42]. Although these data are from 2011 where the prevalence of overweight, and obesity in England was 33.9% [43]. The most recent available data (from the 2019 National Child Measurement Programme) focussed on children aged 4 and 5 years only and showed that 12.6% were living with obesity and an additional 14.4% were living with overweight [42]. No other population level data are currently available for Wales (e.g. for children aged 10 to 11 years as per the other regions).

1.5.2.4 Northern Ireland

In 2019 in Northern Ireland, using data from the National Child Measurement Programme, an estimated 4% of adolescents aged 11 to 15 years were living with obesity [41]. However, these data were limited by a small sample size and may not be representative of the wider population. The Northern Ireland Department of Health suggests around 20% of children aged 2-15 years were living with overweight, and 6% were living with obesity [44].

Figure 3: BMI category prevalence for 10 and 11 year old children in England, by sex

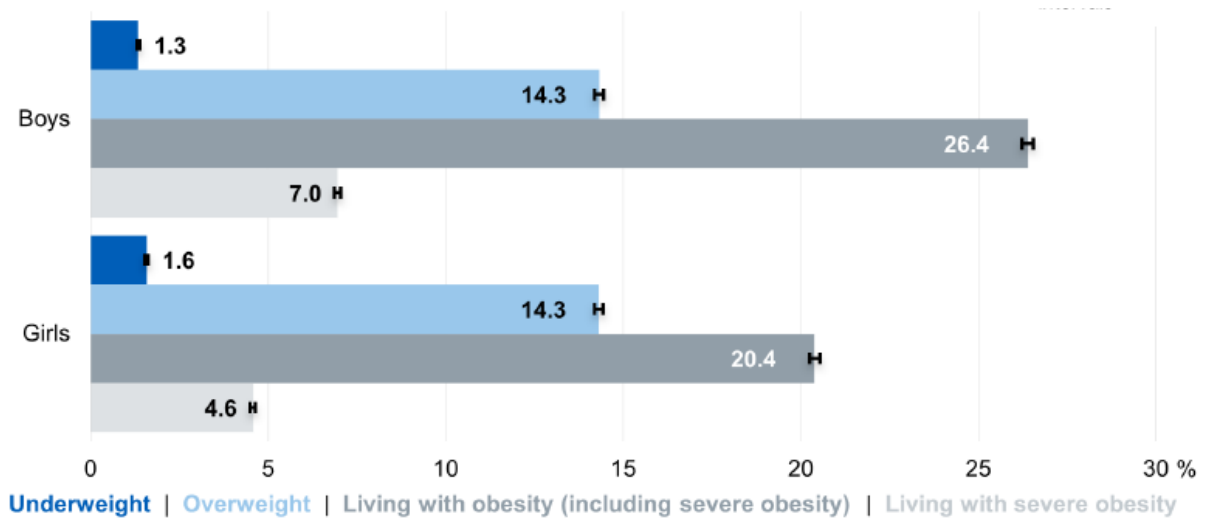


Figure taken from: House of Commons Obesity Statistics Research Briefing. 2022.

Figure 4: Prevalence of children living with obesity in Year 6 by IMD decile (based on postcode of child)

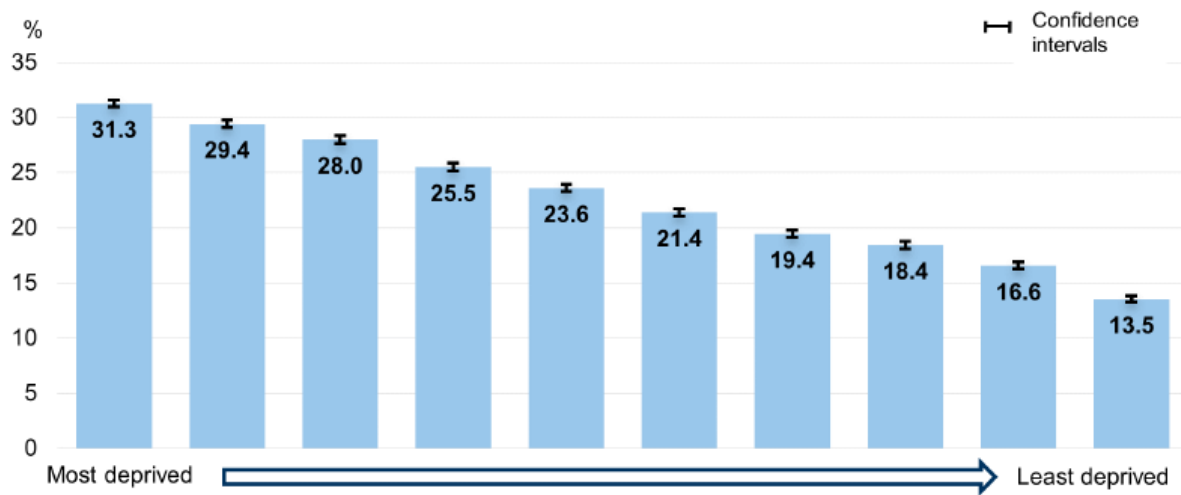


Figure taken from: House of Commons Obesity Statistics Research Briefing. 2022.

1.6 Prevention of adolescent obesity

Given the high prevalence of adolescent obesity, it is important to find effective preventative measures. Rose's population strategy of prevention suggests greater benefits may be produced through treating a whole population rather than high-risk individuals exclusively (e.g. a high-risk strategy of prevention) [45]. For example, a large number of adolescents at small risk of obesity may give rise to more cases than a small number of adolescents at high-risk. However, strategies to reverse obesity are also necessary; in keeping with Rose's idea of population shifts, there is a need to consider both the determinants of individual cases, and the determinants of population incidence rate [45]. However, prevention of adolescent obesity should be prioritised because reversal is particularly challenging due to the engrained behaviours. Options for intervention to reverse adolescent obesity, including expensive behavioural, pharmacological, surgical, and device-based treatment, have also largely been ineffective at reducing adolescent obesity at the population level [46]. This makes a stronger case for the value of prevention of excessive weight gain, despite the complexities surrounding such efforts (e.g. adoption of a "whole-systems approach" with collaboration between many sectors). Increasing our understanding of factors which drive the development of obesity during adolescence can underpin the development of effective methods of preventing obesity during adolescence, which also contribute to reversal by decreasing the mean level of risk factors and shifting the whole population distribution in a favourable direction [45].

In light of the substantial physical, and mental health, and economic burdens attributable to excess adiposity levels in contemporary populations including adolescents (see section 1.4), preventive efforts need to identify the aspects of adolescent's environments that can be ameliorated to prevent obesity during adolescence. Substantial research has been completed to understand what causes obesity. The next section (section 1.6) highlight the importance of the wider environment for adolescent health behaviours and obesity through a complex systems approach and a discussion of individual, and environmental factors possibly related to adolescent obesity.

1.6.1 Obesity as a complex systems problem

The most common cause of obesity is a positive energy balance driven by excess caloric intake and insufficient caloric expenditure [27]. However, obesity during adolescence is complex and factors at the individual level (e.g. biological, physiological, and genetic) and the environmental level (e.g. policy, social, digital, and physical environment) may play a role in making it difficult for adolescents to consume appropriate amounts of food and have “healthy” levels of 24 hour movement behaviours (physical activity, sedentary behaviour, sleep) to enable them to maintain a healthy weight. Figure 5 shows the Foresight Obesity Map [47] which highlights the “complex system” and multi-factor development of obesity. The Foresight Obesity System map displays how media, social, psychological, economic, food, activity, infrastructure, developmental, biological, and medical factors may interact to make it challenging to maintain a healthy weight. This map suggests that the true cause of a positive energy balance and associated obesity may be as a result of a combination of individual, and environmental factors [48].

Figure 5: The Foresight Obesity System Map

Foresight
Obesity System Map

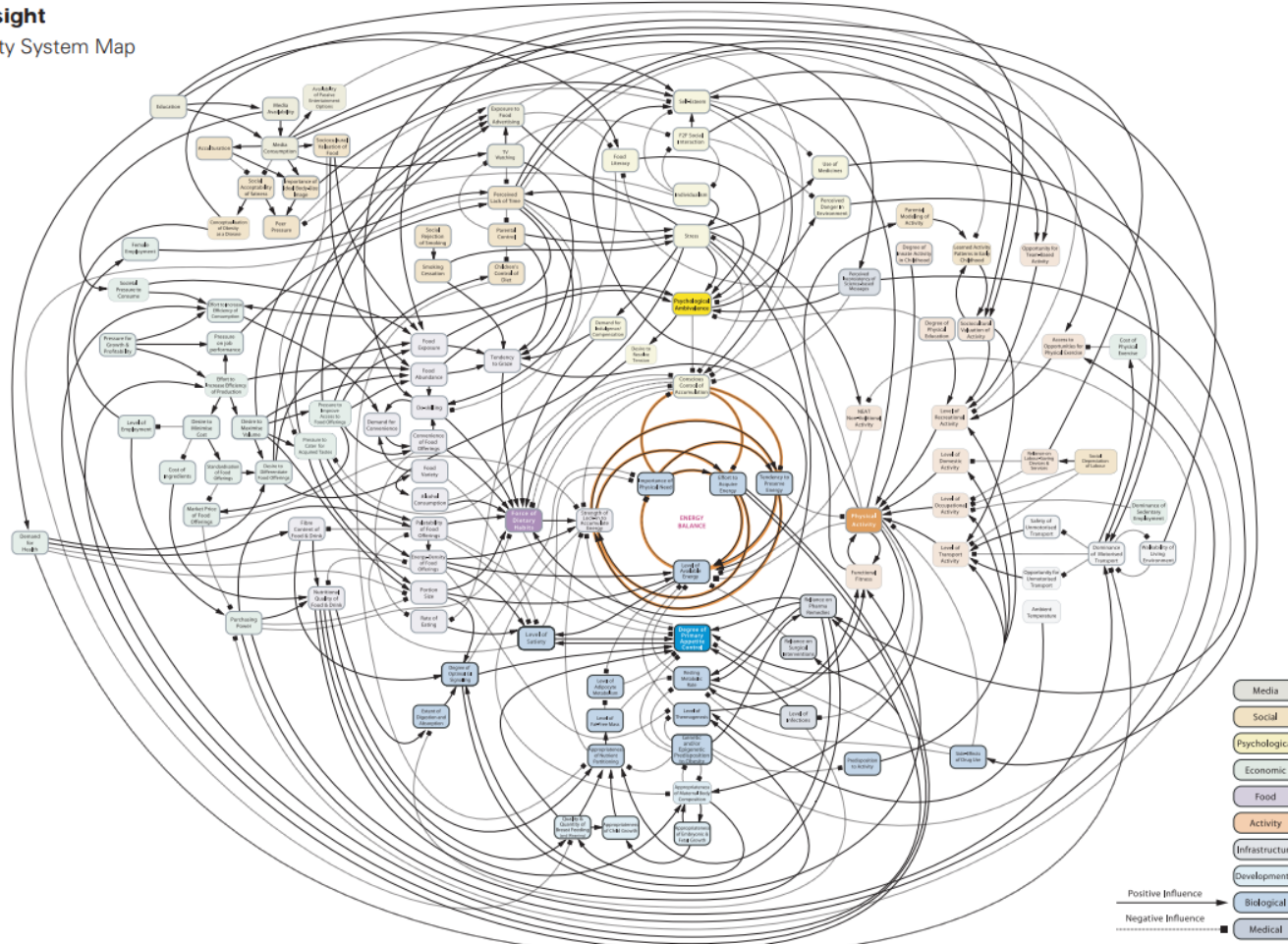


Figure taken from: Gov.uk (2007). Foresight's Tackling Obesities: Future Choices Report

1.6.2 Individual factors relating to adolescent obesity

1.6.2.1 *Biological and genetic factors and adolescent obesity*

Individual biological, and genetic factors affect obesity and may operate via diet and physical activity. For example, biological factors such as sensory stimulation (e.g. smell, sight, and taste), gastrointestinal signals (e.g. peptides, neural signals), and hormones (e.g. ghrelin, leptin) influence eating behaviours and may differ between adolescents [48]. Genetic factors relating to adolescent obesity can be segmented into two areas: monogenic, or polygenic. Monogenic obesity, which means single-gene defect obesity, is uncommon and only comprises around 3% of children living with obesity which is driven by genetic mutations in the hypothalamus (the region of the brain which controls satiety, body weight, and energy metabolism) [48]. On the other hand, polygenic obesity is the result of hundreds of defects which may each have a small effect and follows a pattern of heritability similar to other diseases (e.g. 40-70%) which contributes to individual variation in weight status and response to the “obesogenic environment” [49]. Although additional bio-behavioural factors at the individual level such as poor sleep, adversity, stress, and medications may also cause dysfunctional energy regulation which brings rise to excess adiposity [48], these are beyond the scope of this thesis.

1.6.2.2 *Energy balance (diet and physical activity) and adolescent obesity*

It is generally considered that of the two predominant factors contributing to energy balance (diet and physical activity), diet is the key contributor to adiposity (obesity) [50] [51]. This is understood from an energy-balance perspective (i.e. the time and effort to expend a certain number of calories via physical activity is much greater than consuming equivalent calories in food intake [50]). Obesity prevention interventions comprising of dietary factors alone are also generally more successful than interventions comprising of physical activity components alone (although greatest success comes from a combination of both diet and physical activity components) [51]. For this reason, dietary factors at the individual level are often viewed as the principle causes of obesity and upon which obesity prevention interventions are targeted. Although physical activity also may play a role in weight gain and has multiple benefits outside of obesity (as will be discussed in section 1.7.5).

Major dietary factors such as the overconsumption of calorific, obesogenic foods may be the dietary factor which contributes most to adolescent obesity [52]. Although what compromises obesogenic foods is contested and often dependent on dietary dogma party lines (e.g. sugar vs. fat). Foods consumed in high quantity suggested to increase risk of adolescent overweight or obesity are processed foods, fast foods, sugar-sweetened beverages, and candies/sweets whereas foods with low levels of sugar and fat such as fruits, vegetables, whole grains, fish, nuts, and legumes are associated with a lower risk of developing overweight or obesity [52]. For example, adolescents reporting to consume carbonated soft drinks more than twice a day and fast food at least once a day may be significantly at higher risk of living with overweight and obesity [53]. Dietary factors which may contribute further include excessive focus on diet quality rather than quantity (e.g. portion sizes), macronutrient intake, and glycaemic load [52].

1.7 Physical activity and adolescent obesity

This thesis places a greater focus on physical activity. The relevant background information to physical activity is presented below.

1.7.1 Defining physical activity

Physical activity is defined as “any bodily movement produced by skeletal muscles that requires energy expenditure” [54]. Physical inactivity is considered insufficient physical activity to meet current physical activity guidelines (see section 1.7.3). Aerobic, moderate-to-vigorous physical activity (MVPA) is the predominant physical activity type that is pushed in global health agendas. Aerobic physical activity is defined as “activity in which the body’s large muscles move in a rhythmic manner for a sustained period of time” (e.g. walking, running, swimming, and bicycling) [54]. To understand what constitutes MVPA it is important to understand an additional term, metabolic equivalent of task (MET). The metabolic equivalent of task is a physiological measurement of the intensity of physical activity where one MET is an individual’s energy expended while seated at rest [54]. MVPA, on a fixed/absolute scale, is equivalent to expending >3 METs, or >3 times the intensity of rest [54]. Additional scales are used to help the lay individual understand physical activity intensity such as the rate of perceived exertion. A rate of perceived exertion at 5 out of 10 is usually considered to be moderate intensity activity. The physiological response an individual can expect to experience and be able to identify MVPA is an increase in perspiration, body temperature, and breathing rate. During MVPA, the individual will also not be able to sustain a regular conversation.

1.7.2 Physical activity measurement

There are various methods of estimating physical activity including self-report (e.g. questionnaire-based recall), device-measured (e.g. accelerometers), and criterion/gold-standard measures (e.g. doubly-labelled water, and indirect calorimetry). In line with self-reported metrics of adolescent obesity, self-reported physical activity is generally only valuable in resource-limited settings where no other measurement method is available due to self-report biases. Self-reported physical activity is

particularly unreliable due to the often forgotten, sporadic bouts of physical activity engaged in during daily life. Direct measures of physical activity are costly, require specialist equipment, and have a high participant burden which limits their use in population health surveillance. Device-measured physical activity, and specifically physical activity that is assessed by accelerometers, are the most commonly used physical activity measure in the existing literature to date. However, accuracy of measurement may be dependent on accelerometer type, device placement (e.g. hip vs. wrist) and wear protocol (e.g. invasiveness for the adolescent of wearing a device in a 24/7 wear protocol). Accelerometers have shown strong validity and reliability in free-living conditions (vs. objective/gold standard measures). Validity and reliability are important terms to understand to appraise epidemiological investigations in physical activity. Validity is defined as the ability of a measurement technique to measure what it is supposed to measure (e.g. accuracy/construct validity), which comprises both sensitivity and specificity components [55]. Reliability is the extent to which a measurement technique will provide the same estimate across repeated measurements (i.e. the consistency of a measure when reproduced under similar conditions [55]).

Sensitivity and specificity, for detecting individuals with sufficient vs. insufficient physical activity accurately, when compared in a review versus indirect calorimetry were 46% and 96% (median sensitivity), and 71% and 96% (median specificity) respectively, with greatest accuracy when detecting sedentary behaviour, and lowest accuracy for light-intensity physical activity [56]. However, in a review of accelerometer validity and reliability compared to doubly-labelled water (for physical activity energy expenditure, and total daily energy expenditure), data suggested that accelerometers underestimated criterion-measured total energy expenditure due to the inability of accelerometers to detect increased caloric expenditure during different types of physical activity [57]. For example, physical activity devices are currently not capable of identifying physical activities such as cycling, and swimming, or the additional intensity when loads such as school backpacks are carried. However, accelerometers are currently the best available measure of estimating adolescent physical activity

outside the laboratory environment to categorize health risk. Categorisation of health risk is often classified by undertaking insufficient levels of physical activity.

1.7.3 Physical activity guidelines

The WHO physical activity recommendations for adolescents younger than 18 years is to participate in an average of 60 minutes per day of MVPA, and vigorous activities (including muscle-strengthening activities) at least three days per week [54]. UK guidelines are also similar to the WHO guidelines with a focus on accruing 60 minutes of physical activity per day across the week. However, population estimates of physical activity in the UK and worldwide suggests that many adolescents fail to meet this guideline.

1.7.4 Physical inactivity is a global problem

Data from 1.6 million adolescents aged 11-17 years from 146 geographies in 2016 suggested 81% of adolescents do not do enough physical activity [9]. This equates to around 4 out of 5 adolescents not meeting physical activity guidelines [9]. Worldwide, girls are more inactive than boys [9]. However, these data are self-reported from a single-item which may bring rise to social-desirability bias. Figure 6 shows global prevalence of insufficient physical activity among 1.6 million boys and girls. In the UK, physical inactivity is similarly high in prevalence. In England, in 2020/2021 (the most recently available data from the British Government, 44.6% of children are sufficiently physically active (self-reported physical activity, no distinction by age) [58]. The COVID-19 pandemic has affected physical activity levels. Compared to pre-pandemic levels, from device-measured physical activity data of 1,296 adolescents aged 10-11 years, MVPA was 7-8 minutes per day lower in 2021 when restrictions were lifted vs. before the pandemic in 2017/2018 [59]. However, this is a broadly comparable decrease when compared with anticipated declines over a three year period at this age group. For example, physical activity may decline during adolescence equivalent to a reduction of 7 minutes of daily MVPA[60].

Figure 6: Global prevalence of insufficient physical activity among 1.6 million boys and girls

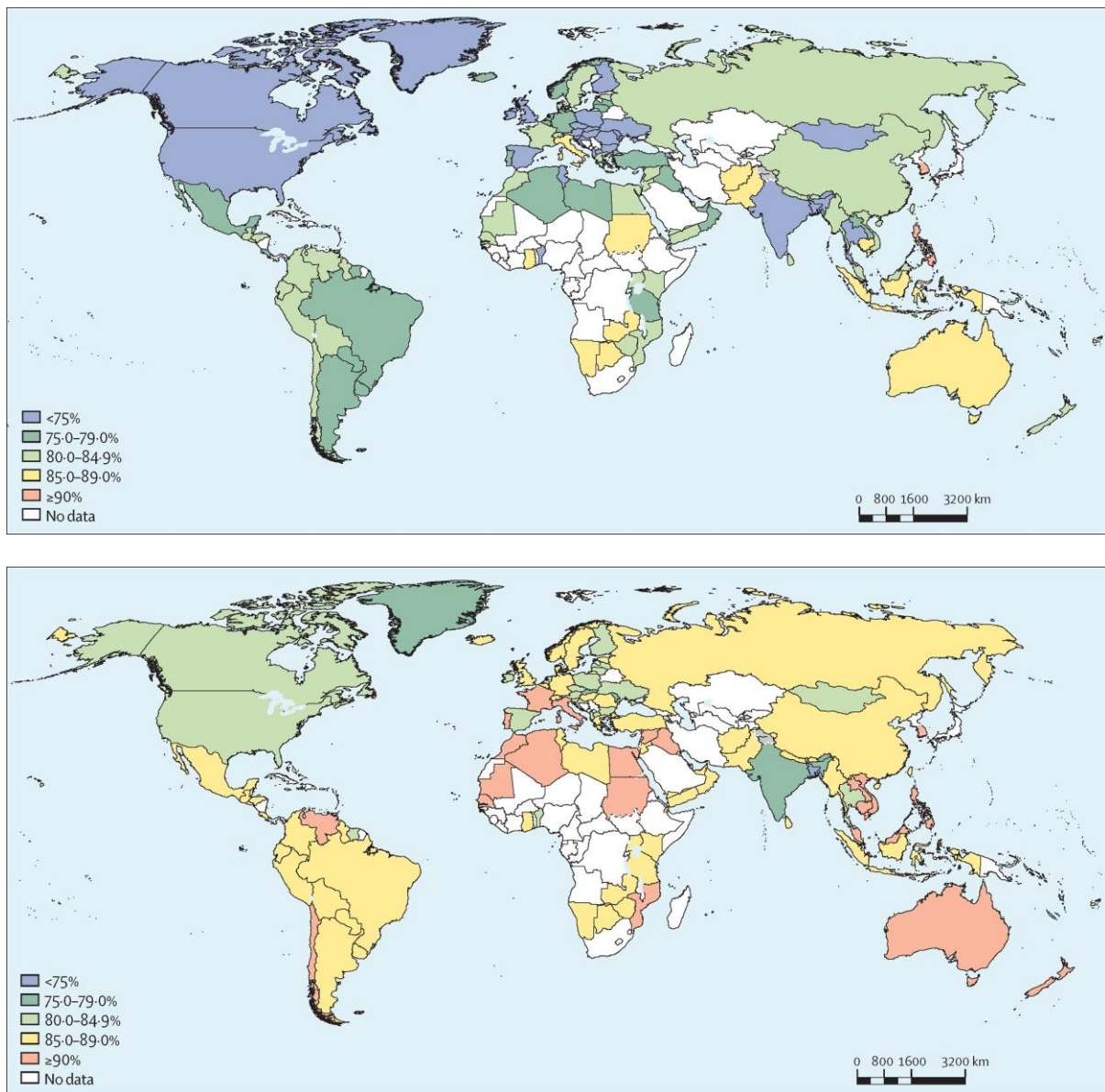


Figure from: Guthold, R., et al. (2019). "Global trends in insufficient physical activity among adolescents: a pooled analysis of 298 population-based surveys with 1.6 million participants." The Lancet Child & Adolescent Health.
Top figure = boys. Bottom figure = girls. Aged 11 to 17 years.

1.7.5 Physical inactivity and adolescent health

Physical activity can impact upon adolescent's physical and mental health, both in the short and long-term. There are many convincing arguments for why adolescents should be supported to increase their physical activity. For the adolescent, meeting physical activity guidelines could protect against depression and anxiety [61]. However, immediate/acute benefits of physical activity (vs. the long-term impact on health), such as enhanced wellbeing, having fun, and social integration [62], may be most important for adolescents [63]. For educators and members of the school community, physical activity during the school day may reduce adolescent behavioural issues [64] and also improve adolescents' cognitive functioning [65], and performance in maths [66]. For healthcare professionals and organizations concerned with adolescent health (e.g. the United Nations [UN], WHO), outcomes most relevant to these groups are that increased MVPA is associated with improved cardio-metabolic health during adolescence [67] and adolescent physical inactivity hinders progress towards the sustainable development goals [68]. Physical inactivity also likely costs global economies a significant amount in direct healthcare costs (an estimated United States Dollar [USD] 54B per year) [69]. The relationship between physical activity and soft outcomes relating to mental health are strongest for improvements in physical self-perceptions (e.g. enhanced self-esteem) [70].

The evidence base surrounding the association between physical activity and adolescent obesity is relatively weak with physical activity considered to have a moderate, negative association with adolescent obesity [71]. There are differences between adolescents' (aged 11 years) physical activity levels by BMI category where the gap between adolescents living with healthy weight and overweight may increase by 1.7 minutes per day (95% CI = 0.8-2.6), and between adolescents living with healthy weight and obesity increasing by 2.0 minutes per day (95% CI = 0.9-3.1) each year from age 6 to 11 years (n=2,132 children living in England) [72]. Physical activity is often a component of adolescent obesity prevention interventions [73-75]. However, interventions are mainly multi-component and do not disaggregate the effect of physical activity alone on adolescent obesity. Systematic review level evidence of adult physical activity interventions with follow up between 12-18 months identified a

mean difference in weight loss ranging from -0.4 to -2.3 kgs (n=5 trials) [51] which may not be clinically significant. As discussed in section 1.6.2, diet (over physical activity) is viewed as the key contributor to obesity; however, when diet and physical activity is combined in multicomponent interventions the effect of programmes are greatest, perhaps as a result of the weight maintenance capability of the addition of regular physical activity to dietary interventions [51] and may be clinically significant (e.g. standardized mean difference >5kgs [50]). It is important to identify approaches to increase adolescent physical activity worldwide.

1.8 The “obesogenic” environment, adolescent physical activity and adiposity

The previous section highlighted that many factors at the individual level can impact our energy-balance-related behaviours (e.g. physical activity) which underpin adiposity (obesity). However, Bronfenbrenner’s socio-ecological model suggests that behaviour is affected by both factors at the individual level and broader social, physical, policy, and digital environment [76]. Figure 7 shows the socioecological model, highlighting the many environmental factors that are thought to potentially influence adolescent physical activity and obesity. Many changes have occurred with the advent of modern times to components of the socioecological model which may have led to worsened adolescent obesity prevalence in both high-income, medium-income, and low-income countries [7]. For example, changes at the family level highlighted in light green (e.g. modelling of physical activity behaviours, dietary habits, sleep, and screen use), changes at the community level (dark purple) (e.g. schools, green space, public transport and food outlet accessibility), and also at the socio-political level (light blue) where there is limited political will, and government policies (e.g. fiscal, agricultural), and big industry strategy (e.g. food marketing) make it challenging to maintain a healthy weight [77, 78]. Given that overweight and obesity arise from sustained energy imbalance - excess energy intake relative to energy expenditure over time – these changes have led to an ‘obesogenic’ environment; one that encourages the development of excess weight. Approaches are required which progress beyond focussing on a single mechanism that is incapable of bringing rise to meaningful and sustainable change in the system as a whole [79]. For example, increasing adolescent physical activity worldwide may require multi-level, multi-sectoral action including macro-level intervention addressing policies, micro-level intervention focussing on individual behaviours, and meso-level intervention focussing on organizational (e.g. school) strategies [80]. A systems-based approach to increasing physical activity would involve pursuing investment in key areas (e.g. “whole-of-school” programmes, active transport, active urban design, healthcare, public education including mass media, sport and recreation for all, workplaces, and community-wide programmes [81]). The rationale behind this approach is to recognize that supportive environments are key drivers of adolescent

physical activity [63] and allow stakeholders within the system to understand how each part of the system contributes to making it challenging to do enough physical activity. However despite the fact that humans are all presented with an 'obesogenic' environment, there is still substantial variation in obesity levels at a population level, suggesting that individuals differ in their susceptibility to these environmental factors [82]. This thesis pursues increasing our understanding of the variation in the 'obesogenic' environment with a specific focus on the school, and digital social environment.

Figure 7: A socioecological model for understanding individual and environmental factors influencing adolescent obesity

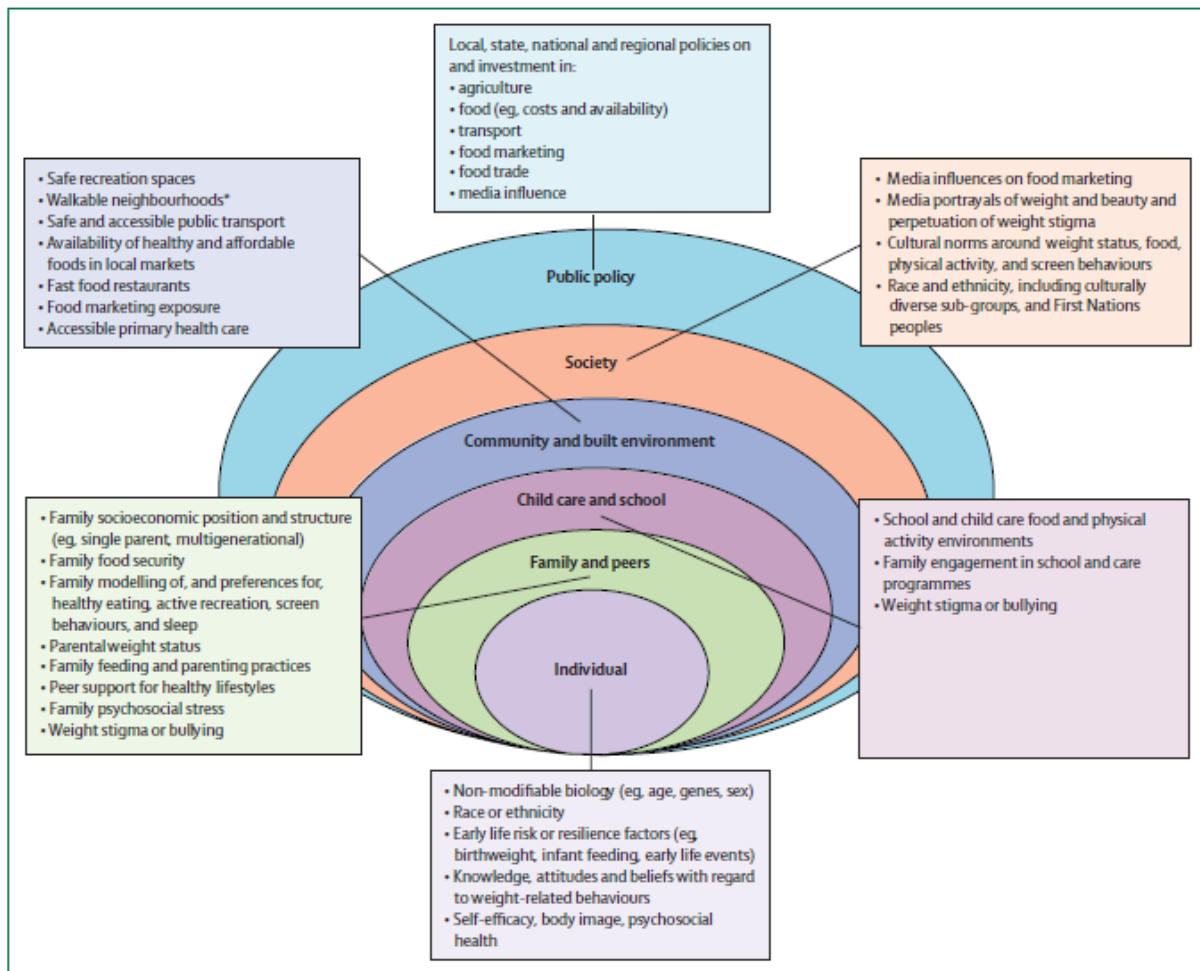


Figure 1: A socioecological model for understanding the dynamic interrelationships between various personal and environmental factors influencing child and adolescent obesity
Adapted from the Centers for Disease Control and Prevention social-ecological model framework for prevention.³⁸ *Defined as being traversable on foot, compact, physically enticing, and safe.

Figure taken from: Jebeile, H., et al. (2022). "Obesity in children and adolescents: epidemiology, causes, assessment, and management." *The Lancet Diabetes & Endocrinology* **10**(5): 351-365.

1.9 Environmental influences on adolescent obesity and physical activity

Predominant environmental factors proposed to relate to adolescent obesity may be from the home, neighbourhood, school, and digital environments due to these being the settings in which adolescents may spend the majority of their time. Most reviews of environmental determinants were completed in the 2000s, focus on children and a combination of settings (e.g. home, and school), have energy-balance-related behaviours as outcomes (e.g. fruit and vegetable consumption, as opposed to adiposity metrics), are of low methodological quality, and are inconclusive (e.g. present mixed, or null findings) [83] [84] [85]. Below, I will briefly discuss the current evidence on respective environmental influences before describing the aims and objectives of my thesis. A more detailed background specific to the two sections of my PhD, the school environment and the digital environment, is provided at the start of Part 1 and 2, respectively.

1.9.1 Home environmental influences

Few investigations have explored the relationship between the home environment and adolescent obesity. Findings from the most recent (2021), high quality systematic review (e.g. provides sufficient information to allow replication and follows best practices in reporting) focussing on the home environment specifically (rather than a combination of environments) are inconsistent regarding which physical factors contribute to children's adiposity [86]. Most evidence is derived from cross-sectional investigations, studies in North America, and Europe, and using exposures related to the home environment were self-reported by caregivers which brings rise to social-desirability bias [86]. In this systematic review, most studies identified (8 of 15) found null associations between the physical food environment and higher child (aged 12 or under) adiposity, whereas 6 of the 15 studies found positive associations between obesogenic food environments (e.g. the types and quantity of certain foods available in the home, such as sugar-sweetened beverages) and child adiposity [86]. In the same systematic review, findings were also mixed regarding physical activity environment components (e.g. physical activity equipment, and garden space) with most studies (4 of 7) suggesting a null association [86]. The most convincing evidence of an association between the home environment and child

adiposity relates to media factors. For example, 21 out of 29 studies suggested a positive association between availability and access to electronic media devices in the home (and specifically in children's bedrooms) and child adiposity [86]. Additional media-related factors from the home environment will be discussed in the digital environment section (section 1.9.4). From the totality of the research base, research into the home environment has focussed primarily on factors beyond the physical environment (e.g. modelling of eating, and physical activity behaviours) which relate to the home social environment [87].

1.9.2 Neighbourhood environmental influences

More evidence (vs. the home environment) has focussed on the relationship between neighbourhood environments and adolescent adiposity. Proximity to the food retail environment and physical activity-supportive built environments (e.g. safety of pavements to promote walking, cycle lane infrastructure) are thought to be important physical environment factors [88]. However, physical activity supportive environments have received comparatively more attention (vs. food environment factors). Street connectivity, defined as the directness of links and density of connections in street networks, has been shown to be consistently associated with greater children and adolescent's physical activity (meta-analysis, 22 studies), with sub-group analysis restricted to neighbourhood street connectivity showing a significant pooled effect (Odds ratio/OR = 1.06, 95% CI = 1.01-1.10) compared to examination of street connectivity in school neighbourhoods (OR = 1.28, 95%CI = 0.95-1.71) [89]. A review of studies which used geographical-information-based approaches (n=36), which may have greater validity and reliability than self-reported measures of street connectivity, further supported the view that well-connected neighbourhoods is associated with greater children's physical activity (aged 6 to 13 years) [90].

However, another review of reviews (n=65), which did not segment by age (aged 1 to 18 years), suggested that there is a null or mixed association for street connectivity [91]. This review also pointed towards high certainty for a positive association between transportation physical activity and

walking/cycling/active transportation infrastructure (although did not make a distinction between the specific environment, e.g. neighbourhood, vs. school) [91]. However they also suggested less consistent positive associations between green/open space, street lighting, traffic safety, and residential density (also with no distinction between the settings of these) [91].

1.9.3 School environmental influences

Few reviews have synthesized the relationship between the school environment, and adiposity, or energy-balance-related behaviours. Of six identified related reviews, one focussed on the relationship between the school environment and health with only one cross-sectional study from the year 2007 including a focus on physical activity (one of ten other studies) [92]. Two of six reviews [93, 94] focussed on the food environment with one review restricted to synthesizing results of interventions rather than associations between the environment and food-related components [94]. Two other reviews focussed on diet and/or physical activity as a secondary focus to health inequalities (narrative review) [95], and health (meta-ethnography of qualitative research) [96] respectively. The remaining review focussed on synthesizing the association between the school environment and physical activity comprehensively and is the most cited review in the research area [97] upon which much of our knowledge regarding the relationship between the school environment and adolescent physical activity is based. Findings of the above mentioned reviews are discussed below with an addition of recent large cross-sectional studies to show the expanse of the existing knowledge base with research gaps identified.

1.9.3.1 *The school food environment*

The school food environment encompasses all “spaces, infrastructure and conditions inside and around the school premises where food is available, obtained, purchased, and/or consumed (e.g. tuck shops, kiosks, canteens, food vendors, and vending machines), also taking into account the provision and nutritional content of food in school grounds, all information available (e.g. promotion, marketing advertisements, branding, food labels, packaging, promotions, and pricing of foods and food

products” [93]. School environmental factors shown to relate to obesity include school grounds, school building designs, available facilities, and equipment [98]. It has also been suggested that school environment factors should encompass an adolescent’s journey to school and their exposure to obesogenic food outlets (e.g. fast-food restaurants) or accessibility to “less healthy” foods (e.g. from supermarkets) [99]. However, although suggested to be important, little evidence exists relating the school food environment, and the specific environmental features outlined above, to adolescent obesity [98] and existing evidence synthesized in systematic reviews is considered to be methodologically weak (e.g. differing definitions of the school food environment, questionable exposure assessment validity, heterogeneity of methods) [100].

Of 100 studies identified in a systematic review and meta-analysis of food environment interventions (53% of studies based in the USA, and 10% in the UK), environmental changes to increase the availability of vegetables, the provision of healthy meals with high palatability, and regulation of vending machines and sugar-sweetened beverages were suggested to contribute to improved dietary intake and reduction of BMI z-score [93]. Included interventions had an effect on BMI z-score equivalent to a standardized mean difference [95% CI] of -0.12 [-0.15, -0.10] [93]. This finding is also supported by a systematic review and meta-analysis of observational studies (n=10 studies) which found that the sale of food at school, or in the vicinity surrounding school significantly increases the risk or odds of obesity (OR [95% CI] = 1.14 [1.01, 2.06]), whereas availability of healthy food provided by schools significantly decreased the risk or odds of obesity (OR = 0.89 [0.82, 0.96]) [94]. A third systematic review restricted focus to food-related policies within schools and did not find significant associations with adiposity metrics (n=17 studies), but identified that school policies for the direct provision of fruit and vegetables increased consumption of fruits and vegetables by 0.28 servings per day. However, no effect was found on total calories consumed [101].

1.9.3.2 Physical activity

School physical activity environment factors are more understudied than school food environment factors. The most recent, and most-cited systematic review in the area synthesized quantitative and

qualitative findings (n=93 studies) via a non-quantitative, thematic analysis to show associations between school policy, social, and physical environment features and adolescent physical activity (11 to 18 years) [97]. Heterogeneity of physical activity assessment methods and different definitions of the school environment precluded synthesis by quantitative methods. However, of over 30 environmental features documented, physical environment features potentially important were specific activity settings (e.g. type of activity setting [n=3 of 5 studies reporting positive associations with either self-reported, or device-measured physical activity), and location of activity setting [n = 7 of 16 studies reporting positive associations]). A policy environment feature suggested to influence adolescent physical activity was break time length (although this remains untested quantitatively) [97]. However, this review also proposed that factors beyond the physical environment (e.g. policy environment, and social environment) may be particularly important.

A review of school physical activity policies (e.g. Physical Education class duration, opportunities for physical activity during play-time/recess, or during non-curricular time such as after-school) identified 52 studies reporting on associations between formal written policies, practices and behaviours relating to physical activity. The review identified that most studies were conducted in high-income settings, were cross-sectional in design, and findings suggested a lack of or inconclusive associations [102]. In the absence of further reviews of the existing literature base (e.g. focussing on the school social environment, which is a gap in the existing literature base), it is possible to infer potential relationships between the school social environment and adolescent physical activity from individual, high quality studies. Using data from a nationally representative cohort of adolescents (self-report physical activity), Schmidt et al. showed that out of a possible 1,154 different demographic, psychological, behavioural, biological, social and environmental factors (not only restricting to the school environment), peer-modelling (whether an adolescent's friend participates in exercise) was found to be the most meaningful predictor of physical activity of boys and second most meaningful predictor of physical activity for girls [103]. This suggests the potential importance of the school social environment, and specifically friendship support for physical activity. However, given the few studies

focussing on the school physical activity environment in general, and the many potential predictors which exist within schools (e.g. physical features, policies, and social factors) there is a need for further investigation. The relationship between the school policy, social, and physical environment and adolescent physical activity is explored analytically in this thesis (Chapter 3).

1.9.4 Digital environmental influences

Adolescents are increasingly prone to influence from the digital environment due to heavy use of digital devices. Although no definition of what comprises the digital environment within the context of adolescent health research exists, online environments accessed through screens (e.g. computer, tablet, mobile phone) such as video games, and social media may be particularly relevant. Historically, there has been concern around high levels of screen-based behaviours as a result of their link with sedentary behaviour. Adolescents with the highest category of screen-time may be 1.27 times more likely (95%CI = 1.166, 1.390) to develop overweight/obesity compared to adolescents with the lowest category of screen-time (meta-analysis, n=44 studies, 11 USA, 10 Europe, 11 Asia, 12 other, no information provided on time equivalent, e.g. hours per day, constituting high vs. low screen-time) [104]. The relationship between video games and adolescent adiposity is less clear. Recently published data shows that a greater proportion of boys (age 11 to 15 years) play video games for two or more hours per day compared to girls (51% of boys vs. 33% for girls) [105]. However, despite some proposed disadvantages of higher usage of video games for boys (bullying, and going to bed hungry), and for girls (lower life satisfaction) [106], the association between video gaming and adiposity may be small and not clinically meaningful [107]. The research base has not been synthesized by a systematic review. Based on scoping review evidence of 26 studies (25 cross-sectional, 1 longitudinal), 14 studies suggested no association between playing video games and obesity while 12 studies reported positive associations [108]. Included studies identifying a positive association tended to combine video game use with other screen-based behaviours (e.g. mobile phone, and computer use); this makes it challenging to identify independent relationships. Adolescents are increasingly spending large amounts of time online via social media. This has led to concerns about content they are being

exposed to and digital environmental factors which may relate to adiposity (e.g. food marketing). However, only two studies have focussed on the relationship between social media use and adolescent adiposity. This is a key research gap. These studies will be discussed in greater detail in Part two of my thesis in the broader introduction to social media use shown in Chapter 4. Given the lack of research in the area, I explore this relationship between social media use and adolescent adiposity cross-sectionally, and longitudinally in Chapter 5, and 6 respectively.

This thesis is split into two Parts. Part one focusses on the school environment, and Part two focusses on the digital environment. What follows is a brief introduction to these, which will be elaborated on later in the thesis ahead of the respective analytical chapters for each Part.

1.10 Thesis Part One - The school environment

1.10.1 Defining the school environment

The whole school environment is defined in my PhD as the physical and aesthetic surroundings of the school and/or the psychosocial climate and culture of the school [97].

1.10.2 The secondary school system as a setting for health promotion

Worldwide, schools are considered an important setting for health promotion [63]. Beyond fostering academic attainment, schools are also an important environment for adolescents to build friendships, emotional control, and lifelong health [4]. School systems are strategic platforms for delivering preventative healthcare services to adolescents due to the opportunity to reach adolescents at the population level, irrespective of background characteristics, to equitably distribute resources and services. Schools are viewed as promising settings to intervene to increase physical activity and reduce adiposity at a population level as adolescents spend half of their waking hours at school [109], and due to their near universal reach of and consistent access to adolescents over multiple years. Promoting physical activity and preventing obesity in schools is challenging, but school-based interventions are the recommended setting to target preventative measures [109]. Many physical activity promotion and obesity prevention strategies during adolescence have targeted the school setting with limited success [71, 110-112].

1.10.3 Obesity prevention within the school setting

An umbrella review of 13 systematic reviews of interventions (n = 95 RCTs, and non-RCTs = 13) aimed at reducing overweight and obesity during adolescence (10 to 19 years) identified most reviews were from high-income countries and were of moderate to low quality (only one was considered high quality) with the totality of evidence suggesting little or no effect of interventions on BMI (or physical activity level) [20]. The most cited systematic review included in this review of reviews is from the Cochrane library. In this Cochrane review, 153 RCTs targeting obesity prevention in children aged 0 to 17 years via diet, physical activity, or both were included from the USA, and Europe [113]. Findings of

these studies were segmented by age (0 to 5 years, 6 to 12 years, and 13 to 18 years) with 85 of 153 trials targeting children aged 6 to 12 years. For children aged 6 to 12 years, from 14 RCTs (n=16,410 children), physical activity interventions (vs. control groups) reduced BMI (mean difference [95%] CI = -0.10 kg/m² [-0.14 to -0.05]) but had little or no effect on BMI z-score (-0.02 [-0.06 to 0.02]) [113]. In contrast, for adolescents aged 13 to 18 years, the mean difference in BMI (95% CI) between intervention and control groups across 4 RCTs (n = 720 adolescents) was -1.53 kg/m² (-2.67 to -0.39) with only one RCT (n = 100 adolescents) exploring effect on BMI z-score (-0.2 [-0.3 to -0.1]). For diet-only interventions there was high certainty of evidence for children aged 6 to 12 years that interventions had little impact on BMI z-score (no segmentation by BMI only) while the same was true for adolescents aged 13 to 19 years but the evidence was considered to be of low certainty (e.g. methodologically weak). For physical activity and diet combined, for children aged 6 to 12 years, from 20 RCTs (n = 24,043), for intervention group participants (vs. control) there was a reduction in BMI z-score of -0.05 kg/m² (-0.10 to -0.01) (no segmentation for BMI only), while for adolescents aged 13 to 18 years, there was no statistically significant difference in mean difference in BMI z-score between intervention and control groups (low certainty of evidence) [113].

Schools are the most common setting in which obesity prevention interventions are based [20]. It is challenging to identify common features of successful school-based interventions given that both successful and unsuccessful interventions share similar elements. Although multi-component interventions may be more effective at reducing BMI z-score (vs. single-component interventions), specific characteristics of multi-component interventions have not been found to be consistently associated with the improved efficacy of interventions [74]. However, for single-component interventions (e.g. physical activity components only, targeting decreased BMI), emphasizing enjoyment in physical activity sessions, and curricular sessions (vs. extracurricular) were found to be associated with improved intervention efficacy. There was no significant associations found between dietary-related components with improved intervention efficacy [74]. Most school-based

interventions targeting obesity prevention include components based on established relationships between specific factors, obesity, and energy-balance-related behaviours (e.g. self-esteem, friendship support, and self-efficacy) [114-116]. However, it may be that obesity prevention interventions during adolescence have been unsuccessful potentially as a result of being primarily based in schools with limited consideration for environments beyond the individual level (e.g. the digital environment including social media) [20].

1.10.4 Physical activity promotion within the school setting

Meta-analysis evidence suggests that current school-based physical activity interventions are not successful at positively impacting adolescent's physical activity across the whole day [110]. Love et al.'s paper presents strong evidence that school-based physical activity interventions are not effective as they harmonised device-measured physical activity across trials [110]. Pooling of comparable device-measured physical activity (full day MVPA) is novel in the literature due to the high burden of asking respective intervention authors to re-analyse their data which ultimately facilitates a greater number of studies eligible for meta-analysis. Figure 8 shows a forest plot of standardized mean difference of change in physical activity between intervention and control groups of school-based physical activity interventions (n= 17 studies) [110]. These meta-analysis findings show a limited pooled effect of interventions on full day MVPA (standardized mean difference [95% CI] = 0.02 [-0.07, 0.11] min/day). Most interventions were implemented in Europe with the mean baseline sample size of 464 (median [IQR] = 436 [178-700]), and mean number of schools was 20 (14 [12-18]). Key intervention components included educational (14 of 17 interventions included), social environmental (17 of 17), and physical environmental components (3 of 17) while most interventions included school plus afterschool/community components (76.5%). This paper synthesized evidence only up until February 2017. One additional systematic review is relevant to close the gap on interventions between 2017 and currently in 2022.

A Cochrane review published in late 2021 expands upon Love et al's paper by synthesizing evidence up to June 2020 [117]. The purpose of Neil-Sztramko et al's review was to summarize evidence on effectiveness of school-based interventions increasing device-measured MVPA and fitness among children and adolescents aged 6 to 18 years. Of 89 studies (n = 66,752 participants) of which 26 studies were undertaken in the USA, 22 focussed on adolescents only, and a further 10 focussed on both children and adolescents. From meta-analysis of 11 studies targeting change in minutes per day of MVPA in adolescents, mean difference (95%CI) between control and intervention groups was 1.84 (0.34, 3.35) minutes per day which is likely not clinically significant (n = 4,994 intervention participants, n = 4,905 control participants) [117]. The aforementioned two synthesizes of school-based trials focussed on increasing adolescent physical activity shows that these studies have been largely ineffective at increasing physical activity over the full day. A number of reasons may explain why interventions have not been effective.

Figure 8: Forest plot of standardized mean difference of change in physical activity between intervention and control groups of school-based physical activity interventions

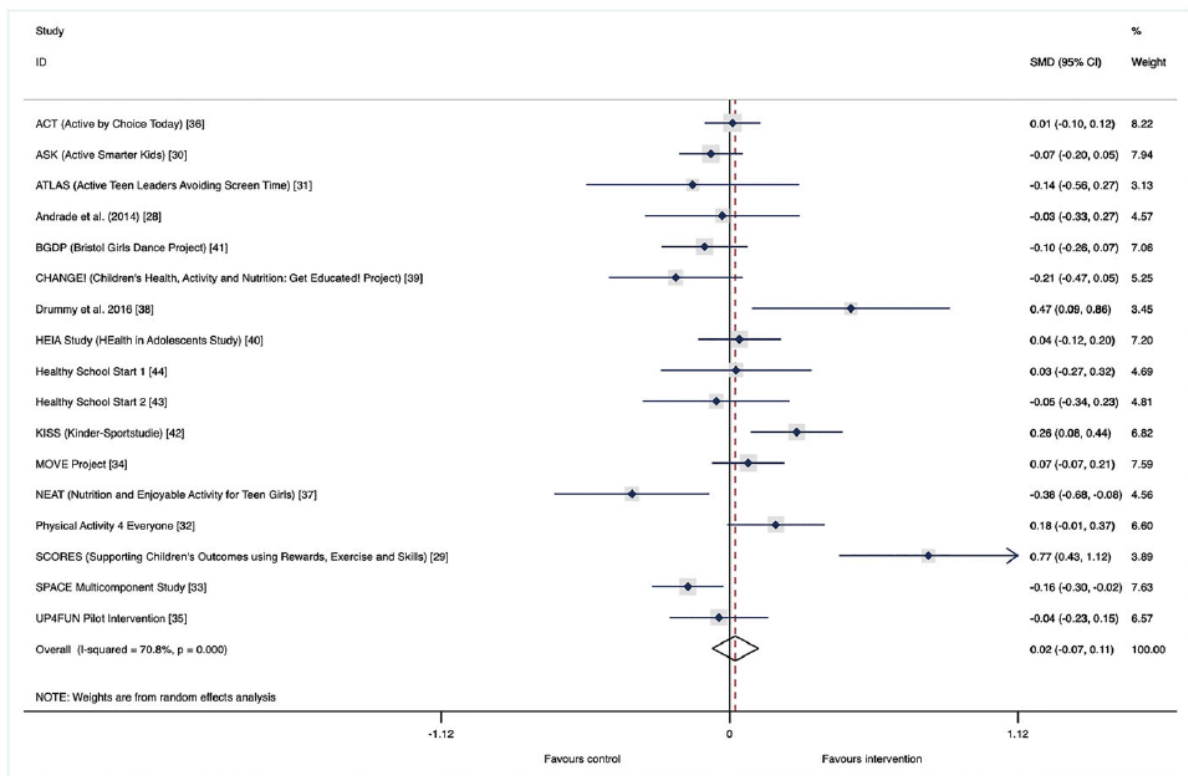


FIGURE 2 Main effect. Forest plot of standardized mean difference of change in physical activity between intervention and control groups of school-based physical activity interventions (study name [reference]) [Colour figure can be viewed at wileyonlinelibrary.com]

Figure taken from: Love, R., et al. (2019). "Are school-based physical activity interventions effective and equitable? A meta-analysis of cluster randomized controlled trials with accelerometer-assessed activity." *Obes Rev* 20(6): 859-870.

Physical activity intervention effectiveness can be impeded at every stage of the intervention process including through poor adoption (e.g. via competing priorities within schools), ineffective scaling (e.g. poor intervention fidelity) and failed maintenance [118]. However, few studies have examined whether barriers to intervention effectiveness may preclude intervention effectiveness before the intervention is even rolled out. Environmental context (e.g. the school environment) may impact intervention effectiveness. It has been suggested that physical activity promotion interventions may have failed due to lack of a consideration for the wider school environment as a whole. However, few studies in the UK have explored the association between the school environment and physical activity during adolescence [77] [97]. This is a key research gap. The school environment may have a strong impact on trajectories of physical activity into later life [119] but little is known about which specific features of the school environment predict change in physical activity. Increasing our understanding of the school context will support the development of physical activity interventions that can operate successfully within this setting [120]. In Chapter 3, I explore the relationship between the school policy, social, and physical environment and change in physical activity to contribute evidence toward filling this research gap.

1.11 Thesis Part Two - The digital environment

As discussed in the previous section, this thesis is segmented into two parts. Part one focusses on the school environment and physical activity as a hypotheses generating exercise of which features may be most important (e.g. policy, social, and physical). The finding of Part one informed the direction for Part two. Part two explores the role of the adolescent social environment in obesity. This is achieved by examining the cross-sectional, and longitudinal relationship between social media use and BMI z-score across two studies (Chapter 5, and 6). An in depth rationale behind why social media use may be potentially important for adolescent obesity is provided in Chapter 4. What follows is a brief introduction to set the scene regarding why social media use may be important for adolescent health, energy-balance-related behaviours, and obesity.

1.11.1 Defining social media use

Social media is increasingly driving social interactions during adolescence [121]. Social media can be defined as “a group of internet-based applications ... that allow the creation and exchange of user-generated content” [122] (e.g. Facebook, Twitter, Instagram, and Youtube). Users engage with social media by posting their own personal information (such as their thoughts, actions, whereabouts, and photographs), or interacting (e.g. “liking”, “following”, watching, or “sharing”) their friends’, or celebrities’ posts. Most adolescents worldwide have not experienced the world before social media and are considered “digital natives” [123]). Digitally-mediated interactions have challenged our understanding of what the social environment during adolescence comprises. Adolescents are provided with novel channels for communication with peers, and others who they may have difficulty meeting face to face through social media-enabled asynchronous communication [124] which eliminate barriers relating to geographic scale, time zones, and/or parental monitoring.

1.11.2 Adolescent social media use is highly prevalent

Social media is now a primary method of communication for adolescents [125]. In the UK in 2022, 69% of adolescents aged 12 to 15 years [126] and 97% of individuals aged 16 to 24 years [127] are signed

up to at least one social media platform. Adolescents on average spend as much as 7 to 21 hours/per week on social media [128]. Adolescents are generally early adopters of new technologies which can both heighten vulnerabilities and provide opportunities for health improvement. I expand upon the descriptive epidemiology of adolescent social media use in Chapter 4 including highlighting key differences in use by sex, social media use cases, and social media platform preferences.

1.11.3 Social media use and adolescent health

It is important to understand the potential health implications of social media use in adolescents. There have been calls for policies to restrict adolescent time spent on social media due to fears surrounding negative social interactions (e.g. bullying, exploitation, and radicalization). However, there are likely also benefits to adolescents in using social media. For example, social media may be a source of social support, and be used to build digital and interpersonal skills for economies in the future [129]. For these reasons, social media has been increasingly researched in the adolescent health literature base. Chapter 4 expands upon social media's potential influence on adolescent health through a narrative exploration of why adolescents may be particularly prone to the influence of social media, and a narrative review of the relationship between social media and adolescent physical and mental health including obesity.

1.12 Chapter 1 Summary

This chapter has provided a general introduction focussed on the individual and environmental influences on adolescent obesity with a specific focus on the school environment and physical activity, and social media use and adiposity. The low levels of physical activity and high prevalence of obesity are associated with later cardiovascular disease risk factors [23], morbidity [130, 131] and mortality [132]. Preventing the decline in physical activity and increase in adiposity during adolescence is a global health priority. Although many factors are related to adolescent physical inactivity and obesity, the school and digital environments may be particularly important. Schools are the recommended setting for intervening to promote adolescent physical activity and prevent obesity. Despite extensive research in the setting, most interventions have been unsuccessful, potentially as a result of a lack of consideration for the wider school environment. There has been comparatively less research into the relationship between the digital environment (e.g. social media) and adolescent adiposity, particularly when considering how widespread fears are regarding potential negative effects. There is a need for further research to examine respective relationships between the offline environment (schools) and adolescent physical activity, and the online environment (social media) and adolescent adiposity.

2 Chapter 2 Thesis objectives and aims

2.1 The behavioural epidemiology framework

In my thesis, I will study potential associations between the adolescent school and digital environment, and physical activity and adiposity respectively to underpin further progress through the behavioural epidemiology framework in future research and ultimately bring rise to translatable research to improve adolescent health. Sallis and colleague's [133] behavioural epidemiology framework specifies a systematic order of studies on health-related behaviours which leads to evidence-based, population-level interventions. The phases of the behavioural epidemiology framework are as follows - 1: establish links between behaviour and health, 2: develop measures of the behaviour, 3: identify influences on the behaviour, 4: evaluate interventions to change the behaviour, and 5: translate research into practice. The analytical chapters of this PhD primarily focus on Phase 1 and 3 of the behavioural epidemiology framework (Establish links between behaviour and health, and Identify influences on the behaviour). During each phase of the framework, key research objectives are pursued. For example, in phase 1, the aim is to provide evidence towards an association between behaviours and outcomes. Phase 1 includes evidencing dose-response relationships (where increasing levels of the exposure are associated with an increase or a decreased risk of the outcome) which lends support towards relationships between behaviours and health outcomes being causal in line with Bradford hill's criteria [134]. During phase 3, research explores potential influences on these behaviours (e.g. correlates, and determinants). These findings can support the identification of factors that may be harnessed for change.

2.2 PhD Aim and Objectives

The overall aim of this thesis is to explore relationships between the obesogenic environment and adolescent weight status and physical activity. Given the important gaps in the literature on the offline and online environments for adolescent physical activity and obesity, the specific objectives of this thesis are:

- (1) To explore associations between the school policy, social and physical environment and change in adolescent physical activity to test many potential predictors of change as a hypotheses-generating exercise. In this study I also ascertain how sex and socioeconomic status (SES) modify the relationship between the school policy, social and physical environment and change in adolescent physical activity. These objectives are addressed in Chapter 3.
- (2) To examine the sex-specific cross-sectional association between social media use and measured BMI z-score at age 14 years, and potential explanatory pathway variables of this association (dietary intake, sleep duration, depressive symptoms, cyberbullying, body weight satisfaction, self-esteem, and wellbeing). These objectives are addressed in Chapter 5.
- (3) To explore the prospective association between social media use at age 14 years and change in BMI z-score from age 14 to 17 years in boys and girls. These objectives are addressed in Chapter 6.

3 Chapter 3: The school policy, social, and physical environment and change in adolescent physical activity: An exploratory analysis using the LASSO

This work is published as:

Foubister, C., et al. (2021). "The school policy, social, and physical environment and change in adolescent physical activity: An exploratory analysis using the LASSO." PLoS One **16**(4): e0249328.

The work was selected as a "Top 10" oral presentation at the International Society for Behavioural Nutrition and Physical Activity conference, New Zealand, 2020 (Presented virtually due to the Covid-19 pandemic).

Kirsten Corder and Esther van Sluijs designed the GoActive study. I designed the analyses presented here alongside Kirsten Corder which used secondary data from the GoActive study. I contributed to collecting follow-up data during my role as a Research Study Assistant, and data cleaning during my role as a Research Assistant prior to undertaking my PhD. I conducted all of the analyses, interpreted the results and drafted the manuscript. My supervisors and co-authors reviewed and provided input to the manuscript preceding this chapter.

This is the first of three analytical chapters in this thesis comprising an exploratory analyses of potential predictors of change in physical activity in the school policy, social, and physical environment. Except from some minor edits (e.g. dropping repetition of factors discussed in the general introduction such as highlighting the need to intervene to promote physical activity), this chapter is presented as per the published article.

3.1 Abstract

Purpose: I examined the association between the school policy, social and physical environment and change in adolescent physical activity (PA) and explored how sex and socioeconomic status modified potential associations. **Methods:** Data from the GoActive study were used for these analyses. Participants were adolescents ($n = 1765$, mean age \pm SD 13.2 \pm 0.4y) from the East of England, UK. Change in longitudinal accelerometer assessed moderate-to-vigorous physical activity (MVPA) was the outcome. School policy, social and physical environment features ($n = 267$) were exposures. The least absolute shrinkage and selection operator variable selection method (LASSO) was used to determine exposures most relevant to the outcome. Exposures selected by the LASSO were added to a multiple linear regression model with estimates of change in min/day of MVPA per 1-unit change in each exposure reported. Post-hoc analyses, exploring associations between change in variables selected by the LASSO and change in MVPA, were undertaken to further explain findings. **Findings:** No school policy or physical environment features were selected by the LASSO as predictors of change in MVPA. The LASSO selected two school social environment variables (participants asking a friend to do physical activity; friend asking a participant to do physical activity) as potential predictors of change in MVPA but no significant associations were found in subsequent linear regression models for all participants (β [95%CI] -1.01 [-2.73;0.71] and 0.65 [-2.17;0.87] min/day respectively). In the post-hoc analyses, for every unit increase in change in participants asking a friend to do PA and change in a friend asking participants to do PA, an increase in MVPA of 2.78 (1.55;4.02) and 1.80 (0.48;3.11) min/day was predicted respectively. **Conclusions:** The school social environment is associated with PA during adolescence. Further exploration of how friendships during adolescence may be leveraged to support effective PA promotion in schools is warranted.

3.2 Background

In Chapter 1, I showed that most adolescent physical activity interventions are based in schools and have limited success in increasing physical activity over the full day, partly as a result of a lack of consideration for and understanding of the wider school environment as a whole. Here I will first discuss the importance of schools for health promotion activities and discuss the current evidence on the association between the school environment and physical activity before presenting longitudinal analyses of the GoActive dataset.

Schools are often targeted as settings for physical activity promotion but previous school-based physical activity interventions have not been effective at increasing physical activity over the whole day [110]. A common critique of school-based physical activity strategies is the focus on behaviour change at the individual level and lack of acknowledgement of the multidimensional influences on adolescent physical activity within schools [135]. Adopting a socioecological approach and intervening at multiple levels to address the wider school environment may bring rise to sustained increases in adolescent physical activity [136]. This may also support effective intervention implementation, which is a major challenge faced by schools, particularly when translating evidence-based interventions into routine practice [137].

The school policy, social and physical environment can influence adolescent physical activity and may contribute towards adolescent health inequalities [97]; yet has been understudied. School physical environment features, such as settings for specific activities (e.g. indoor gym), the school social environment, including perceived teacher support for physical activity, and the school policy environment, for example provision of opportunities to be physically active, have been shown to positively influence adolescent physical activity [97]. The school environment may have a long-term impact on physical activity during adulthood [10]. As physical activity declines during adolescence [60] it is important to identify and target factors associated with change in adolescent physical activity. However, the association between adolescent physical activity and other features of the school environment – including school funding levels, peer support for physical activity and the overall school

ethos surrounding physical activity is not clear. Existing evidence is largely comprised of cross-sectional investigations from the United States that use self-report physical activity measures [97]. Few studies in the UK have explored which elements of the school policy, social and physical environment influence adolescent physical activity and for whom this may be more or less likely.

Inequalities may arise within schools despite apparent exposure to the same school environment as the most socioeconomically disadvantaged adolescents have been found to experience school differently to those from more affluent backgrounds and have lower levels of self-reported physical activity than more affluent adolescents [138]. Further exploration of the association between the school environment and adolescent physical activity and potential moderating role of socioeconomic status (SES) using device-measured physical activity would allow stronger conclusions to be drawn on how inequalities may widen within schools. Similarly, findings from the most recent systematic review in this area – that collated both quantitative and qualitative evidence – found features of the school environment (such as access to equipment, fostering of autonomy, competence and relatedness and provision of extracurricular opportunities) impacted boys and girls differently [97]. Further high-quality research is required to establish whether certain school environment features are mechanisms underlying inequalities in physical activity during adolescence.

A large number of school environment features plausibly relate to adolescent physical activity (as discussed in Chapter 1, section 1.9.3). The primary objective of this study is to explore associations between the school policy, social and physical environment and change in adolescent physical activity to test many potential predictors of change as a hypotheses-generating exercise. The secondary objective of this study is to ascertain how sex and SES modify the relationship between the school policy, social and physical environment and change in adolescent physical activity.

3.3 Methods

3.3.1 Study sample

This paper describes secondary analyses of the GoActive study data [139], a randomised controlled trial to increase MVPA among adolescents. The results of the GoActive trial showed that adolescents become more physically inactive over time with no difference found between control and intervention participants' physical activity [140], therefore the cohort for this study included all participants from control and intervention schools. Methods of the GoActive trial have been described in detail elsewhere [139]; a brief summary of the methods relevant to the current analyses is provided below.

3.3.2 Recruitment and Ethics

Baseline data collection took place September 2016-January 2017 with follow up April-July 2018. Participants (all year 9 students, aged 13 to 14 years) were recruited from 16 non-fee-paying, co-educational secondary schools across Cambridgeshire and Essex, UK. Ethical approval for the GoActive study was obtained from the Cambridge Psychology Research Ethics committee (PRE.126.2016). The GoActive study was prospectively registered (ISRCTN31583496).

3.3.3 Outcome measure

MVPA was measured by wrist-worn accelerometers (Axivity AX3, UK). Participants were asked to wear the accelerometers for 7 days continuously on their non-dominant wrist. Trained research assistants fitted the devices during data collection visits in schools and participants were encouraged to return the accelerometer to their tutor group (homeroom) teachers at the end of the 7 days. Participants were also given a freepost envelope to return accelerometers to the study team. A novel data processing approach was developed to ensure that the 24-hour wear time protocol was adhered to [140]. This process is separate from the creation of the outcome variable. Data were processed by first separating days of possible wear into quadrants: morning (6am-12pm), afternoon (12pm-6pm), evening (6pm-midnight), and night (midnight-6am). Participants were included if over six hours of wear time spread over at least two days was recorded in each of the first three quadrants (i.e. ≥ 6

hours from 7 possible mornings, ≥ 6 hours from 7 possible afternoons, and ≥ 6 hours from 7 possible evenings). Participants were excluded (i.e. did not proceed to be included in the creation of the outcome variable, a process which took place during data processing for the main intervention analysis for which I had no input to) if they had less than these amounts based on being identified as not having sufficient data to follow the 24-hour wear time protocol. As an example of this, the approach would allow for segments from multiple days to be “stitched together” to produce one full day of wear. This was a process which was previously validated prior to being applied in the GoActive trial. The night quadrant was considered sleep time. An individual hour was included for analyses when at least 70% of possible wear time was recorded. A diurnal adjustment was used to reduce bias arising from the 24-hour wear protocol. I decided to follow the same approach as the main trial analyses for determining wear time as opposed to using other approaches for consistency in publishing of the outcome variable. Accelerometer output was processed to provide average daily minutes of MVPA at baseline and follow up which is equivalent to ≥ 2000 ActiGraph counts per minute [139]. Change in average daily minutes of MVPA was then calculated via the following equation:

$$\text{Change in average daily minutes of MVPA} = \text{Follow up MVPA} - \text{Baseline MVPA}$$

Accelerometer time periods were used in this study for identifying participants who had sufficient wear time only (as opposed to for looking e.g. specific time periods of physical activity such as week vs. weekend, during school vs. after school). Change in average daily minutes of MVPA was selected as the outcome measure – as opposed to change in school time MVPA – because certain school environment features have a theoretical basis to influence physical activity both during and outside of school time. For example, schools may allow access to school sports facilities during weekdays after school or support extracurricular activities at weekends [141].

3.3.4 Exposures

A full list of exposure variables can be found in S1: Table 1: Exposure Variables. School level policy, social and physical environment features (n=98) – including break time length, physical activity

opportunities at school and hours of Physical Education (PE) per week – were self-reported by contact teachers at all schools in a survey based on a questionnaire previously used in schools in the East of England as part of the Speedy-3 Study [142]. The survey used to collect these features can be found in Supplementary Material 1: GoActive School Environment Survey. Individual level (n=3) friendship support for physical activity variables were derived using three items from the European Youth Heart Study [143] self-reported by participants in baseline questionnaires. Additional school level exposure variables (n=167) – including Office for Standards in Education (Ofsted) rating and school funding levels) were collected from publicly available data based on previous evidence [97] and after discussion with school-based physical activity promotion stakeholders from policy and practice. School funding levels and Ofsted overall effectiveness rating – which assesses schools on factors including motivational climate, school connectedness, teacher support of pupils, teacher leadership behaviours and teacher and pupil skill building [144] may provide insight into the challenging-to-measure school social environment. These data were obtained from the following website: <https://schools-financial-benchmarking.service.gov.uk/>.

3.3.5 Descriptive data and covariates

Sociodemographic data (age, sex, ethnicity, language spoken at home, religious affiliation, family structure, family SES and BMI) were self-reported by participants at baseline. Participants reported their ethnicity from 20 response options and values were recoded to the following categories: White; Mixed ethnicity; Asian; Black; Other ethnicity. Religious affiliation was reported from eight response options and values were recoded to the following categories: No religion; Any religion. Language spoken at home was reported from 26 response options and values were recoded to the following categories: English only; English and other language(s); Other language(s) not English). Participants reported one or two main care-givers from eight response options and family structure was recoded to the following categories: Birth Mother and Father; Any other family structure. Participants reported six items from the Family Affluence Scale [145] (family car ownership, holidays, computers, availability of bathrooms, dishwasher ownership and having their own bedroom) and values were summed (possible range 0-13) and used as a proxy measure of family SES (affluence: low =0-6, medium =7-9, high =10-13) [146]. Height and weight were recorded by research staff trained in anthropometric assessment and BMI z-score was calculated from height, weight, age, and sex [147].

3.3.6 Statistical analyses

Analyses followed two key steps, first, identifying the most important potential predictors of change in physical activity from the school environment using the LASSO, and second, testing these variables selected by the LASSO using regression. As a large number of school environment features plausibly relate to physical activity, the least absolute shrinkage and selection operator (LASSO) variable selection method was used to determine the features of the school environment that are most relevant to change in MVPA [148]. The LASSO is applied in Stata via the following format: Lasso (outcome variable) (list of potential predictors), (tuning penalty). The tuning penalty applied to the LASSO – which determines the amount of shrinkage applied by capping the sum of the absolute coefficients - was the Extended Bayesian information criterion which accounts for collinearity [149].

The LASSO provides an output of estimates of the coefficients of the list of potential predictors where excluded covariates have an estimated coefficient of zero (i.e., the potential predictors are unrelated). This covariate selection method suggests which school environment features are potentially most important for change in physical activity. These variables selected as potentially important by the LASSO were then added to a multiple linear regression model as exposure variables to identify features significantly associated with change in physical activity (outcome variable). Change in MVPA from 13 to 15 years (average follow up = 18 months) acted as the dependent variable and the school policy, social and physical environment features served as independent variables. Estimates of change in minutes per day of MVPA per 1-unit change in each independent variable were reported. As GoActive was a cluster-randomized controlled trial and this study used data from the whole cohort, treatment group (intervention and control) was added to each LASSO, along with adjustments for baseline physical activity, baseline BMI and sex. This process was repeated separately by sex (Male, and Female) and SES (Low, Medium, and High) to stratify the analyses, looking for differences in effect. To account for the non-independence of participants (clustering within schools and SES), robust standard errors were calculated. LASSO variable selection has previously been used to identify the most meaningful correlates of adolescent physical activity using self-report physical activity data [103]. The LASSO method is different from traditional approaches to variable selection such as the stepwise approach which uses p-values to determine which variables to include. Instead, the LASSO shrinks the absolute value of the magnitude of regression coefficients of unrelated school environment features to zero by regularization. The main driver for using this method was that a large number of school environment features plausibly related to change in MVPA. As this was an exploratory analyses, intended to test many potential predictors of change as a hypotheses-generating exercise, LASSO variable selection was used to allow only the most relevant school environment variables to physical activity to be included in the model. This was in order to produce a robust and parsimonious model via minimizing prediction error and improving interpretability [150]. The number of independent variables that regression analysis is capable of dealing with is a subject of

contention [151]. The LASSO approach is justified to counteract the rise in biases (e.g., overfitting, multicollinearity) when there are greater than five independent variables in a multiple regression equation [152]. To improve understanding of these findings, post hoc analyses were performed to explore the association between change in the variables selected by the LASSO and change in MVPA. Statistical analyses was performed in STATA version 15.1 [30] (using the lassopack (v1.2) installation package to run the LASSO. The analytical sample had complete data for all variables, where participants with incomplete data were dropped from the analyses. I made the decision to follow a “complete case analyses” method implemented in the GoActive intervention main trial analyses which operates under the assumption that follow-up data for the outcome variable was “missing at random”. Complete case analyses is the standard method of treatment for missing data and is completed through case wise deletion with the main advantage being simplicity of statistical analyses. Disadvantages of the approach, and therefore potential limitations of my analyses through loss of information, are potential reduced precision of estimates, and increase in bias through the breaking of the “missing at random” assumptions where the “complete case” samples are not able to be considered a random sample of all observations. Analyses of the impact of deviations from this assumption was performed for the main trial analyses (but not my analyses) and identified that, when simulating that participants with missing data were assumed to do 10 minutes per day of physical activity more and less relative to the mean level, the intervention effect and 95% confidence intervals were similar to the primary analyses [140].

3.4 Results

1765 participants (51% female) had both baseline and follow up physical activity data from which to derive change in MVPA. Participant characteristics are displayed in Table 2. Participants were predominantly of White British ethnicity, medium or high SES, had no religious affiliation, spoke English only at home, and lived in a traditional family structure.

Change in MVPA from baseline (Mean [SD]) (35.6 [18.6] min/day), to follow up (26.6 [21.1] min/day) was 9 min/day, a decline of around 25%, which is in line with the expected population decline during adolescence. The substantial variation in change (e.g., SD) at baseline and follow up allows for the required heterogeneity for these analyses.

Table 2: Baseline descriptive characteristics

	Male	Female
	n=879	n=906
Age (mean (SD) in years)	13.23 (0.42)	13.21 (0.41)
BMI SDS (mean (SD))	0.23 (1.19)	0.36 (1.20)
Ethnicity (N (%))		
White	740 (85.0)	789 (87.9)
Mixed/multiple ethnic background	66 (7.6)	39 (4.3)
Asian or Asian British	39 (4.5)	33 (3.7)
Black or Black British	17 (2.0)	21 (2.3)
Other Ethnic Group	9 (1.0)	16 (1.8)
Family SES (N (%))		
Low	89 (10.2)	114 (12.7)
Medium	345 (39.5)	401 (44.6)
High	439 (50.3)	385 (42.8)
Religious affiliation (N (%))		
No religion	662 (77.2)	674 (75.9)
Any religion	196 (22.8)	214 (24.1)
Language spoken at home (N (%))		
English only	795 (93.2)	824 (93.3)
English and other language(s)	16 (1.9)	21 (2.4)
Other language(s) not English	42 (4.9)	38 (4.3)
Family structure (N (%))		
Mother and Father	742 (85.2)	716 (79.6)
Any other family structure	129 (14.8)	184 (20.4)

3.4.1 Main analyses

A total of 267 school environment features were included in the LASSO variable selection technique, a full list of variables included in the LASSO is shown in S1: Table 1: Exposure Variables. Estimates of effects for the variables selected by the LASSO and included in the main analyses are shown in Table 3. No school policy or physical environment features were selected by the LASSO as potential predictors of change in MVPA. Only 3 variables (baseline MVPA, having a friend ask participants to do physical activities or play sports with them, and a participant asking a friend to do physical activities or play sports with them) were selected and added to the regression model when running the analyses with all participants. In this regression analysis, only greater baseline MVPA was found to be independently associated with lower change in MVPA.

Table 3: Estimated effects of the variables selected by the LASSO on change in MVPA during adolescence

Variable	All Participants	Boys	Girls	Low SES	Medium SES	High SES
Baseline MVPA	-0.54 (-0.65, -0.45)	-0.59 (-0.71, -0.47)	-0.47 (-0.64, -0.30)	-	-0.48 (-0.64, -0.32)	-0.58 (-0.72, -0.44)
Participant asks friends to do physical activity	-1.01 (-2.73, 0.71)	-0.63 (-3.57, 2.31)	-	-	-2.57 (-3.71, -1.43)	-1.76 (-3.61, 0.08)
Friend asks participant to do physical activity	0.65 (-2.17, 0.87)	-2.40 (-4.78, -0.02)	-	-	-	-

Estimates (β (95%CI)) are from linear regression models adjusted for other variables in the model. Estimates can be interpreted as change in average daily minutes of MVPA per 1-unit change in the independent variable. Bold denotes significant association.

3.4.2 Stratified analyses by sex

For boys (n=879), the LASSO selected the same 3 variables but only baseline MVPA and boys having a friend ask them to do physical activities or play sports with them were found to be associated with change in MVPA in the regression model. For every unit increase in number of times per week male adolescents have a friend ask them to do physical activities or play sports with them, a decrease in physical activity of (β (95%CI)) -2.40 (-4.78, -0.02) minutes of MVPA is predicted, as shown in Table 3. When repeating the analysis process for girls only, no school policy, social or physical environment features were selected by the LASSO and explored in regression analyses.

3.4.3 Stratified analyses by SES

For adolescents with a low SES, no school policy, social or physical environment variables were selected by the LASSO. For adolescents with a medium SES, the LASSO selected baseline MVPA and participants asking friends to do physical activities or play sports with them to be included in regression models. For every unit increase in number of times per week participants with a medium SES asked their friends to do physical activity or play sports with them, a change in physical activity of -2.57 (-3.71, -1.43) minutes of MVPA is predicted. For adolescents with a high SES, the LASSO selected having a friend ask them to do physical activities or play sports with them but only baseline MVPA was found to be significantly associated in regression models.

3.4.4 Post hoc analyses

Longitudinal associations between change in friendship support for physical activity and change in MVPA are shown in Table 4. For all participants, greater change in both friendship support for physical activity variables was associated with increased change in MVPA. For every unit increase in change in participants asking friends to do physical activity, a change in MVPA of 2.78 (1.55, 4.02) minutes per day is predicted. For every unit increase in change in friends asking participants to do physical activity, a change in MVPA of 1.80 (0.48, 3.11) minutes is predicted.

Table 4: Estimate effects of change in the variables selected by the LASSO and change in MVPA

Variable	All Participants	Boys	Girls	Low SES	Medium SES	High SES
Change in participant asking friend to do physical activity	2.78 (1.55, 4.02)	3.70 (2.12, 5.27)	1.22 (-0.47, 2.92)	2.73 (-1.57, 7.03)	3.18 (1.43, 4.92)	2.36 (0.24, 4.48)
Change in friend asking participant to do physical activity	1.80 (0.48, 3.11)	2.65 (0.84, 4.45)	0.25 (-1.49, 1.99)	3.42 (-0.13, 6.97)	1.47 (-0.23, 3.17)	1.75 (-0.19, 3.69)

Estimates (β (95%CI)) are from linear regression models adjusted for baseline variable values. Estimates can be interpreted as change in average daily minutes of MVPA per 1-unit change in the independent variable. Bold denotes significant association.

In sub-group analyses by sex, for boys only, positive associations were found for both measures of friendship support for physical activity; whereas, for girls only, no associations were found for either measure of friendship support for physical activity. In sub-group analyses by SES, positive associations were found for participants with a medium and High SES, but no associations were found for participants with a low SES.

3.5 Discussion

The primary objective of this study was to explore associations between the school policy, social and physical environment and change in adolescent MVPA. Of a possible 267 school environment features investigated, no school policy or physical environment features were selected as potential predictors of change in MVPA during adolescence and therefore none were explored via regression analyses in the main analyses. Potential explanations for the lack of associations are unenforced school policies, subjective physical environment features, and a disconnect between what the scientific community perceive to plausibly relate to physical activity and subsequently measure vs. what school environment features actually relate to adolescent physical activity. For example, scheduling of PE throughout the school day, presence of a PE uniform policy [153] or other, largely quantitatively untested features such as school friendship networks, and relationships with teachers [97]. In the main analyses, despite two social environment features being identified by the LASSO as potential predictors of change in MVPA, neither variable was significantly associated in a priori regression analyses. Significant associations were found in a priori analyses for boys (but not girls) and for participants with a medium SES (but not participants with a low or high SES) when exploring the influence of the school social environment and change in MVPA during adolescence. In post-hoc analyses, longitudinal findings revealed positive associations between change in the social environment and change in MVPA, in line with previous research highlighting the potential for harnessing the social environment to promote physical activity during adolescence [154, 155]. However, in sub-group analyses, only boys (not girls), and only adolescents with a medium and high SES (not low SES) had positive associations.

3.5.1 Main analyses findings

3.5.1.1 *The school physical environment*

No school physical environment features were identified as potential predictors of change in MVPA by the LASSO. In the most recent systematic review exploring the school environment and adolescent

physical activity [97], 17 studies were found that included a total of 8 unique exposures corresponding to the school physical environment. The only consistently associated physical environment feature found by Morton and colleagues was activity setting (e.g. presence of indoor gym, sports hall and increased physical activity), whereas access to physical activity or sports equipment was consistently not associated with physical activity. In this study, none of the 33 physical environment features explored (including activity setting and size, and access to physical activity or sports equipment) were associated with change in MVPA during adolescence. It may be possible that no associations were found because of the subjective measurement of school physical environment features which could have brought rise to self-reporting biases. However, no associations between the school physical environment and adolescent physical activity have been found in one study [156] while only weekday physical activity was found in another study [157] which both used geographic information systems (GIS) as the quantification method (the current gold standard). GIS-mapped neighbourhood walkability is associated with device-measured physical activity of adolescents [158]. As adolescents accumulate physical activity across many settings (e.g. the home, the neighbourhood, and during commuting), it is plausible that other physical environments may be stronger predictors of change in MVPA during adolescence. Furthermore, the relationship between the physical environment and adolescent physical activity can be moderated by the social environment [159]. A school with a physical environment that can plausibly support physical activity (e.g. excellent equipment and activity settings) but lacking of a social or policy environment that is supportive of physical activity may limit the potential beneficial impact of the physical environment on physical activity during adolescence [97].

3.5.1.2 The school policy environment

This UK study found no associations between the school policy environment measures (e.g. number of hours of PE provided per week, access to sports facilities and equipment at breaks and after-school) and change in adolescent MVPA. Significant and positive changes in physical activity have been found previously when school physical activity policies are implemented effectively in the USA [160]. School

physical activity policies can influence school practices by providing additional opportunities to be active throughout the school day [161]; however, schools face considerable challenges implementing physical activity policies. A lack of equipment, time, staff, and facilities can impede the implementation of school physical activity policies [162]. For these reasons, actual school practice surrounding physical activity may differ from official school physical activity policies [163]. There was not data on the fidelity of school policies but it is plausible that school policies (e.g. formal written physical activity policies) were tokenistic and not enacted. It may be worth exploring in schools in the UK whether improving the implementation of school physical activity policies has a positive impact on physical activity during adolescence. In order to improve implementation of school physical activity policies it may be necessary to bring rise to a wider shift within schools to a climate that is supportive of physical activity.

3.5.1.3 The school social environment

No school social environment features were found to be associated with change in adolescent MVPA after being identified as potential predictors of change by the LASSO. In the main analyses, a lack of association is at odds with previous findings which suggest that social support for physical activity is beneficial for adolescents [164, 165] perhaps due to differences in levels of motivation. A systematic review of systematic reviews found compelling evidence that having a companion for physical activity was one of the most evidence-based socio-cultural determinants of physical activity for adolescents [166]. Social support for physical activity includes any behaviour that could facilitate another individual to be active. Types of support friends may offer each other include emotional support (e.g. encouragement and/or praise), instrumental support (e.g. providing sports equipment to play with together), informational support (e.g. feedback or advice on physical activity), co-participation (performing physical activity with each other), and modelling of behaviour [115]. Encouragement and co-participation may be particularly important for adolescents, with consistent, positive associations being found between these factors and physical activity in adolescents [155, 167]. However, it has previously been shown that encouragement from friends to be physically active may be less important

for adolescents who have existing, and well-established physical activity habits [168]; hence a lack of association in this study may be explained by differences in intrinsic motivation where inactive participants feel like they require the support from their friends in order to participate in physical activity. This hypothesis assumes that adolescents who do not need to ask or be asked to do physical activity may already be intrinsically motivated to participate in physical activity which prevents a decline in physical activity for these adolescents. However, our longitudinal associations are more likely to reveal causal relationships since they account for fixed propensities to do activity that vary across individuals.

3.5.2 Longitudinal post hoc findings

A positive association between change in friendship support for physical activity and change in MVPA during adolescence was found. This finding is in line with the totality of the literature surrounding friendship support for physical activity. It has consistently been demonstrated that a positive association exists between friendship support for physical activity and physical activity during adolescence [115, 155]. Our findings lend support to the hypothesis that friendship support for physical activity may be an important mechanism for continued participation in physical activity throughout adolescence [168]. However, it is not possible to rule out that effects were not attributable to reverse causation, where an increase in physical activity prompted an increase in participants asking friends or being asked by friends to do physical activity. Further research is required to help explain how friendship influences physical activity during adolescence.

Friendships during adolescence may be positively or negatively influential on physical activity [169]. It has previously been demonstrated that girls receive less friendship support for physical activity than boys [170]. Friendship support for physical activity may have a greater influence on different types of physical activity, as stronger and more consistent associations were found between friendship support for physical activity and vigorous physical activities and competitive sports which may be preferred, at the population level, by boys [167]. Adolescents often report having a higher number of same-sex

friendships [171] and tend to rely upon their peers to define acceptable and desirable behaviours [172, 173]. A gendered culture within British secondary schools, where boys and girls are encouraged to participate in different physical activities; may bring rise to gendered social norms and explain differences in gender peer modelling [170]. Gender stereotyping of physical activities, where social norms consider certain physical activities to be masculine or feminine, can negatively impact physical activity participation in girls [174] as adolescents may be more likely to imitate the physical activity of their same sex peers [171] and girls are less likely to do sufficient physical activity [175]. Female adolescents may have fewer active friends (relative to boys) on which they can model desirable physical activity behaviours. Further investigation is needed to confirm these hypotheses in order to aid the development of interventions designed to overcome inequalities in physical activity between boys and girls.

An alternative explanation for the finding of a positive association for boys (and not girls), is differences in motivation for physical activity between sexes. Motivation is a significant predictor of physical activity during adolescence [176]. However, correlates and determinants of physical activity often differ by sex and variations in adolescent's motivation to be physically active have been found between boys and girls [177]. A difference in intrinsic motivation to participate in physical activity between boys and girls may also explain why a longitudinal, positive association was found between social support and change in MVPA in boys only. For example, boys may have higher intrinsic motivation to be active than girls and might seek more opportunities to participate in physical activity with friends.

3.5.3 Strengths and Limitations

The main limitation of this study was the subjective quantification of school environment features which may have brought rise to self-report biases. A further limitation is that I was only able to analyse the social environment features longitudinally and it was not possible to analyse the school policy, and physical environment features longitudinally. These analyses were exploratory, rather than

confirmatory. Selection/homophily or influence processes in adolescent friendship networks (e.g. whether individuals become friends and then friends influence physical activity during adolescence or whether friends select friends based on similarity in physical activity) is also a highly debated topic with mixed findings [178]. Therefore, selection bias within friendship groups may have impacted findings and identified variables should be considered potential correlates rather than causal mechanisms. It is also possible that effects were not found in participants with a low SES due to a small sample size. There is also currently no consensus in the existing literature on how to classify intensities of physical activity which brings rise to the possibility of a degree of misclassification. Only 16 secondary schools were included. This number of schools was limited as this data was drawn from a trial and the trial's sample size calculation indicated this was the required number of schools. The following parameters were applied to estimate the required sample size for the trial to detect a 5 minute difference in change in MVPA per day at follow-up: power = 85%, significance level = 5%, SD = 17.8 study), intraclass correlation coefficient = 0.034, correlation between baseline and follow-up MVPA = -.59, and average cluster size = 100. These values were based on the GoActive pilot and another large physical activity intervention in the East of England (Speedy-3). An estimated 1,310 participants were required for assessing primary effectiveness of the intervention with the aim of recruiting 16 schools with 150 participants in each school (2,400 total participants to account for potential drop-out. However, given purposive sampling, it is likely that the participants are not representative of the wider UK population (especially regarding ethnicity). Further implications of the limited number of schools included for my analyses is limited variability in school-level variables (e.g., school environment features). This may have negatively impacted the ability to detect associations with these variables. Strengths were the longitudinal, device-measured physical activity measurements and relatively large representative sample size. These longitudinal associations are more likely to reveal causal relationships since they account for fixed propensities to do activity that vary across individuals.

3.6 Conclusion

This study was an exploratory analyses, intended to test many potential predictors of change in MVPA within the school policy, social, and physical environment as a hypotheses-generating exercise. No policy and social environment features were selected by the LASSO as potential predictors of change in MVPA. Two social environment features were identified by the LASSO but were not associated with change in MVPA in the main analyses. Post-hoc analyses suggested friendship support for physical activity could be harnessed to increase adolescent physical activity levels. Making changes in the school environment to promote friendship support for physical activity may increase adolescent physical activity [179]. Future research to better understand the school social environment, in particular exploring how friendships during adolescence influence physical activity via social network analysis, may provide insight into how to prevent the decline in physical activity during adolescence.

Given that the school social environment, and in particular friendship support for physical activity was identified as potentially important for change in adolescent physical activity in these analyses; there is a need for further analyses of the social environment and friendship's potential influence on health during adolescence. Due to technological innovation, and in the wake of the Covid-19 pandemic, friendship dynamics are increasingly taking place in the online social environment, e.g. social media. However, little is known about how social media use relates to adolescent BMI z-score, and energy-balance-related behaviors. In part two of this thesis, I explore these relationships.

4 Chapter 4: The online social environment and adolescent adiposity

4.1 Introduction to Thesis Part Two

The preceding chapter suggested friendship support may be potentially important for physical activity during adolescence. Part two of this thesis explores relationships between the adolescent social environment, social media and adolescent adiposity. The shift in focus to the social environment, and in particular the online social environment (e.g. social media use) was driven by two key reasons. First, as friendships during adolescence grow in salience, coinciding with technological advances and social changes in the wake of the Covid-19 pandemic, adolescent friendship dynamics increasingly play out online on social media. Second, was due to my evolving interests in technology use, and the potential health consequences of adolescent obesity throughout the life course. The present chapter (Chapter 4) expands upon the brief introduction to social media use during adolescence provided in Chapter 1, General Introduction. Here I provide a detailed overview of the descriptive epidemiology of social media use during adolescence, potential benefits and harms of social media use for adolescent health, and a discussion of why adolescents may be particularly prone to the influence from social media use which may present opportunities for psycho-education and interventions to prevent obesity and sub-optimal health behaviours. This narrative review chapter is intended to set the scene for and provides a rationale for the ensuing data analysis studies which examine the cross-sectional, and longitudinal relationship between social media use and BMI z-score across two studies in Chapter 5, and 6. The chapter is broadly split into the first section which focuses on the social environment, offline friendships and obesity, which is followed by the second section, an in-depth review of the literature on social media use, adolescent health behaviours and adiposity in adolescents.

4.2 Defining the social environment

The social environment is most widely defined as *“the conditions which shape norms, enforce social control patterns, and provide or inhibit opportunities to engage in specific behaviours”* [180]. I will apply this definition in my thesis.

4.3 Adolescents are particularly open to influence from the social environment

Trying new experiences (“sensation seeking”) is common during adolescence due to maturing brain systems supportive of decision-making [181]. This means that, in comparison to adults, adolescents appear particularly open to influence from their social environment as adolescents are routinely presented with new opportunities from friends, teachers, and commercial entities. A heightened openness to change provides opportunities for intervention to improve adolescent health (e.g. through obesity prevention and physical activity promotion). However, sensation seeking also increases adolescent vulnerability to commercial exploitation as companies aim to secure the next generation of consumers (e.g. through targeted marketing on social media [182]). Adolescents’ social environment predominantly includes their parents, teachers, and friends. While supportive families and school connectedness during adolescence are protective for adolescent health problems [183] adolescents may be particularly prone to influence from their friends due to social changes including adjustment of attention and motivation towards peers, status and prestige [123]. For example, compared to children under 10 years, adolescents spend greater amounts of time with their friends (vs. their family). As adolescents reorient to their friends, they become more prone to the effects of peer influence on risk-taking, risk perception, and reasoning while being hypersensitive to social exclusion [184]. Although puberty and cognitive development are mostly determined by biology; the majority of psychological and social development is dependent on environmental influences [185]. Due to these factors, the social environment, and particularly friendships, during adolescence is particularly important for health [186-188].

4.4 Social environments can consist of offline friendships, online friendships, or both

Friendship groups form a part of social networks and are structured hierarchically based on frequency of interaction and emotional closeness where interaction time and emotional closeness are positively correlated [189]. As displayed in Figure 9 below, human's social network layers broadly follow a layer format including layers of 5, 15, 50, 150, 500, and 1500 individuals. Each level, from 5 to 1500 individuals, corresponds to reduced interaction time and emotional closeness [189]. The first three network layers (5-50 individuals) may, in general, include family members, and friends with the primary limiting factor of network size being finite social time [190]. The outer layers of social networks may include acquaintances, and may be limited by the most number of faces humans can recollect the name of (1500 individuals) [191]. This structure however is relatively static and needs updating in light of the new ways in which friendships and networks can play out online.

Figure 9: Social network structure

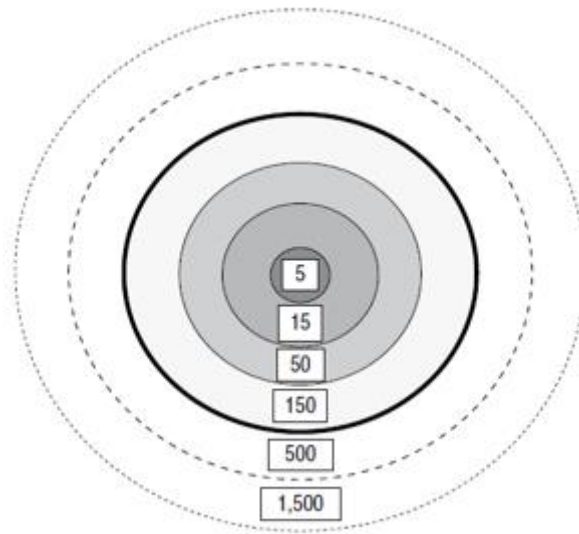


Figure taken from: Dunbar, R. I. M. (2014). "The Social Brain." Current Directions in Psychological Science **23**(2): 109-114.

Humans (both adults and children) spend about 20% of their waking time in social interaction (22.5 hours/week) with around 40% of this time invested in interacting with their first network layer (their five closest social relationships who individuals tend to rely on for emotional support) [192]. The layer of 15 individuals is known as the “sympathy group” and tends to be individuals who provide high-cost instrumental support (e.g. loans, help with projects, child care) whereas the layer of 150 individuals may provide low-cost support (e.g. information) [189]. Time as a finite resource is relevant in the discussion around friendships, and particularly social media use due to concerns around displacement of time from health-promoting activities given that social media enables the engagement with a much larger network more frequently, and for a longer duration.

Whilst there are limits in offline social networks to the number of people humans can communicate with (due to time constraints), there is no limit to the number of people humans can interact with online due to the permanence and accessibility of posts. Hypothetically there is greater potential for more acquaintances in the various spheres of social network structures via online social networks as adolescents can have hundreds or even thousands of others within their online networks. This is especially true because the term “friend” is often used more loosely online in studies comparing online vs offline adolescent friendships [193]. However, research in online communication has suggested that digitally-mediated communication mirrors face-to-face communication in so far as individuals with large networks do not devote more time to communication with weaker connections (e.g. those in the outer layers) and spend a large amount of time communicating with a relatively small number of individuals (mirroring the inner layers) [190]. There is a limit to network size in humans due to cognitive constraints and the time cost of maintaining relationships [191]. There is evidence to suggest that social media is not able to overcome cognitive constraints and the time cost of maintaining relationships as the “inner layers” of networks are of similar sizes offline and online [191]. This is of note because there is increasing support for the theory that online friendships may emulate offline friendships in some aspects (e.g. communication with the inner layer of social networks) [190] but there is gaps in our understanding of how friendships operate online (e.g. friendship support

mechanisms). This is relevant for adolescent health because the hypothesis follows that if adolescents have strong/beneficial offline friendships, it may be likely that their online friendships are also beneficial. As identified in Chapter 3, friendship support for physical activity was associated with change in adolescent physical activity. However, the evidence base surrounding online friendships is comparatively less advanced when compared to offline friendships. For example, as will be discussed in the following section, offline friendships have been suggested to be related with adiposity and energy-balance-related behaviours; however it is currently unclear how online friendships, and specifically time spent using social media influence adiposity and energy-balance-related behaviours.

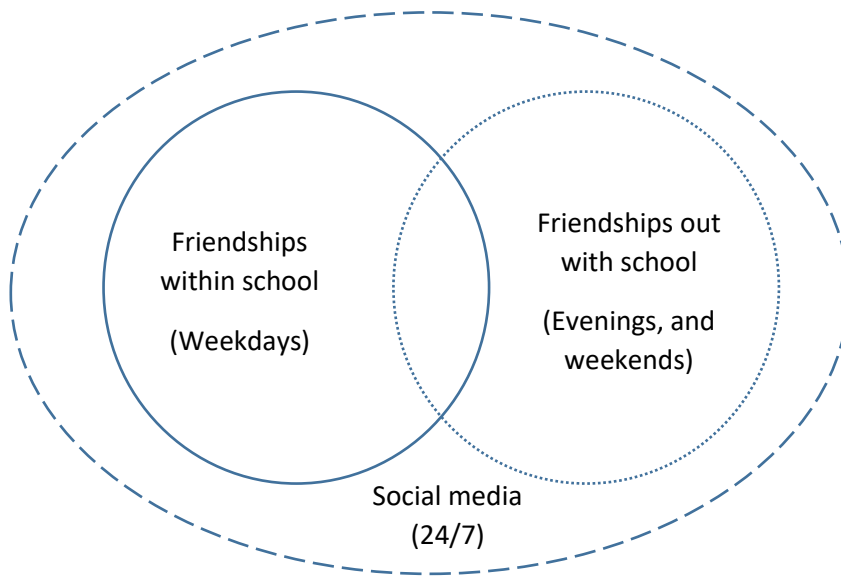
4.5 Friendships and adolescent obesity

Friendships become increasingly important during adolescence and with that form a key influence on the development of obesity. Many changes occur in adolescents social environment during the formative years of adolescence including an increase in the number of peers (e.g. from transitioning from primary to secondary education). Adolescents also spend increased time with friends relative to time spent with family where social reorienting causes friends opinions to become more important than family opinions [6]. Adolescent's increased sensitivity to peer influence and hypersensitivity to social rejection increases the likelihood of both risky and pro-social behaviour when adolescents are with their peers [17]. In line with my finding in Chapter 3 that greater friendship support for physical activity was associated with increased change in physical activity, this has led researchers to believe friendships are factors of an adolescent's social environment which are particularly important for adolescent health. Given that adolescents spend a third of their waking time in school, the school setting is commonly viewed as a key environment in which friends may have an influence on adolescents (as discussed in Chapter 1). However, in society social media use is now highly prevalent during adolescence and high levels of social media use enables friends to have a greater potential influence on adolescents in other ways, and out with school time (as show in Figure 10). Friendships' potential influence on adolescent obesity and physical activity in the offline social environment (e.g.

school), and in the online social environment (e.g. social media) are the key focusses of this thesis. Therefore a focus on friendship influences on obesity in adolescence is relevant.

It is important to understand potential mechanisms underpinning social influences on adolescent obesity to better understand why, how and when peer effects are potentially important for adolescents (e.g. why friendship support, and social media use may be influential). The literature investigating these influences is summarised below.

Figure 10: Social media and the potential for friendship influence



4.5.1 Potential mechanisms underpinning friendships' influence

Friends acting as per their friends during adolescence (either through selecting friends with similar behaviour, or being influenced by their friends' behaviour) has been demonstrated in a variety of health areas including smoking, substance abuse, physical activity, and obesity [188, 194, 195]. Broadly speaking potential mechanisms underpinning friendships' influence on adolescent obesity are social support, behavioural modelling, social norms, and social comparison [196]. All of these factors may contribute to why friendships may influence adolescent adiposity. In Table 5, I briefly define the most salient theories underlying these mechanisms and then contextualise as to how these mechanisms, and friendship are closely linked to adolescent health behaviours, and further downstream, measurable health outcomes such as obesity. Although these potential mechanisms all can plausibly operate via social media; these have not been tested.

Table 5: Potential mechanisms underpinning friendship influences on adolescent adiposity

Potential Mechanism	Description	Example related to adolescent adiposity
Social support	<p>An individual's provision of psychological and material resources intended to benefit an individual's ability to cope with stress [197]</p> <p>Social support can be segmented into four types; emotional, instrumental, appraisal, and informational [198]</p>	<ul style="list-style-type: none"> • Emotional support can include being empathetic, reassuring, and expressing care [197] • Instrumental support involves meeting tangible needs such as the assistance with daily tasks (e.g. collecting groceries, cooking, cleaning) [198] • Appraisal support assists with decision-making, or provision of feedback [198] • Informational support may comprise the sharing of advice, information, or instruction [198]
Behavioural modelling	The observation of behaviours conducted by others, and reproduction of those actions [199]	<ul style="list-style-type: none"> • Adolescent behavioural modelling of consumption of sugar-sweetened beverages [200]
Social norms	Rules and standards that are understood by a group that guide and/or constrain social behaviours [201]	<ul style="list-style-type: none"> • Sedentary behaviour at break times in schools
Social comparison	The process people use to evaluate their actions, accomplishments, and opinions in contrast to those of other people [202]	<ul style="list-style-type: none"> • Frequency of consumption of fast foods

4.5.2 Friendship's influence on obesity and obesogenic behaviours

Whilst classically conceptualised as a non-communicable disease, obesity is thought to potentially 'spread' between social connections [39] and friendships during adolescence may directly and indirectly influence adiposity [40]. Within the area of obesity, in addition to obesity-related behaviours of adolescents being associated with those of their friendship group [203]; BMI has also been found to cluster within adolescent friendship groups [204] and adolescents tend to have friends with similar weight status to their own [205]. For this reason, energy-balance-related behaviours may be "contagious" and if adolescents have friends with health-promoting energy-balance-related behaviours there may be protective effects on BMI. Whereas adolescents with friends who have harmful energy-balance-related behaviours, adolescents' personal choices to live a healthful life may be more challenging. These are potential social mechanisms for how overweight and obesity spreads between friendships during adolescence (e.g. social norms, and behavioural modelling surrounding food, and physical activity choices as discussed in the previous section).

Self-reported behaviours of adolescents relating to diet may be associated with those of their friends. For example, an adolescent may be more likely to eat in fast food restaurants if their friends do (National Longitudinal Survey of Adolescent Health data from 3,898 adolescents in the USA) [206], adolescents may also have similar screen-based behaviours, and frequency of consumption of high-calorie foods to their friends (based on data from a social network analysis of 13 to 14 year olds from two independent middle schools in a major Australian city, and a systematic review of 13 to 19 year olds from 32 studies) [203, 207]. Only one study identified in this systematic review, a cross-sectional survey study in the USA, explored the relationship between adolescents' and their friends' beverage consumption and found a significant positive association for high school friend groups diet soda and sports drinks, while for "best friends" significant positive associations were found for regular soda, and energy drinks (n=2,043 adolescents, aged 14 years, 80% non-White) [208].

A systematic review of 13 observational studies has shown that friendships during adolescence may influence physical activity [209] but the existing literature base is largely comprised of cross-sectional examinations (9 of 13) using self-report physical activity measures (8 of 13) which bring rise to biases [210] (e.g. social desirability bias). Cross-sectional research is problematic in this research area because it is not possible to disentangle friendship selection and influence processes or make causal inference. It has been demonstrated using device-measured physical activity, which are more representative of actual physical activity levels (vs. self-report) of 10 to 11 year olds [211, 212], that physical activity is associated in same-sex, school-based friendship networks. Friends may influence adolescent's physical activity through various ways, including modelling of behaviour (as discussed in the previous section), but also via co-participation, encouragement [213] [210], and peer victimization [214]. Greater friendship support for physical activity has been found to be the most consistently associated social support type with increased physical activity [215].

Sex differences in friendship support for physical activity have been found with boys self-reporting to receive more friendship support for physical activity than girls [216] which may partially explain differences in physical activity levels worldwide as girls may have fewer sufficiently active friends upon which to receive support from, or model their behaviours [171] (as discussed in Chapter 3, section 3.5.2); although as mentioned previously, most of this evidence is cross-sectional in nature. With regard to sex differences in friendships' influence on physical activity, one cross-sectional study from Brazil found that encouragement may be more important for girls, whereas co-participation may be more important for boys (n=2,859 adolescents age 14 to 19 years) [215]. Girls may also rely more on an individual friend's support for physical activity while boys may prefer being active with a friendship group [213]. Interaction effects for associations between adolescents and their friends weight-related behaviours have also been found for sex elsewhere [207]. This means that the influence of friends on weight status may differ between boys and girls. Sex differences in friendships' influence on physical activity may also play a role in the association between social media use and adolescent adiposity

being different between boys and girls due to it being unclear how these social support factors translate to social media. However, it is unclear whether this association is different and this is a key research gap which will be covered in more detail in the next section.

The previous section introduced the social environment during adolescence and explained why adolescents may be particularly prone to friendship's influence on physical activity and obesity, through a discussion of potential mechanisms of influence. In light of technological advances and social changes in the wake of the Covid-19 pandemic friendship dynamics also, and increasingly so are playing out online. Social media use during adolescence has grown in popularity and has become the default option for communication for adolescents. In the next section, I will introduce the online social environment and explain why, in addition to the factors outlined in the previous section, adolescents may be particularly prone to the influence of social media use through a discussion of key definitions, trends, and relevant theories linking social media use to health outcomes. This section sets the scene for two subsequent analyses in Chapter 5, and 6 that address the key research gaps identified.

4.6 Adolescent social media use

4.6.1 Social media use: Definitions and terminology

There are different definitions of social media use available which provide varying levels of detail. Below I expand upon the most widely used definition of social media which I discussed in Chapter 1, section 1.12.1 (social media is “a group of internet-based applications ... that allow the creation and exchange of user-generated content” [122]). I do this to help shape my discussion of the different functionalities of social media use which are not alluded to in the widely used definition.

“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” [217].

The above definition comes directly from the reference manuscript. I think this definition is gaining traction due to the inclusiveness for the multifaceted ways in which social media can be used (e.g. publicly vs. privately, bi-directionally vs. uni-directionally - i.e. actively consuming content by responding to messages, commenting on posts vs. passively consuming content either from friends or strangers/celebrities) and varying ways in which social media can be interpreted. The definition also includes a consideration for the fact that social media is increasingly being accessed by different means for example through watches, and vehicles which blur the lines between online and offline settings [217].

Social media is present in most aspects of adolescents social lives, which via different combinations of features, tools and technological interfaces facilitate peer-to-peer communication [218]. Participants in social media have unique identifiable profiles which may comprise of both content supplied by the user, and by other users on the site. Social media sites also have the capability of showing the connections of users, and allowing users to consume and interact with user-generated content (written, video, or image-based). Most social media platforms provide channels to communicate with friends and other users. Users may include friends, celebrities, news organisations, and strangers.

Examples include traditional social networking sites comprising messaging platforms which facilitate direct communication between individuals (e.g. Facebook, and Twitter). But may also include sites such as discussion forums (e.g. Reddit), or online dating sites (e.g. Bumble).

4.6.2 Social media use and adolescent friendships

Adolescents suggest social media benefits their friendships. However, it is likely that the Covid-19 pandemic may have influenced social media use and opinions about social media heavily (although there is a lack of data on this topic). All of the following is drawn from data collected pre-pandemic unless stated. Adolescents state that they use social media for similar reasons to traditional methods of communication including to stay in touch with friends, organising plans, and making stronger connections with others [125]. However, this evidence is drawn from a narrative review of 13 USA-based studies, of which 8 studies are based on findings from undergraduate students with the age range omitted [125]. This is a key limitation of the literature surrounding social media use during adolescence given both a lack of investigations in general, and of the few studies completed, most provide insufficient information to allow replication. It has been suggested that the primary reason for adolescents using social media is for friendship maintenance (as opposed to making new friends) in the face of declining offline contact [191]. Adolescents reported using social media to feel more connected with their friends (81% of 743 adolescents surveyed in the USA), and access social support during tough times (68%, with no further info provided regarding specific types of support, e.g. emotional, instrumental, etc.) [219]. Drawing from other studies, in the context of social media, social support may include minor actions such as engaging with social media posts (e.g. “liking”) with “likes” on posts being described as a virtual form of gift-giving [193]. Other core qualities of offline friendships may translate into the online environment, for example: self-disclosure, validation, companionship, instrumental support, conflict, and conflict resolution [193]. The potential visibility and permanence of posts on social media may also change the characteristics of online friendships [193]. However, this study is also a narrative review of studies (n=36, predominantly USA-based) with a broad inclusion criteria out with adolescence (e.g. young adults up to aged 30, and children under

10 years) which would be challenging to replicate given the limited methods reported. This means that there is a clear gap in our understanding of how social media use relates to adolescent friendships. To understand how friends may influence adolescents via social media it is important to understand to what extent, when and how social media is used by adolescents.

4.6.3 Social media measurement

Given that social media use is multi-faceted, as discussed in section 4.2, questions remain as to how to capture the multidimensionality of the behaviour, which consist of time, frequency, time of day, access tool (e.g. PC vs tablet vs smartphone), platform, type of activity, type of content consumed, etc. The most common approach in the literature to date to measuring social media use is through self-reported quantity of social media use (e.g. hours per day). In theory, self-reported measurement of social media use is inexpensive, and easy to collect alongside other metrics via surveys. However, social media use has varying patterns of use, comprising of irregular and often fleeting periods of use across most locational settings (e.g. at the dinner table, commuting, in bed) which makes it especially difficult to recall accurately. Self-reported social media use has low validity due to being retrospective and data collection is removed from when social media was used [220].

Other methods of measuring social media use exist, although are used infrequently in the literature (e.g. ecological momentary assessment, where in-situ measurement occurs with little or no time-lag from when social media is used). Objective measurements of social media use (e.g. through extraction of social media use duration from an individual's smartphone screen time) are rare in the literature base to date [221]. This is usually due to ethical challenges, institutional red tape, and unwillingness of participants to share their social media use data. This is currently a key limitation of studies in the field of social media research.

4.7 Descriptive epidemiology of social media use during adolescence

4.7.1 Smartphone ownership

In 2022, the global smartphone penetration rate was 78% [222]. In the UK, for adolescents aged 16-24 years, smartphone ownership in 2021 was 99% (vs. 66% in 2012) [223]. Smartphone ownership is also common for adults living in low-and-middle-income countries, with little data available on adolescent smartphone ownership in these settings [222]. In the UK, 90% of adolescents primarily access social media via their smartphone [224]. Increasing adolescent smartphone ownership, as shown in Figure 11, has accelerated adolescent's access to and use of social media and increased adolescents' capacity to be influenced by friends and other users, including commercial entities.

Figure 11: Smartphone ownership in the UK, by age

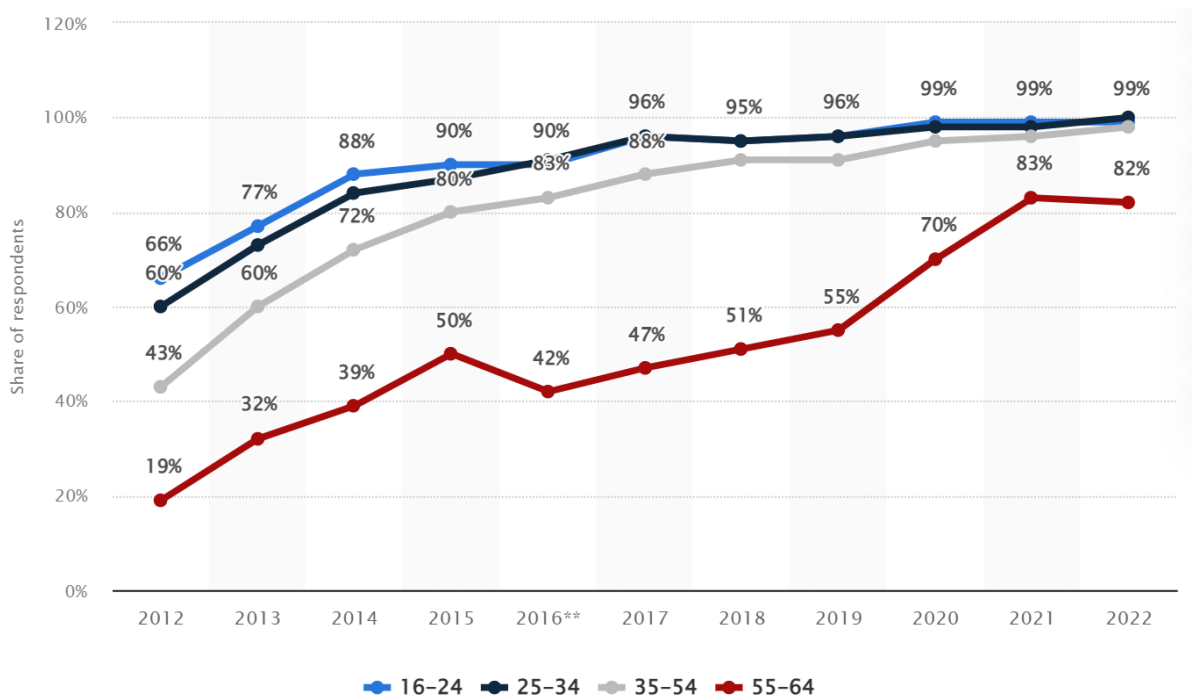


Figure taken from: Statista (2022). "Smartphone ownership penetration in the United Kingdom (UK) in 2012-2022, by age." from <https://www.statista.com/statistics/271851/smartphone-owners-in-the-united-kingdom-uk-by-age/>.

4.7.2 Social media use frequency

Social media use during adolescence is widespread and adolescents may spend as much as a fifth of their waking time per week using social media [128]. Two surveys from the USA and the UK respectively will be discussed throughout the next few sections relating to adolescents' social media use frequency, platform preferences, and demographic differences.

The Pew Research Centre's survey of adolescents' (aged 13 to 17 years) use of digital devices, social media and other online platforms is one of the most frequently referred to resources for inferring adolescent social media use worldwide. The 2022 analyses surveyed 1,316 adolescents in the USA and was conducted online from April 14th to May 4th 2022 by Ipsos (a market research company) [225]. The survey is weighted to be representative of USA-based adolescents who live with their parents by age, gender, race, ethnicity, and household income. Figure 12 shows USA-based adolescents social media use from the Pew Centre's survey. The survey reported that more than 1 in 3 adolescents (35%) reported using social media "almost constantly" [225]. Most adolescents (55%) perceive using social media "about the right amount of time" whereas around one third said they "spent too much time on social media".

In the UK, a comparable survey (the Ofcom Children and Parents: Media use and attitudes report) has collected data on self-reported social media use during childhood and adolescence (aged 8 to 17 years) on an annual basis. The most recent survey contains data collected from 6,622 children in the UK across two data collection phases (c.3,300 children per wave) via online panels from July to August 2021, and September to October 2021 [224]. The report suggests 91% of adolescents aged 12-15 years use social media, with this proportion increasing to 97% at age 16 to 17 years. 90% of adolescents aged 12 to 17 years are reported to access social media via their own smartphones. Although no further information is available regarding quantity, or frequency of use; 59% of children aged 8 to 17 years said social media made them feel happy, while 61% said it made them feel closer to their friends. When compared to 2018 (pre-Covid-19 pandemic), only 69% of children aged 12 to 15 years had social

media sites (although these data were drawn from the 2019 iteration of the Ofcom survey which had a different methodological approach to the one discussed earlier of using in-home interviews with 1,430 children aged 8 to 15 years, with no data being collected for adolescents aged 16 to 17 years) [226]. From Millennium cohort study data (n=11,872 adolescents aged 14 years), which will be discussed in further detail in Chapter 5, UK adolescents may spend between 7 to 21 hours/week using social media [128].

Figure 12: USA-based adolescent social media use (aged 13-17 years)

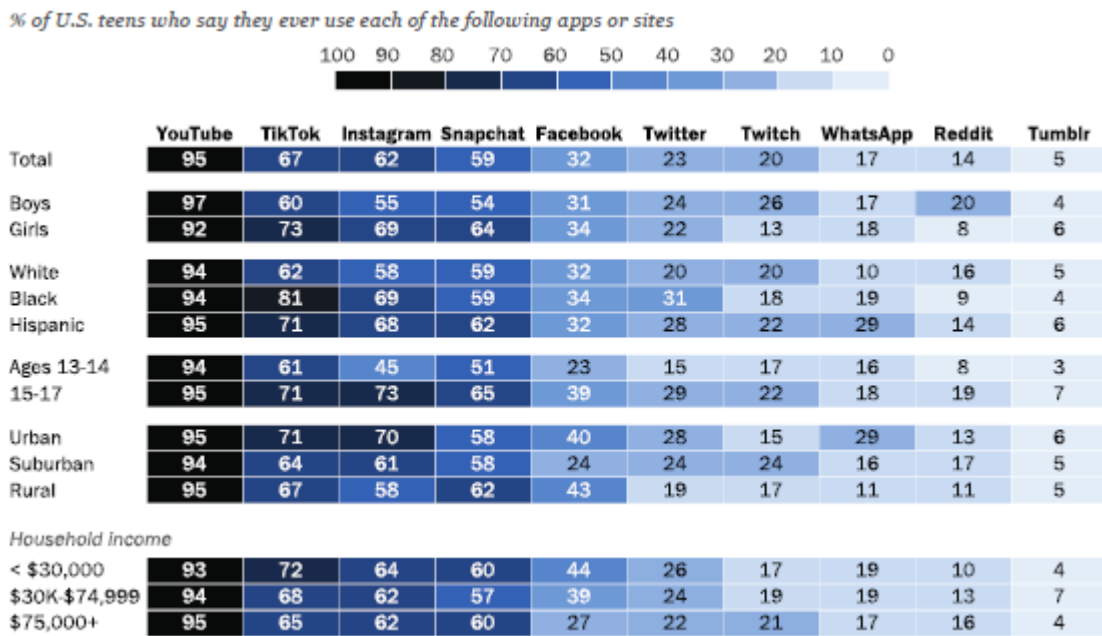


Figure taken from: Pew Research Center (2022). "Teens, Social Media and Technology 2022."

4.7.3 Social media use platform preferences

Figure 13 shows adolescent social media use platform preferences and how these have changed over time. The Pew Research centre's survey identified that the most popular social media sites for adolescents in the USA are now Youtube (95% of adolescents reported 'ever using'), TikTok (67%), Instagram (62%), and Snapchat (59%) in the year 2022 [225]. The percentage of adolescents in the USA saying they ever used Facebook was 32%, down from 71% in the previous survey (2014-2015) with both Youtube, and Tiktok not being recorded in the 2014-2015 survey (TikTok launched in 2018).

Figure 14 shows UK children's (aged 3 to 17 years) use of online social media platforms drawn from two waves of the Ofcom survey data (2018, and 2022). Although it is not possible to differentiate by adolescents preferences only, the data suggest the most popular social media site in 2022 for UK-based children is Youtube followed by Whatsapp, and Tiktok [224]. There was also a continued increase in use from 2018 for the three social media platforms investigated (Facebook, Snapchat, and Instagram) in adolescents aged 12-15 years [226].

These data highlight that what is being accessed on social media is a moving target which makes research challenging as social media preferences may change quicker than research can be undertaken and reviewed causing it to risk becoming a lagging indicator if new approaches to data collection are not adopted. However, given that it is currently unclear whether specific platforms have different associations with adolescent adiposity, a logical first step is to explore the relationship with overall quantity of social media use (e.g. hours per day).

Figure 13: USA-based adolescents switching social media platform preferences

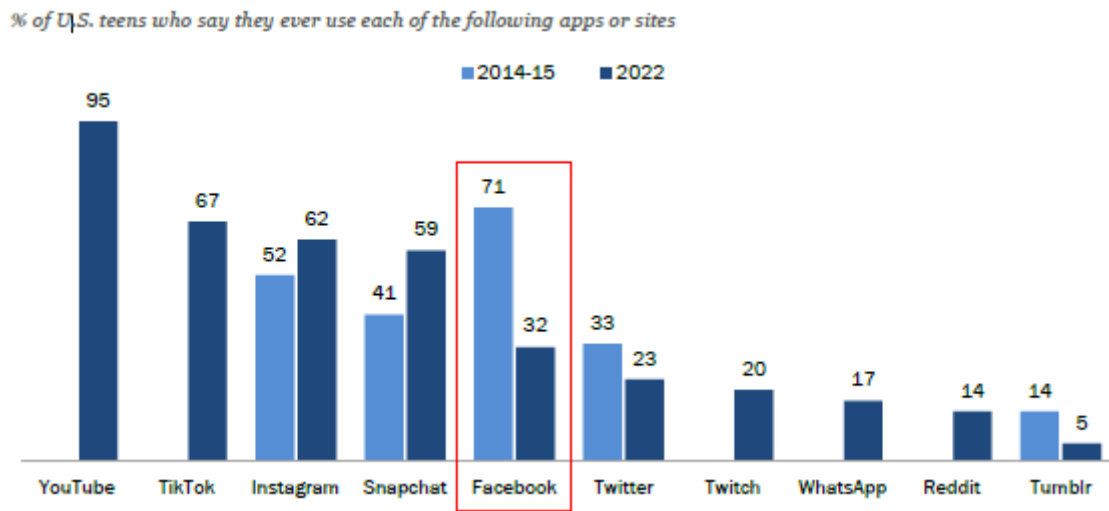


Figure taken from: Pew Research Center (2022). "Teens, Social Media and Technology 2022.". Red box added to highlight decline in Facebook use

Figure 14: UK-based children switching social media platform preferences, 2017 to 2022

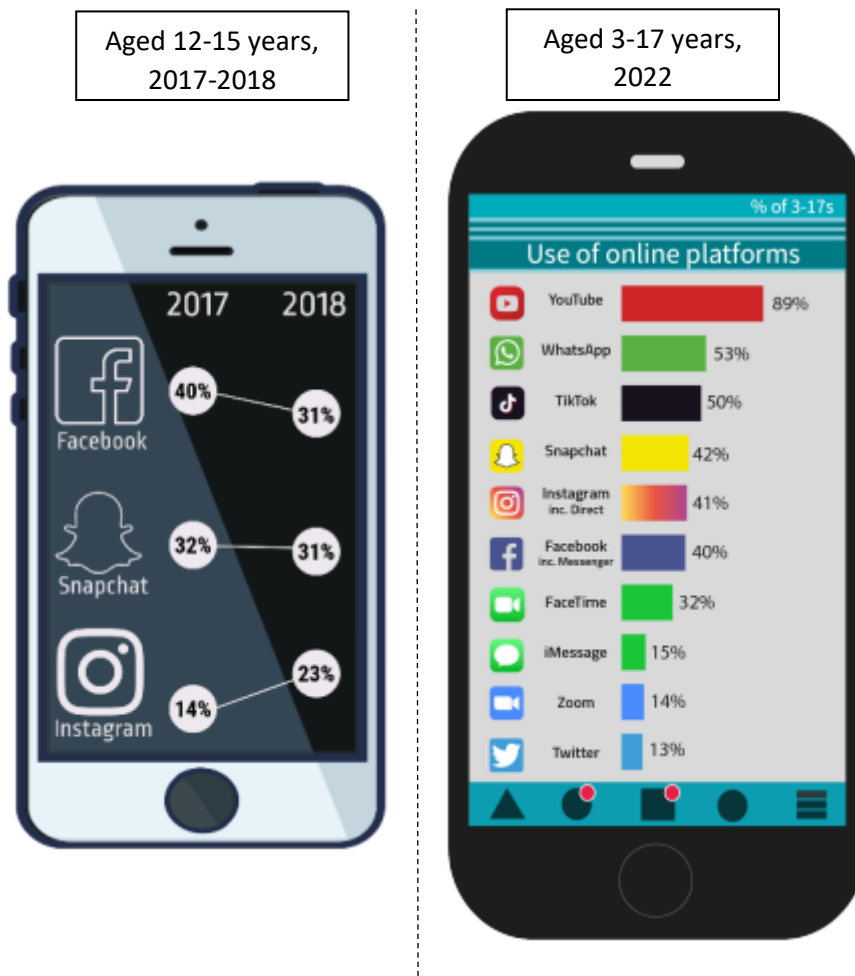


Figure taken from: Ofcom (2022). Children and Parents: Media use and attitudes report 2022. And Ofcom (2019). "Children and parents: Media use and attitudes report 2018." Text boxes showing differences in ages added.

4.7.4 Social media use demographic differences

The Pew Research Centre's 2022 survey also highlighted some demographic differences in USA-based adolescents social media use. For example, boys (vs. girls) were more likely to report use of Youtube, Twitch, and Reddit; whereas girls (vs. boys) were more likely to use TikTok, Instagram, and Snapchat. More black and Hispanic adolescents also reported using TikTok, Instagram, Twitter, and WhatsApp compared with White adolescents. Whereas "high social media users" (defined as >10 times per day) are more likely to be girls, White, and have parents who work in manual occupations [227].

The Ofcom survey does not distinguish between boys and girls in terms of levels of use, but suggested UK-based boys may be more likely than girls to report that Youtube was their favourite social media platform [224]. Girls (aged 5 to 16 years) were more likely to use Tiktok every day (48% vs. 34% of boys). However, the survey suggests social media use may also differ between boys and girls in other ways which may relate to adolescent adiposity. For example, girls (aged 12 to 17 years) reported being more likely to use social media to send supportive messages to their friends if they were having a hard time (75%, compared to 47% of boys) [224].

In summary, social media use has increased in prevalence in USA, and UK-based adolescents from 2017 to 2022. Our understanding of total time spent on social media is stronger for adolescents living in the USA compared to the UK. Given high social media use, and the fact that social media use is predominantly a sedentary behaviour, it is important to identify whether social media use is related to adolescent adiposity. Reported differences in social media use cases between boys and girls suggest that a potential association between social media use and adolescent adiposity may also differ between boys and girls; however, this is a clear research gap.

4.8 Mechanisms underpinning the potential influence of social media use on adolescent adiposity

In recent times, a number of theories and potential mechanisms have been proposed to explain the potential influence of social media on adolescents' health, and adiposity. I have selected and will discuss the six main relevant, salient and most widely recognised theories, including the Displacement

hypothesis, the “Rich get Richer” hypothesis [228], the Social-compensation hypothesis [229], the Goldilocks hypothesis [230], Goffman’s theory of strategic self-presentation[231], and Cultivation theory[232]. Table 6 shows the hypothesis behind each theory/potential mechanism and how they could relate to adolescent adiposity. I then discuss the extent of existing evidence supportive of these theories. As will be discussed in the next section little evidence exists within the context of adolescent adiposity to suggest which theories may be most relevant; although all theories may be plausible, our understanding of social media use is currently limited. There is a gap in our understanding of, if social media use relates to adolescent adiposity, what the explanatory pathway variables explaining this association are.

Table 6: Potential mechanisms explaining the influence of social media use on health, and adiposity

Potential Mechanism/Theory	Hypothesis of theory	How theory potentially relates to adolescent adiposity
Displacement hypothesis	Time spent on social media may displace time spent participating in other activities protective of adolescent health	Displacement of: <ul style="list-style-type: none"> • Physical activity • Sleep • Time spent engaging with offline friends to improve mental health • Time spent engaging with family members
The “rich get richer” hypothesis	Those with strong (vs. weak) offline friendships and social skills will benefit most from social media [228]	Existing friendship influences are enhanced, for example, adolescents who have friends with health-promoting energy-balance-related behaviours may experience protective effects on BMI which exceed those of adolescents with harmful energy-balance-related behaviours
The social compensation hypothesis	Social media will benefit socially anxious or isolated individuals more than individuals with strong offline friendships [229]	Adolescents who do not have access to friends with health-promoting behaviours offline may gain access to these health-promoting behaviours online
The goldilocks hypothesis	Technology use at moderate levels is not intrinsically harmful and may be advantageous [230]	There may be benefits of moderate social media use, whereas excessively low or high social media use may have negative consequences for adolescent adiposity

Theory of strategic self-presentation	The tendency for individuals to present themselves in a way that furthers their own agenda [231]	Viewing edited photos on social media use may bring rise to a negative impact on weight status through a potential explanatory pathway of impaired body weight satisfaction
Cultivation theory	Extended exposure to media content results in a perception that the media content portrays reality [232]	Skewed perceptions around society's definition of attractiveness may bring rise to psychological problems

4.8.1 The displacement hypothesis

The displacement hypothesis suggests that time spent on social media may displace time spent participating in other activities protective of adolescent health (e.g. physical activity) [233]. Few studies have explored the displacement hypothesis in the context of adolescent adiposity. There is evidence to suggest that high overall social media use is related to poorer sleep outcomes, with timing of use around bedtime strongly predicting poor sleep independent of overall social media use [234]. This is suggestive of a sleep displacement mechanism. Sleep and physical activity were also suggested to be displaced by social media use in girls, but not boys (n=12,866 adolescents aged 13 to 16 years in the UK [233]).

4.8.2 The “rich get richer”, social compensation, and “Goldilocks” hypothesis

The “rich get richer” hypothesis suggests that individuals with strong (vs. weak) offline friendships and social skills will benefit most from social media [228]. In opposition to the “rich get richer” hypothesis, the social compensation hypothesis suggests that social media will benefit socially anxious or isolated individuals more than individuals with strong offline friendships [229]. The goldilocks hypothesis suggests technology use at moderate levels is not intrinsically harmful and may be advantageous in this context [230]. There is no studies that have explored the use of the hypotheses in relation to screen-viewing and adolescent obesity. Within the context of adolescents’ feelings surrounding closeness to their friends, there is evidence supportive of the “rich get richer”, and social compensation hypotheses [235]. Whereas there is also evidence within the research area of adolescent wellbeing in support of the “Goldilocks” hypothesis [230]. More research in this area is therefore needed.

4.8.3 Goffman’s theory of strategic self-presentation

Goffman’s theory of strategic self-presentation describes the tendency for individuals to present themselves in a way that furthers their own agenda [231]. To reinforce this theory, Goffman used a metaphor to describe a dramaturgical approach to life whereby individuals view themselves as

“actors” who keep control over what members of society see as the “audience” [231]. Social media can facilitate greater control over how individuals portray themselves online with evidence suggesting that it is common for individuals to remove undesirable photos of themselves which are uploaded by other users (84% of n=112 individuals surveyed reported “untagging” photos, mean age = 29.54 years) [236]. Online self-presentations of individuals have also been found to be misleading when evaluated by their offline peers [237]. Social media allows adolescents to share information with one or many individuals with different levels of truthfulness, and openness. For example, social media users have reported not checking in at fast food restaurants due to the potential embarrassment of being seen to be there (n = 3 of 18 adults interviewed in the USA, no age reported, no data from adolescents available) [193]. Research suggests that, although social media facilitates self-disclosure, adolescents curate information that they share dependent on who will access the information [125]. This phenomenon has led to social media being described as the “highlight reel” of an individual’s life where social media posts are skewed towards their most positive life experiences [238] which are often perceived as representative by adolescents [239]. This false impression may heighten upward social comparison and bring rise to a negative impact on weight status through a potential explanatory pathway of impaired body weight satisfaction. However, no evidence of this exists and this is a clear research gap.

4.8.4 Cultivation theory

Cultivation theory suggests that extended exposure to media content results in a perception that the media content portrays reality [232]. Implications of the cultivation theory is best understood by interpreting in specific contexts. Within the context of adolescent obesity, this can result in skewed ideals of the value or disvalue of a certain body type and the internalization of these ideals as society’s definition of attractiveness [240]. Greater social media use has been found to be associated with the internalization of a thin ideal in a meta-analysis of females; a potentially harmful consequence exacerbated by the widespread use of digital editing software to “achieve” unrealistic beauty ideals [232] which may also further self-objectification [241]. Internalization of a thin, and muscular ideal as

a result of social media use has also been reported in boys [242]. This internalized ideal may be unattainable for many adolescents and bring rise to body dissatisfaction and psychological problems which impact BMI via eating disorders, depression, and low self-esteem [243]. However, the evidence base is weak surrounding these potential explanatory factors and there is a need for further research.

4.8.5 Advertising

Content viewed on social media, such as advertisements, may also shape energy-balance related behaviours and adiposity in adolescents. Commercial advertisements are rife on social media platforms with global social media advertising spend projected to reach almost USD 226B in 2022 [244, 245]. Adolescents may see as many as 900 food adverts in an average week [246, 247], and exposure to food cues in advertising is associated with increased intake of snack foods among children [248]. Increased snacking due to social media use may also occur at abnormal times which could negatively impact on sleep quality and duration [249]. Meta-analysis findings have demonstrated that adolescents sleeping for shorter durations (vs. adolescents sleeping for longer durations) had twice the risk of living with overweight or obesity [250]. An additional danger of social media is that messages are increasingly being designed for mass audiences which are seemingly interpersonal/individual when in reality are carefully crafted by teams of social media groups or automated, algorithmic processes [217]. These falsely personal, and arguably unethical interactions can influence decision-making processes (e.g. through advertising) and bring rise to risky behaviour (e.g. excess consumption of calories [248]).

In the previous section I introduced social media use, its descriptive epidemiology, explained why adolescents may be particularly prone to the influence of social media use, and introduced mechanisms underpinning the potential influence of social media use on adolescent health (which may be potential explanatory pathway variables, but is currently unclear). In the next section I review what is currently known about the relationship between social media use and adolescent health.

4.9 Narrative review of social media use and adolescent health

4.9.1 Historical concerns surrounding new technologies

There has historically been concerns of potential negative health implications when new technologies emerge and are adopted in society (e.g. the telephone, television, and internet). Diffusion of innovations is the process by which an idea or technological innovations spreads within and is adopted by society [251]. In line with the diffusion of innovations theory, adolescents are often early-adopters of new technologies, including social media, due to their predisposition to sensation seeking [7] (see section 4.3). This heightens concerns about social media from adults who are generally “laggard adopters” [252]. Increasing social media use during adolescence has driven rising concerns from parents, teachers, clinicians, researchers, government officials, and (even some) adolescents that social media use may bring rise to negative consequences (e.g. health, academic, social). In the next section, I will present the existing evidence on the association between social media use and health outcomes to explore the scientific evidence for these concerns.

4.9.2 Methods of narrative review on social media use and health outcomes

I performed a narrative review to study the relationship between social media use and outcomes relating to mental and physical health in all age groups. I included peer-reviewed, original research studies only (e.g. no editorials, or pre-prints), written in English, regardless of age given the limited research available conducted in adolescent populations. I restricted my search to apparently healthy populations only (e.g. I excluded papers focussing on pregnancy, intellectual disabilities, severe mental illness, etc.). I also excluded studies aiming to identify mental health status of individuals based on social media posts (e.g. natural language processing, with no measures of mental health). Studies focussing on health promotion via social media use (e.g. access to health information, engagement via social media use) were also excluded. To focus on the most relevant evidence and for logistical reasons I reviewed the top 10 pages of two databases (PubMed, and Google Scholar, ordered by best match) in September 2022. I used the following search terms: “social media” AND (“mental health” OR

“physical health” OR “obesity”). Given the relative infancy of the social media use literature, I included all studies type (e.g. observational, experimental, cross-sectional, longitudinal, and qualitative). I chose to undertake a narrative review vs. a systematic review based on having published four systematic reviews previously which meant I was keen to allocate my time to other professional developmental goals (e.g. using new analytical methods in other chapters which I had no experience in and required me to invest more time in undertaking training courses in these skills). The implication of these results not being drawn from a systematic approach is that included studies were selected based on a less stringent selection criteria, data evaluation and syntheses are a qualitative summary of results rather than a pooled estimate across studies which could be generated from a clearly defined and focussed research question, and implications drawn are not concrete based on a comprehensive, structured appraisal of the literature.

4.9.3 Results of narrative review on social media use and health outcomes

Overall my search returned 122 unique studies (78 overlapping studies between databases), of which I included 47. S2: Table 2 describes the included studies. Included studies are presented in alphabetical order. Main findings reported are those of the study authors. This is a biased sample as the narrative review did not follow a systematic evidence-based criteria. Not reported in S2: Table 2, but discussed in the following section, are a few additional studies which were not identified in my search of the literature but were identified through independent, more specific searches prior to undertaking this review (e.g. for high quality studies). These may not have been identified because the databases have a bias for showing more recent manuscripts, and/or the search strategy was not exhaustive to encapsulate all potential key words.

The majority of papers were cross-sectional (n=28 studies) with only 5 studies reporting on prospective results. There were 14 reviews, with the majority not providing sufficient information relating to methods used to allow replication. Most sample sizes were small to moderate (defined as n = <1,000 adolescents), and the majority of studies had been undertaken in Europe (N=12 studies), USA (7 studies) or China (5 studies). Most papers reported on associations with mental health (45 studies) with one study each discussing sleep, cyberbullying, racial discrimination, and alcohol and illicit drug use, respectively. Only one identified study explored the relationship between social media use and adiposity in adolescents. A second study exploring this relationship was identified through independent search of the literature prior to undertaking the narrative review. Most studies used depression (self-reported on a variety of scales) as the outcome measure, and social media use (self-reported, hours per day) as the exposure. For both mental, and physical health, and specifically adolescent adiposity the evidence base relating to social media use is weak. Given limited research identified, most investigations reported on are individual cross-sectional studies with self-reported outcomes, which dominate the literature. These findings, although valuable as preliminary evidence of potential associations in absence of higher-quality evidence, should be interpreted cautiously with greater weight being afforded to the systematic reviews mentioned below.

4.9.3.1 Mental health

Table 7 synthesizes the strength of potential association between social media use and respective mental health outcomes identified in my search of the literature.

Table 7: Strength of evidence of the potential association between social media use and mental health outcomes

Outcome	Strength of Evidence	Rationale
Self-harm and suicidality	Weak	Although several systematic reviews have been completed with a large sample size, findings are inconsistent (e.g. direction of association) and social media use is largely self-reported
Anxiety and depression	Moderate	Several systematic reviews, including a review of reviews have been completed, but findings are weak and inconsistent with regard to the direction of association
Increased risky behaviours (e.g. drug use, risky sexual behaviours)	Weak	Only one systematic review was identified which suggested a positive association. However, all studies included used cross-sectional approaches
Alcohol and illicit substance use	Weak	Only one systematic review was identified which suggested a positive association. However, all studies included used cross-sectional approaches
<p><u>Key (based on my own method of critical appraisal)</u></p> <ul style="list-style-type: none"> • Weak: little evidence has been undertaken • Moderate: the evidence base has been reviewed in several systematic reviews but findings are inconsistent, or the evidence is formed predominantly from cross-sectional, self-report approaches • Strong: several systematic reviews have been undertaken with consistent findings, using longitudinal approaches and device-based measurements 		

Investigations have primarily been correlational, have been undertaken in adults samples, and systematic reviews have presented mixed findings (small positive, negative, and null associations [129]). For this reason, there is not strong evidence of the association between social media use and mental health as the evidence base is inconsistent. What follows is a list of potential harms reported in the literature. However, caution in interpretation is required given many of these assertions (unless stated) come from single studies, using self-reported summary measures of social media use, and small sample sizes which may not be representative.

Harmful consequences of social media use during adolescence reported in the literature include increased risk of self-harm and suicidality (via normalisation, triggering, and competition) (systematic review of 46 studies, positive association for 11 studies of a combined 38,191 participants, negative association for 18 studies of 119,524 participants, and mixed findings for 17 studies of 35,235 participants, all aged under 25 years [297]). A further concern is regarding the potential association with anxiety and depression with a systematic review of 13 studies (12 cross-sectional) suggesting a small positive correlation [298]. However, the research base is divided with a review of reviews (n=25 studies) suggesting the relationship is weak and inconsistent [293]. Increased risky behaviours (e.g. substance use and risky sexual behaviours) have also been reported in a systematic review of 27 cross-sectional studies (n=67,407 adolescents) [299]. Alcohol and illicit drug consumption are often advertised, endorsed, and even glorified on social media with a meta-analysis of 19 observational studies showing a significant positive association between young adults' exposure to social media use and self-reported alcohol consumption [300].

Although there are fears surrounding excessive social media use during adolescence, in an increasingly technology-mediated world, there are likely also many benefits of adolescents engaging in social media. From review of the literature, the benefits of social media have been comparatively understudied (vs. potential harms). Social media use may have a mixed effect on adolescent's mental health. Social media use could positively influence adolescents' social capital (n = two cross-sectional studies) [301, 302]. Social media use could also increase adolescents' (mean age not reported) quality

of life through self-identity exploration, aspirational development, and increased self-esteem (n=3 studies) [303] [304, 305]. However, the authors' who suggested this, in the same study, undertook meta-analysis of 121 studies which found a small negative association between social media use and self-esteem, and suggested that the alternate hypothesis of social media use being beneficial for self-esteem was understudied [306]. Social media use may also serve as an avenue at which children receive social support, maintain friendships (self-reported by adolescents) [307], and build digital and interpersonal skills for future positions within the workforce (hypothetical based on expert commentary) [129]. Sub-groups of adolescents, including adolescents with social anxiety (n=15 studies) [308] or adolescents who feel ostracised or stigmatised, (e.g. members of ethnic, racial, gender, and sexual minority groups) are also potentially able to connect with others to receive support and emotional validation on social media that they may not have access to offline [307]. For example, due to barriers including place of residence or financial restrictions preventing participation in social activities. For these adolescents, establishing intimacy online may be preferred due to the ability to have more time to curate responses [193] which lends support to the social compensation hypotheses (as mentioned in section 4.8.2). The social compensation hypothesis suggests that social media would be more advantageous for individuals with weak offline friendships by allowing them to foster social connection online which is unavailable offline while also overcoming a potential stigmatized or constrained identity, or lack of social connection (n = one cross-sectional study) [229]. These individuals may participate in social media via text-based, anonymous channels which facilitate a representation of their true or idealized self-image (n = one cross-sectional study, 1,312 adolescents) [309] (i.e. ethnic or sexual minority adolescents).

4.9.3.2 Social media use and adiposity

Compared with the adolescent mental health literature, there are fewer investigations into social media use and adolescent physical health. Only one study was identified looking at the relationship between social media use and C-reactive protein, whereas only two studies were identified investigating the relationship between social media use and adolescent BMI. These examinations were

both cross-sectional, used self-reported BMI, and had mixed findings relating to sex-specific associations [121, 310]. In these two studies, greater social media use was found to be associated with increased BMI in Iranian adolescents (aged 12 to 17 years, n = 1,860) [121] and boys (but not girls) in a Canadian cohort (n=4,991, mean age = 15.1 years) [310]. Our understanding of the relationship between social media use and adolescent adiposity is currently weak and there is a need for further study which uses measured BMI and longitudinal methods. In Chapter 5, and 6 I undertake this research to fill this research gap.

4.10 Chapter 4 Conclusions

Social media use is highly prevalent during adolescence. Adolescents may be particularly prone to the influence of social media. Social media has expanded the adolescent social environment and heightened friendships capacity for potential influence due to 24/7, digitally-mediated access to their friends. Given the breadth of friendships an adolescent can have online, and the importance that adolescents place on the online environment that encourages long-term use; it is important to understand how social media use relates to adolescent health. I reviewed the potential benefits and harms of social media use for adolescent physical, and mental health. The existing research base is dominated by a focus on the relationship between social media use and adolescent mental health; however, the evidence is inconsistent with studies suggesting both no association, small positive associations, and small negative associations. The evidence base surrounding social media use and the relationship with adolescent adiposity is broadly weak in conclusiveness as existing studies (n = two studies) are limited by self-reported measurement of BMI, single time point data collection, and small sample sizes. My narrative review of the literature identified a key research gap in the literature base in that the relationship between social media use and adolescent obesity is unclear. Given high prevalence of social media use during adolescence, there is a need for further research in the area on the association between social media use and objectively-measured BMI z-score during adolescence. In Chapter 5, and 6 I provide further evidence towards the relationship between adolescent social media use and BMI cross-sectionally, and longitudinally.

5 Chapter 5: Social media use and BMI z-score: a cross-sectional explanatory pathway analysis of 10,798 14-year-old boys and girls

This work is accepted for publication in *Pediatric Obesity*.

This work was selected as an oral presentation at the European Childhood Obesity Group conference, Budapest, 2021 (cancelled due to the Covid-19 pandemic).

I designed the study alongside Esther van Sluijs. I conducted the analyses and interpreted the results with support from Stephen Sharp. I drafted the manuscript. Russell Jago, Stephen Sharp, Andrea Smith, and Esther van Sluijs reviewed and provided input to the manuscript preceding this chapter.

This chapter is the second of three analytical chapters and comprises a cross-sectional analyses of the relationship between social media use and BMI z-score in 14 year old boys and girls living in the UK enrolled in the Millennium Cohort study.

5.1 Abstract

Purpose: The association between adolescent time spent on social media use and body mass index z-score (BMI z-score) is unclear. Pathways of association and sex differences are also unclear. This study examined the association between time spent on social media use and BMI z-score (primary objective) and potential explanatory pathways (secondary objective) for boys and girls. **Methods:** Data are from 5332 girls and 5466 boys aged 14 years in the UK Millennium Cohort Study. BMI z-score was regressed on self-reported time spent on social media use (h/day). Potential explanatory pathways explored included dietary intake, sleep duration, depressive symptoms, cyberbullying, body-weight satisfaction, self-esteem, and well-being. Sex-stratified multivariable linear regression and structural equation modelling were used to examine potential associations and explanatory pathways. **Results:** Using social media for ≥ 5 h/day (vs. < 1 h/day) was associated with increased BMI z-score for girls (β [95% CI]) (0.15 [0.06, 0.25]) (primary objective, multivariable linear regression). For girls, the direct association was attenuated when sleep duration (0.12 [0.02, 0.22]), depressive symptoms (0.12 [0.02, 0.22]), body-weight satisfaction (0.07 [-0.02, 0.16]), and well-being (0.11 [0.01, 0.20]) were included (secondary objective, structural equation modelling). No associations were observed for boys and potential explanatory pathway variables were not examined. **Conclusions:** In girls, high time spent on social media use (≥ 5 h/day) was associated with increased BMI z-score, and this association was partially explained by sleep duration, depressive symptoms, body-weight satisfaction, and well-being. Associations and attenuations between a self-reported summary variable of time spent on social media use and BMI z-score were small. Further research should examine whether time spent on social media use is related to other adolescent health metrics.

5.2 Background

The previous section of this thesis identified that social media use may be associated with adolescent adiposity, however few investigations have explored potential associations. This study seeks to provide evidence towards this research gap.

I have previously mentioned how widespread overweight and obesity is during adolescence and the need to identify underpinning factors due to related costly chronic diseases (see Chapter 1).

Understanding the factors associated with obesity during adolescence can underpin the development of obesity prevention efforts. Social media is increasingly driving adolescent social interactions and may be directly and indirectly associated with obesity [121]. Although there is no agreed definition, social media can be defined as “a group of internet-based applications ... that allow the creation and exchange of user-generated content” [122] (e.g. Facebook, Twitter, Instagram, and Youtube). In 2018, the Pew Research Centre [311] found that 51% of adolescents (aged 13-17 years) in the USA used Facebook, 72% used Instagram, 85% used YouTube, and 45% self-reported to be online “almost constantly”. In the UK in 2019-2020, before the Coronavirus pandemic, 67% of adolescents aged 12 to 15 years self-reported having social media accounts [126]. This increased to 87% in 2020-2021 [312]. UK adolescents spend between 7 to 21 hours/week using social media [128]. Adolescents may be particularly reactive to social media due to the increased emotional sensitivity and evolving reflective processing and cognitive control experienced during this age range [313]. Few studies have explored the association between social media use and measured BMI z-score among adolescents. Existing findings are inconclusive, present contrasting findings (e.g., sex differences and magnitude of effect), and use self-reported height and weight [310, 314] which is subject to measurement error. It is important to enhance the understanding of the association between social media use and BMI z-score to identify the role social media use may play in the burden of obesity during adolescence.

Social media has been suggested to impact BMI z-score in adults via body weight satisfaction, psychological problems [232], dietary intake [315], and sleep [249] but few studies have examined

these potential mechanisms in adolescents. A range of energy-balance–related behaviours relating to social media use plausibly influence BMI and are reported in the literature. These include diet, physical activity, sedentary behaviour and sleep. For example, on Youtube, food and beverage ads may be the most common type of advertisements viewed by children [245] with a study finding that 13 out of every 14 videos featured food or beverage cues (in a sample of 380 videos popular with children created by two social media influencers in the UK with a combined 26 million “followers” [316]). Frequency of watching social media influencer’s vlogs has been shown to be related to children’s consumption of unhealthy beverages two years later [317] and exposure to food cues in advertising is associated with increased intake of snack foods among children [248]. Increased snacking due to social media use may occur at abnormal times which could negatively impact on sleep quality and duration [249].

Meta-analysis findings have demonstrated that adolescents sleeping for shorter durations (vs. adolescents sleeping for longer durations) had twice the risk of living with overweight or obesity (n=11 longitudinal studies comprising 24,821 participants; aged 0.5 to 18 years; OR [95% CI] = 2.15 [1.64-2.81] [250]). The positive association between high levels of social media and poorer sleep patterns (in particular late sleep onset) may be independent of wellbeing [128, 318]. Given that most social media use is sedentary, one could assume that adolescents with high social media use may also have high levels of sedentary behaviour. In absence of research examining the relationship between social media use and sedentary behaviour, drawing from the screen-based behaviour literature, screen time (excluding food advertising) is consistently associated with increased dietary intake [319].

Social media use patterns differ by sex, with girls more likely than boys to have high levels of social media use (equivalent to 4 to 5 hours/day on average) than low social media use (equivalent to around 0 to 2 hours/day on average) (OR [95%CI] 2.02 [1.22, 3.34]) [320]. Social media use may influence boys and girls differently, for example the association between social media use and poor mental health and magnitude of mediation by cyberbullying and sleep has been shown to be stronger in girls

than boys [321]. To guide future research and inform health policy around social media use, it is important to examine whether explanatory pathways differ by sex [322]. This study examined (1) the sex-specific association between social media use and measured BMI z-score (primary objective), and (2) potential explanatory pathway variables of this association (dietary intake, sleep duration, depressive symptoms, cyberbullying, body weight satisfaction, self-esteem, and wellbeing) (secondary objective).

5.3 Materials and Methods

5.3.1 Study sample

This study used data from a nationally representative sample of British children in the Millennium Cohort Study. This is a birth cohort study of around 19,000 children that began in September 2000 and included all children born between 1 September 2000 and 31 August 2001 (for England and Wales), and between 24 November 2000 and 11 January 2002 (for Scotland and Northern Ireland). The study used a stratified, clustered random sampling design, and oversampled from disadvantaged areas and areas with high ethnic minority populations [323]. This study used data from the Age 14 wave (n=11,872 children) that were collected between January 2015 and April 2016. This wave was selected because early adolescence is understudied in social media research [313] and height and weight were directly measured at this age. Although previous findings have been found to differ by periods of adolescence (e.g. early, mid, and late); I chose to focus on early adolescence (10-14) [324] in this study. Early adolescence is relatively understudied in this research area using objective BMI measurements while early-stage adolescents may be particularly sensitive to social media influence via social rejection and acceptance processes, peer influence, and emotion precedence [313].

5.3.2 Outcome measure: BMI z-score

Height (in metres [m]) and weight (in kilograms [kg]) were measured by trained Research staff using a Leicester height measure and Tanita scale, respectively. BMI (kg/m^2) was derived. One improbable BMI value ($<10 \text{ kg}/\text{m}^2$) was removed from the dataset, in line with two previous studies in this cohort who removed improbable BMI values <10 and $>50 \text{ kg}/\text{m}^2$) [325, 326]. BMI z-score was then calculated based on UK 1990 growth centiles [327].

5.3.3 Exposure: Social media use

Participants self-reported their social media use in private during home visits via computer assisted questionnaires. Questionnaires asked "On a normal week day during term time, how many hours do you spend on social networking or messaging sites or Apps on the internet such as Facebook, Twitter

and Whatsapp?” and selected from the following response options: “None”, “less than half an hour”, “half an hour to less than 1 hour”, “1 hour to less than 2 hours”, “2 hours to less than 3 hours”, “3 hours to less than 5 hours”, “5 hours to less than 7 hours”, and “7 hours or more”. Based on established methods for this dataset [276] responses were collapsed into four categories: “0 to less than 1 hour”, “1 to less than 3 hours”, “3 to less than 5 hours”, and “5 or more hours”.

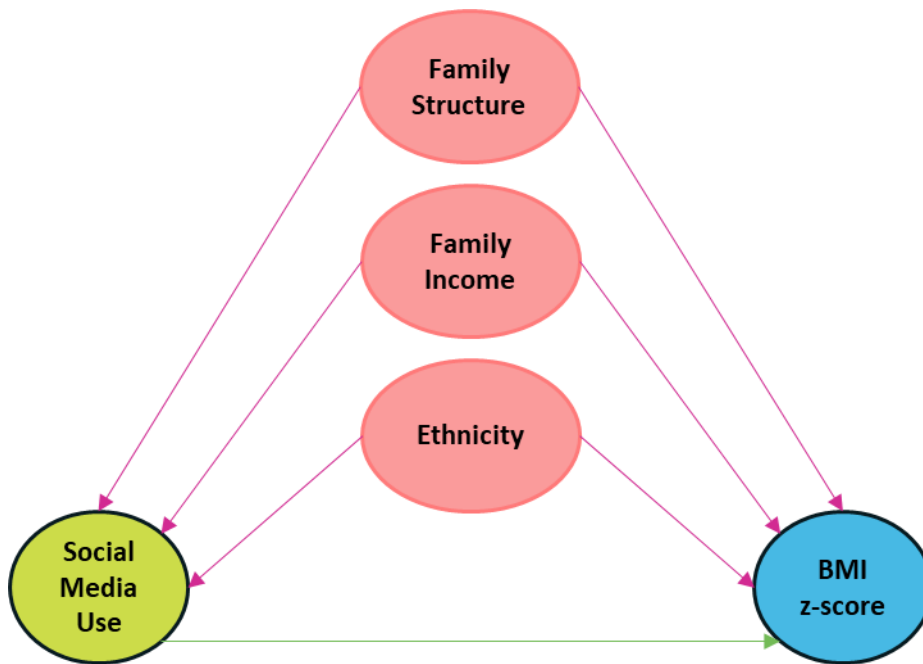
5.3.4 Descriptive data and covariates

Age, ethnicity, and household characteristics were used to characterise the sample. Sex (self-reported) was used to describe the sample and to explore sub-group differences in association. Age was calculated from date of birth and age at measurement. Participants self-reported their ethnicity from 19 response options (e.g., “White Scottish”, “Asian/Asian Scottish”, “Black/Black Scottish”), responses were collapsed into 8 categories: “White”, “Mixed”, “Indian”, “Pakistani”, “Bangladeshi”, “Black Caribbean”, “Black African”, and “Other Ethnic group (including Chinese)”. Participants self-reported their parent(s)/carer(s) in their household from 17 response options (e.g., “Natural Mother”, “Adoptive Father”, and “Sibling”). Family structure was dichotomised as: “Two parents/carers”, and “One parent/carers”. Family income served as a marker of participant’s socioeconomic status, was reported by parents, and was disaggregated into quintiles.

Three potential covariates were added to a Directed Acyclic Graph (DAG) based on existing research into adolescent BMI. These were ethnicity, family income, and family structure which informed the analyses, and these three variables were added to models as covariates. Only these covariates, were added due to the risk of too many covariates causing problems of overfitting in the model, due to unavailability of data (e.g., parental social media use, physical activity, sedentary behaviour) and due to the presumed direction of association whereby variables were considered and explored as potential explanatory pathway variables rather than covariates (e.g., dietary intake, sleep, depressive symptoms, cyberbullying, body weight satisfaction, self-esteem, and wellbeing).

Figure 15 displays the DAG.

Figure 15: Directed Acyclic Graph for the study of the association between social media use and BMI z-score with the covariates family structure, family income, and ethnicity



Notes: Unidirectional arrows show the direction of presumed association. Family structure, family income, and ethnicity are presumed to cause (or be a marker for a cause) of both the exposure (social media use) and the outcome (BMI z-score). Confounding is presumed to be present when assessing the association between social media use and BMI z-score. The minimal sufficient adjustment sets for estimating the total effect of social media use is family structure, family income, and ethnicity.

5.3.5 Potential explanatory pathways

Based on previous evidence (presented in the introduction), the following factors served as potential explanatory pathways: dietary intake, sleep duration, depressive symptoms, cyberbullying, body weight satisfaction, self-esteem, and wellbeing.

5.3.5.1 *Dietary intake*

Participants self-reported how frequently they consume fruit (“How often [do you] eat at least 2 portions of fruit?”), and vegetables (“How often [do you] eat at least 2 portions of vegetables) from the following response options: “Never”, “Some days, but not all days”, “Every day”. Participants self-reported how frequently they consume fast food (“How often [do you] eat fast food?”) and sweetened beverages (“How often [do you] drink sweetened beverages”) from the following response options: “More than once a day”, “Once a day”, “3-6 days a week”, “1-2 days a week”, “Less often but at least once a month”, “Less than once a month”, “Hardly ever or never”. Fruit and vegetable consumption variables were reverse coded, dietary intake variables were summed (range 4-20) and lower values denoted worse dietary intake. Given the larger range of response options for fast food and sugar-sweetened beverage consumption, these items contributed more to dietary intake summary scores. Dietary intake was included for analyses due to previous research suggesting associations between obesity and weight-related behaviours and fast food, soft drink, fruit, and vegetable consumption during adolescence [328-330]. Given the larger range of response options for fast food and sugar-sweetened beverage consumption, these items contributed more to dietary intake summary scores.

5.3.5.2 *Sleep*

Sleep duration was derived from self-reported time going to bed and waking up. Participants self-reported the time they usually go to sleep at on a school night (“About what time do you usually go to sleep on a school night?”) from the following response options: “Before 9pm”, “9-9:59pm”, “10-10:59pm”, “11-midnight”, “After midnight”. Participants self-reported the time they usually wake up in the morning on a school day (“About what time do you usually wake up in the morning on a school

day?") from the following response options: "Before 6am", "6-6:59am", "7-7:59am", "8-8:59am", "After 9am". Sleep duration was calculated for each participant and responses were collapsed into the following 4 categories: "7 hours or less", "8 hours", "9 hours", "10 hours or more" as per previous methods in this dataset [128].

5.3.5.3 Depressive symptoms

Depressive symptoms was derived from 13 questionnaire items from the Mood and Feelings Questionnaire (Short Version) [331]. This measure has demonstrated satisfactory validity and reliability in diagnosing depressive symptoms for boys and girls in cross-cultural adolescent populations [332, 333]. Questionnaire items asked how frequently participants experienced a range of negative feelings including the following. Participants selected from the following response options: "Not true", "Sometimes", "True". Responses were summed and a cut off score of ≥ 28 was used to differentiate between participants living with depressive symptoms and participants living without depressive symptoms [333]. Higher scores denoted worse depressive symptoms.

5.3.5.4 Cyberbullying

Participants self-reported (single item question) whether other children bullied them online ("How often have other children bullied you online?") from the following response options: "Most days", "About once a week", "About once a month", "Every few months", "Less often", "Never".

5.3.5.5 Body weight satisfaction

Body weight satisfaction was calculated from three questionnaire items ("Which of these do you think you are": "underweight", "about the right weight", "slightly overweight", "very overweight"; "Have you exercised to lose weight or to avoid gaining weight?": "Yes"; "No"; "Have you ever eaten less food, fewer calories, or foods low in fat to lose weight or to avoid gaining weight?": "Yes", "No"). In line with previous research, a body weight satisfaction variable (satisfied vs. dissatisfied) was derived, coding positive and negative response options in the appropriate category [276]. Participants were

considered dissatisfied if at least two out of three items were in support of dissatisfaction with body weight.

5.3.5.6 Self-esteem

Self-esteem was derived from five questionnaire items from the Rosenberg self-esteem scale [334]. Questionnaire items asked participants to what extent they agreed with the following statements: “On the whole, I am satisfied with myself”, “I feel I have a number of good qualities”, “I am able to do things as well as most other people”, “I am a person of value”, and “I feel good about myself”. Participants selected from the following response options: “Strongly Agree”, “Agree”, “Disagree”, and “Strongly Disagree”. Responses were summed (range 0 to 15) and higher responses denoted worse self-esteem. All Rosenberg self-esteem scale item responses were required for participants to be included in the summary variable.

5.3.5.7 Wellbeing

Wellbeing (overall happiness with life) was derived from six questionnaire items which examined adolescent’s overall happiness with their life. Questionnaire items asked participants “On a scale of 1 to 7 where 1 means completely happy and 7 means not at all happy, how do you feel about the following parts of your life?” – “schoolwork”, “the way you look”, “your family”, “your friends”, “the school you go to”, and “your life as a whole”. Items were summed (range 6 to 42) and a summary score was produced where higher scores denoted lower wellbeing.

5.3.5.8 Missing Data

To be included in summary variables, unless stated, at least 70% of item responses were required. The average response of the missing item was imputed for participants that met these criteria. I did not use multiple imputation in these analyses because the “missing at random” assumption could not be considered plausible which may lead to misleading results, and due to computational intensiveness where the approximation of a high proportions of missing data is not possible due to the functionality of STATA.

5.3.6 Statistical analysis

First, the association between social media use and BMI z-score was examined using multivariable linear regression models which also adjusted for ethnicity, family income, and family structure (primary objective). Second, for statistically significant associations, potential explanatory pathways were then added to separate models. Adding and removing explanatory pathway variables in subsequent models was used to identify which variables attenuated the association between social media use and BMI Z-score. Third, potential explanatory pathway variables attenuating associations by at least 30% were explored via structural equation modelling (SEM) [335] (using the SEM command in STATA). Structural equation models were used to examine whether and by how much potential associations between social media use and BMI z-score were explained by potential explanatory pathways (secondary objective). Structural equation modelling allows the fitting of a series of independent regression equations simultaneously with higher validity and greater reliability than regression models alone [336]. An a priori decision was made to only explore the secondary objective if an association was identified. Outputs were beta coefficients (95%CI) describing:

- The effect of social media use on BMI z-score
- The effect of social media use on the potential explanatory variable
- The effect of the potential explanatory variable on BMI z-score
- The effect of social media use on BMI z-score when the potential explanatory pathway variable was included in the model

The proportion of the total effect explained by the potential explanatory pathway, the ratio of indirect to direct effect, and the ratio of total to direct effect were derived from structural equation model outputs. As there are differences in social media use by sex [310, 314] and the sample size is sufficiently large to detect small and meaningful associations in subgroups all analyses were stratified by sex. Survey weights were used to allow for the study sampling design [337]. The “dovwt2” survey weight was used in line with study guidance documentation. Analyses was performed in STATA

(version 16.1). Potential explanatory pathway variables were not added to the DAG because the purpose of the DAG was to assess dependence/independence and not the functional relationship between variables which structural equation modelling allows.

5.4 Results

5,332 girls and 5,466 boys had valid data on social media use and BMI z-score at the Age 14 wave in the Millennium cohort study (91% of wave respondents). Participant characteristics of those included are displayed in Table 8. Both girls and boys were predominantly of White ethnicity, and had a two parent/carer family structure. The most common social media use category for boys was between 0 and less than 1 hour/day, and for girls between 1 and 3 hours/day. Participants excluded from analysis (9% of wave respondents who did not have valid data on social media use and BMI z-score at the Age 14 wave) were also predominantly of White ethnicity, and had a two parent/carer family structure. The most common social media use category for boys excluded from analysis was between 0 and less than 1 hour/day and for girls between 1 and 3 hours/day. Table 9 shows potential explanatory pathway variables of the analysis sample.

Table 8: Descriptive characteristics of the analysis sample

	Boys	Girls
	n=5,466	n=5,332
Age (Mean (SD) in years)	13.8 (0.5)	13.8 (0.4)
BMI z-score (Mean (SD))	0.69 (1.23)	0.75 (1.16)
Social media use h/day (%)		
0 to <1	43.8	22.7
1 to <3	32.2	31.2
3 to <5	10.4	18.2
5 or more	13.5	27.9
Ethnicity (%)		
White	80.3	81.8
Mixed	6.0	4.8
Indian	2.2	1.9
Pakistani and Bangladeshi	4.6	5.2
Black or Black British	4.5	3.7
Other ethnic group (inc. Chinese, Other)	2.4	2.7
Income quintiles (%)		
Lower quantile	18.7	18.7
Second quantile	18.8	19.9
Third quantile	20.4	20.5
Fourth quantile	21.3	20.0
Highest quantile	20.9	20.9
Family structure (%)		
Two parents/carers	71.6	70.6
One parent/carers	28.4	29.4

Note: SD = standard deviation.

Table 9: Potential explanatory pathway variables of the analysis sample

Potential Explanatory Pathway Variable	Boys (n=5,466)	Girls (n=5,332)
Dietary intake (Mean (SD))	12.0 (2.2)	12.3 (2.2)
Sleep duration (%)		
7 hours or less	0.9	1.0
8 hours	25.2	26.3
9 hours	22.7	24.3
10 hours or more	51.2	48.4
Depressive Symptoms (%)		
Participants living without depressive symptoms	90.7	76.1
Participants living with depressive symptoms	9.3	23.8
Cyberbullying (%)		
Most days	0.4	1.4
About once a week	1.0	2.2
About once a month	1.4	3.5
Every few months	2.7	5.5
Less often	16.2	25.2
Never	78.3	62.3
Body weight satisfaction		
Satisfied	63.8	54.8
Dissatisfied	36.2	45.2
Self-esteem (Mean (SD))	11.3 (2.6)	9.6 (3.0)
Wellbeing (Mean (SD))	14.2 (6.2)	16.6 (7.0)

Note: SD = standard deviation. Dietary intake (range 4-20), lower values denote worse dietary intake. Self-esteem (range 0-15), higher responses denote worse self-esteem. Wellbeing (range 6-42), higher scores denote lower wellbeing.

5.4.1 Primary objective: Association between social media use and BMI z-score

Table 10 shows estimates of the association between social media use and BMI z-score for boys and girls. Only social media use at ≥ 5 hours/day (vs 0 to < 1 hour/day) was associated with increased BMI z-score for girls (β [95%CI]) (0.17 [0.05, 0.29]). No associations between social media use and BMI z-score were found for boys.

Table 10: Association of social media use with BMI z-score, stratified by sex

	Model 0	
	Beta-coefficient (95% CI)	
	Girls (n = 5,332)	Boys (n = 5,446)
0 to <1 (reference)		
1 to <3	0.00 (-0.11, 0.11)	0.06 (-0.04, 0.15)
3 to <5	0.07 (-0.06, 0.20)	0.06 (-0.10, 0.22)
5 or more	0.17 (0.05, 0.29)	0.08 (-0.06, 0.22)

Notes: Beta coefficients represent the difference in BMI z-score in kg/m² comparing each category of social media use with the reference category. Model 0 adjusts for ethnicity, family income, and family structure

5.4.2 Secondary objective: Analyses of Potential Explanatory Pathways with SEM

As pre-specified, I explored potential explanatory pathways between ≥ 5 hours/day of social media use (vs. 0 to < 1 hours/day) and BMI z-score for girls only because no associations were found for boys.

5.4.2.1 Girls

The addition of sleep, depressive symptoms, body weight satisfaction, and wellbeing attenuated associations between social media use and BMI z-score in girls Table 11. Figure 16 displays SEM-modelled associations between social media use and BMI z-score via these identified potential explanatory pathway variables (see also Table 12 for tabular format which was included to aid use in future meta-analyses). This confirms that greater social media use was associated with increased BMI z-score (Path c) (β [95%CI]) (0.15 [0.06, 0.25]) when adjusting for ethnicity, family income, and family structure. When adding each potential explanatory pathway variable to the model, for sleep and depressive symptoms, the proportion of the total effect explained by these pathways was 0.3 (30%) and the ratio of indirect to direct effect was 0.4 (40%) and 0.3 (30%) respectively. The respective total effects were 1.25 times their individual direct effects. Body weight satisfaction, the proportion of the total effect explained by this pathway was 0.6 (60%) and the ratio of indirect to direct effect was 1.3 (130%). The total effect was 2.14 times the individual direct effects. For wellbeing, the proportion of the total effect explained by this pathway was 0.55 (55%) and the ratio of indirect to direct effect was 0.73 (73%). The total effect was 1.36 times the direct effect. The addition of dietary intake, cyberbullying, and self-esteem did not attenuate associations between social media use and BMI z-score. I did not examine SEM-modelled associations via these potential explanatory pathway variables (as per my priori analyses plan).

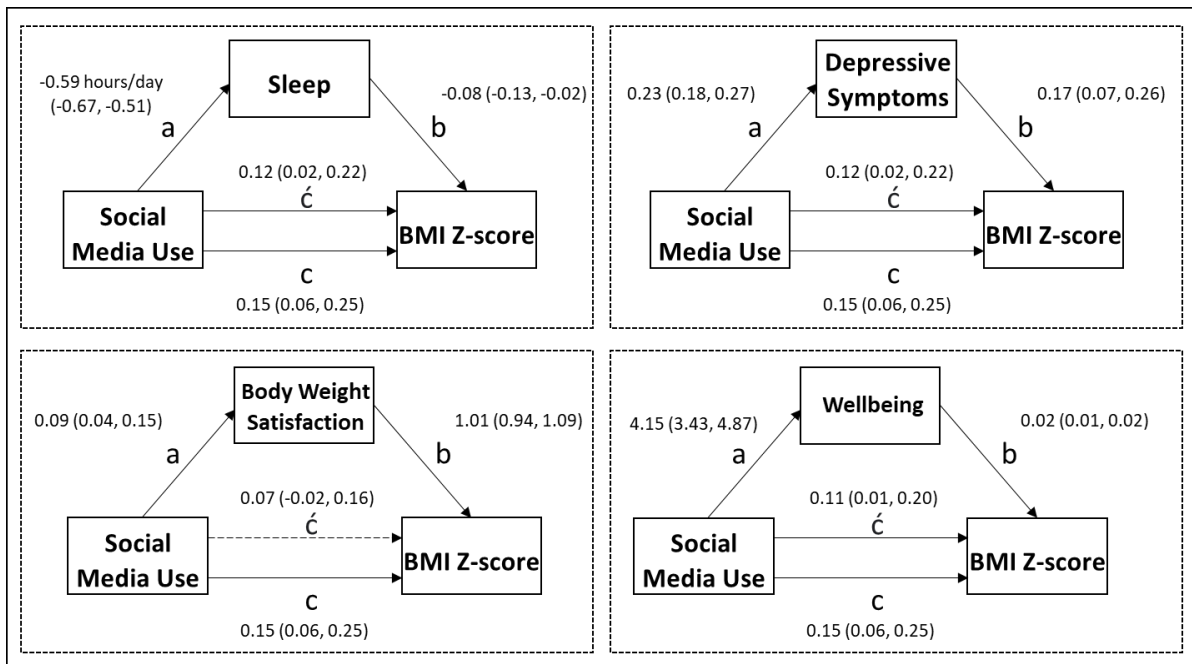
Table 111: Association of social media use with BMI z-score after adjustment for potential explanatory

variables in girls

	Model 1 (M0 + What they eat and drink)	Model 2 (M0 + Sleep)	Model 3 (M0 + Depressive Symptoms)	Model 4 (M0 + Cyberbullying)	Model 5 (M0 + Body Weight Satisfaction)	Model 6 (M0 + Self-esteem)	Model 7 (M0 + Wellbeing)
Girls	n = 5,309	n = 5,323	n = 5,227	n = 5,286	n = 5,252	n = 5,206	n = 5,258
0 to <1 (reference)							
1 to <3	0.01 (-0.11, 0.12)	-0.02 (-0.13, 0.10)	0.03 (-0.08, 0.14)	0.03 (-0.08, 0.14)	0.02 (-0.08, 0.13)	0.02 (-0.10, 0.13)	0.01 (-0.11, 0.12)
3 to <5	0.08 (-0.05, 0.21)	0.04 (-0.09, 0.17)	0.08 (-0.04, 0.21)	0.10 (-0.03, 0.23)	0.02 (-0.09, 0.14)	0.06 (-0.07, 0.19)	0.05 (-0.08, 0.18)
5 or more	0.17 (0.05, 0.30)	0.13 (<-0.01, 0.25)	0.16 (0.03, 0.28)	0.20 (0.07, 0.32)	0.09 (-0.03, 0.21)	0.13 (0.01, 0.26)	0.12 (<0.01, 0.25)

Notes: M0 = Model 0 as defined in Table 2. Beta coefficients represent the difference in BMI z-score in kg/m² comparing each category of social media use with the reference category. All models adjust for ethnicity, family income, and family structure, and the potential explanatory pathway variable

Figure 16: Associations between ≥ 5 hours/day (vs 0 to <1 hours/day) of social media use and BMI z-score via potential explanatory pathways in girls



Notes: Numerical values are beta coefficients (95% CI). Solid lines denotes an association which does not include 0. Dotted line denotes an association which includes 0. The “a” path describes the effect of social media use on the potential explanatory pathway variable. The “b” path describes the effect of the potential explanatory pathway variable on BMI z-score. The “c” path describes the effect of social media use on BMI z-score. The “c-hat” path describes the effect of social media use on BMI z-score when the potential explanatory pathway variable is included in the model.

Table 12: Associations between ≥ 5 hours of social media use (vs 0 to <1 hours/day) and BMI z-score via potential explanatory pathways for girls only (N=5,332)

Potential Mediator	c Path		a Path		b Path		c' path	
	Total effect	(95% CI)	Total effect on mediator	(95% CI)	Mediation effect	(95% CI)	Mediation effect	(95% CI)
	BMI z-score							
Sleep	0.15	(0.06, 0.25)	-0.59	(-0.67, -0.51)	-0.08	(0.13, -0.02)	0.12	(0.02, 0.22)
Depressive Symptoms	0.15	(0.05, 0.25)	0.23	(0.18, 0.27)	0.17	(0.07, 0.26)	0.12	(0.02, 0.22)
Body Weight Satisfaction	0.15	(0.05, 0.25)	0.09	(0.04, 0.15)	1.01	(0.94, 1.09)	0.07	(-0.02, 0.16)
Wellbeing	0.15	(0.06, 0.25)	4.15	(3.43, 4.87)	0.02	(0.01, 0.02)	0.11	(0.01, 0.20)

Notes: The “c” path describes the effect of social media use on BMI z-score. The “a” path describes the effect of social media use on the potential mediator. The “b” path describes the effect of the potential mediator on BMI z-score. The “c'” path describes the effect of social media use on BMI z-score when the potential mediator is included in the model.

5.5 Discussion

For girls, ≥ 5 hours of social media use per day (vs. 0 to <1 hours/day) was associated with increased BMI z-score (primary objective). Social media use was not associated with BMI z-score in boys and explanatory pathway variables were therefore not examined for boys. The association between girls' high social media use and BMI z-score was attenuated by sleep duration, depressive symptoms, body weight satisfaction, and wellbeing (secondary objective). The cross-sectional positive association for girls was small and time spent on social media use may contribute less to BMI z-score than known risk factors (e.g. poor diet, low physical activity, and insufficient sleep) [338]. However, it is important to note that other aspects of social media use (e.g. weekend vs. weekday use, active vs. passive use) could still be important.

To the best of my knowledge, this is the first study to explore the associations between social media and measured BMI z-score. To date, two studies have explored associations using self-reported BMI z-score. In contrast to this study, Sampasa-Kanyinga and colleagues [310] did not find an association in Canadian girls, but boys with >2 hours of social media use per day had a 0.323 higher BMI z-score (vs boys with infrequent or no use) [310]. Greater social media use was also found to be associated with (self-reported) increased BMI scores (0.68 [0.59, 0.77]) in high school students (age 12-17 years) in Tehran; no sub-group analyses were performed by sex [121].

Other methods of characterizing social media use (e.g. problematic social media use) have been found to be associated with self-reported obesity in young adults, where greater problematic social media use was associated with increased self-reported obesity [339]. However, problematic social media use has been criticised for inconsistency surrounding the condition's definition, a lack of proven reliable and valid measurement scales, and poor correlation with objective measures of social media use [340]. Caution is necessary when drawing conclusions about the relationship between social media use and BMI z-score given the majority of studies to date use sub-optimal data.

For girls, the association in this study was attenuated by sleep, depressive symptoms, body weight satisfaction, and wellbeing. Sampasa-Kanyinga and colleagues [310] also found that, for boys only, social media use had an effect on sleep which, in turn, had an effect on BMI Z-score. No other studies have explored explanatory pathways between social media use and BMI z-score. Harmful associations between sleep and BMI z-score [250], and depressive symptoms and BMI z-score [132] are well-known. The relationships between body weight satisfaction and BMI z-score, and wellbeing and BMI z-score have received less attention. Although both factors are suggested to be related to BMI z-score, heterogeneity in units of measurement and lack of established definitions have prevented conclusions from being drawn regarding the directionality of effect [341, 342]. Respective relationships between social media use and sleep, depressive symptoms, body weight satisfaction, and wellbeing are less well-understood and often contentious. Previous evidence has suggested links between social media use and sleep [318], depressive symptoms, and wellbeing, although the magnitude and importance of these links has been contested [298, 321, 343]. Given the lack of strong evidence, additional research which use high quality, longitudinal measures across geographies are required to draw firm conclusions about potential explanatory pathway variables.

When compared to known risk factors for increased BMI z-score, these analyses suggest that time spent on social media use may contribute less to BMI z-score than known risk factors; although a more specific exposure may show different findings (e.g. active vs. passive use, weekday vs. weekend). The specifics of social media use (e.g. use case, time, and location of use) were not measured in the Millennium Cohort Study and small effects over a long time may translate to significant effects on a population level (e.g. through repeated exposure to food or body images which may increase consumption of food or lead to body dissatisfaction) [344]. Only a small positive association may have been found in girls because social media is a behavioural norm for adolescents who are increasingly using social media as their primary method of communication with their peers [345]. Adolescent social media use is also potentially transient in nature and may not infringe upon activities which are supportive of maintaining a healthy weight to the extent initially feared in line with displacement

theory; although this remains untested. Adolescents exist in an environment with overwhelming stimuli which may collectively contribute to impact BMI z-score and make it difficult for adolescents to maintain a healthy weight [346]. These cross-sectional findings are insufficient to support intervening and allocating resources to decrease social media use to improve BMI z-score given the potential marginal gains and outsized costs. It may be necessary to intervene at many levels, including the digital environment, schools, the home, and more to support adolescents to maintain a healthy weight.

In contrast to previous evidence this analysis did not find associations for boys. Possible explanations for the observed sex differences may be differences in the way that boys and girls use social media. At the population level, girls often establish friendship through self-disclosure, whereas boys may establish intimacy through shared experiences [193]. It is possible that shared experiences do not translate to social media while social media serves as an additional avenue for self-disclosure. Boys use video games more than girls [347]. In virtual environments, video gaming may be the preferred avenue for boys to share experiences with friends (as opposed to social media). A further potential explanation for observed sex differences may be that adolescent girls perceive and act on messages on social media differently to adolescent boys due to greater perceived pressures [232]. Adolescent girls may also be more susceptible to these pressures due to psychological differences (on average) between boys and girls [325]. Some hypothesized explanatory pathway variables (e.g., dietary intake, cyberbullying, and self-esteem) were not observed to be explanatory pathway variables between social media use and BMI z-score (Table 11). A potential explanation for a lack of effect for cyberbullying and self-esteem is the increased capacity for individuals to provide social support to the individual experiencing cyberbullying which counterbalances negative comments [29].

5.5.1 Strengths and Limitations

Strengths of this study included the examination of sex differences in a large, representative sample with good representation of ethnic and socio-economic groups, a strong methodological approach, and the use of BMI z-score based on measured height and weight. The key advantage of structural

equation modelling (vs. multiple regression) is the derivation of indirect and direct effects of multiple dependent variables in a single model [335]. However, this was a large-scale sample where compromises have to be made on data collection processes. A key limitation is therefore the use of self-reported social media use data that was characterized by overall quantity alone, which is the only social media use variable available for this cohort. Social media use is complex and, under ideal circumstances, would not be self-reported or characterized by quantity alone. Self-reported use may not be representative of actual social media use recorded via an objective measure due to the challenge of accurately recording potential continual brief spells of time spent on social media, often while concurrently participating in other activities (e.g., when eating meals, or other screen-based behaviours) [340, 348]. A summary variable is also not capable of differentiating between use cases (e.g., content viewed, active vs. passive, public vs. private, and location or time of use [e.g. weekday vs. weekend, day time vs. night time]) [349]. These characteristics may bring rise to different effects on health risk factors [350]. Findings are cross-sectional which prevents inferring a causal effect of social media use on BMI z-score, mediation via explanatory pathway variables, or direction of effects. Social media use was also measured seven years ago (January 2015 to April 2016). Social media is a fast-moving industry, and both the type of content adolescents consume (e.g. shifting platform preferences) and the way adolescents interact with social media may differ from then to today in 2022. However, social media content has likely become better at retaining adolescent attention, and the prevalence of use has increased. Whether and to what extent this influences the association with BMI z-score is unknown. There is strong evidence that physical activity is cross-sectionally associated with BMI z-score [351]. Sedentary behaviour may also be particularly important given most social media use is sedentary. However, I was unable to include data on physical activity and sedentary behaviour due to high levels of missing data in the Millennium Cohort study dataset. I also did not apply bootstrapping due to survey weights increasing the representativeness of this large sample which reduces the need for resampling but also limits the functionality of the STATA command and increases computational intensiveness which may be a limitation. Implications of not bootstrapping

include the potential of a reduction in the accuracy and precision of confidence intervals to account for sampling variability. Future research could counter limitations of the data by using longitudinal study designs, adopting daily assessment methods, such as ecological momentary assessment, and/or pursuing meaningful collaboration with social media companies to analyse privately held data.

5.6 Conclusions

I identified a positive association between ≥ 5 hours/day of social media use (vs. 0 to <1 hours/day) and BMI z-score in girls. However, the association between self-reported, estimated time spent on social media use was small. Sleep, depressive symptoms, body weight satisfaction, and wellbeing were found to attenuate associations. For boys, no associations were found between social media use and BMI z-score. Future research should aim to strengthen the evidence base by exploring the effect of social media use on BMI z-score over time for boys and girls using device-measured social media use or ecological momentary assessment methods, and specific social media use cases (e.g. active vs. passive use, weekday vs. weekend use). In the next chapter, I focus on exploring the relationship between social media use and change in BMI z-score.

6 Chapter 6: Social media use and BMI z-score: a longitudinal propensity score matching analysis of 8,024 14 to 17 year olds

This work is in submission to a peer reviewed journal.

The aim of this study to provide evidence for the potential association between social media use and change in BMI z-score using observational research. For this reason, I sought advice from the University of Cambridge Statistics Clinic for designing of the study, and conducting of analyses using propensity scores. I interpreted the findings with support from Russell Jago, Andrea Smith, and Esther van Sluijs. I drafted the manuscript. Russell Jago, Andrea Smith, and Esther van Sluijs reviewed and provided input to the manuscript preceding this chapter.

This chapter is the final of three analytical chapters which extends upon the cross-sectional findings of the previous chapter by exploring the relationship between social media use at age 14 years and change in BMI z-score from age 14 to 17 years in a cohort of adolescents living in the UK enrolled in the Millennium Cohort study.

6.1 Abstract

Background: There is a lack of longitudinal evidence about the association between adolescent social media use and change in BMI z-score. This is despite concerns that social media use may be associated with weight gain. The purpose of this study was to explore the longitudinal association between social media use and change in BMI z-score during adolescence. **Methods:** Data are from 3,987 boys, and 4,037 girls in the population-based UK Millennium Cohort study. Change in measured BMI z-score (age 14 to 17 years) was regressed on self-reported time spent on social media use at age 14 years (hours/day). Sex-stratified multivariable linear regression and propensity score matching were used to examine potential associations. Propensity score matching emulates the uniform distribution of measured, but not unmeasured, confounders in randomised controlled trial treatment and control groups to increase the likelihood that findings were as a result of the exposure. **Findings:** Self-reported higher daily time spent on social media use at age 14 years was associated with lower change in measured BMI z-score (14-17 years). In boys, social media use between 3 to <5h/day (vs <1h/day) was associated with lower change in measured BMI z-score (β [95%CI]) (-0.55 [-1.00, -0.09]). For girls using social media for 1 to <3h/day (vs <1h/day) was associated with a smaller change in BMI z-score (-0.11 [-0.18, -0.04]). **Interpretation:** The findings of a negative association between social media use and change in BMI z-score must be interpreted cautiously given that associations were small, did not demonstrate a dose-response relationship, and are not consistent with the few (cross-sectional) studies completed to date. As social media and usage patterns continues to evolve, there is growing potential to embrace novel research methods and approaches to investigating potential health, developmental, and academic consequences for adolescents.

6.2 Background

I have previously discussed the many negative consequences of adolescents living with obesity and the need to identify modifiable factors driving its development (see Chapter 1). Many factors within adolescent's social environment are associated with obesity during adolescence [196]. Almost all adolescents in the United States (97%) use social media whereas almost half (45%) reported to be online "almost constantly" in 2018 [219]. Social media is also widespread in the UK where adolescents may spend as much as 1 to 3 hours on social media per day [128]. Adolescents aged 10 to 15 years may be more sensitive to the effects of social media use (compared to adolescents outside this age range) due to heightened susceptibility to social rejection and acceptance, emotion precedence and peer influence mechanisms [313]. It is unclear whether and to what extent social media use is associated with obesity during adolescence.

More time spent on social media use may be associated with worsened energy-balance related behaviours including sleep, physical activity, mental health, and dietary behaviours [298]. However, findings are mixed on the association between social media use and BMI and the evidence base is largely limited to cross-sectional studies with self-reported BMI measures which do not contribute evidence towards determining causality and are at risk of self-report biases [310, 314, 352]. Analysis of prospective studies with social media use and BMI measures at multiple time points will allow exploration of whether higher social media use is a risk factor for increased weight gain during adolescence. Social media use might also affect boys and girls differently with an increased risk of adverse consequences (e.g. depressive symptoms) in girls [353]. Examining whether associations between social media use and change in BMI differ by sex may provide evidence towards which adolescents are most vulnerable to the effects of social media use and whether limiting social media use may be protective against a negative change in BMI.

The primary objective of this study was to examine the association between social media use at age 14 years and change in BMI z-score from age 14 to 17 years in boys and girls.

6.3 Methods

6.3.1 Study design and participants

This study used data from the Millennium cohort study Age 14 and Age 17 waves, respectively collected between January 2015 and April 2016, and January 2018 and March 2019 for $n=11,872$ and $n=10,757$ participants. I previously described this study in detail in Chapter 5, section 5.3. Participants included in the analysis provided data on both social media use at the Age 14 wave (exposure), and BMI z-score at both the Age 14 and Age 17 waves to derive change in BMI z-score (outcome) ($n=8,024$ children).

6.3.2 Data sources/measurement

6.3.2.1 Outcome

Change in BMI Z-score from age 14 to 17 years was the outcome. BMI (kg/m^2) was first derived at both waves using height and weight data measured by trained research staff using a Leicester height measure and Tanita scale, respectively. In line with previous studies using this dataset [276, 325], improbable BMI values ($<10\text{kg}/\text{m}^2$ and $>50\text{kg}/\text{m}^2$) were excluded. Age and sex-standardised BMI Z-score was then calculated at both waves based on UK 1990 growth centiles [327]. Change in BMI Z-score was calculated using the following equation:

$$\text{Change in BMI Z-score} = \text{BMI Z-score at age 17} - \text{BMI Z-score at age 14}.$$

6.3.2.2 Exposure

Social media use at age 14 years was the exposure. This is the same exposure as in Chapter 5. Social media use was self-reported by participants at age 14 when no-one else was present during home visits via computer assisted questionnaires. Questionnaires asked: "On a normal week day during term time, how many hours do you spend on social networking or messaging sites or Apps on the internet such as Facebook, Twitter and Whatsapp?". Participants selected from the following eight response options: "None", "less than half an hour", "half an hour to less than 1 hour", "1 hour to less than 2 hours", "2 hours to less than 3 hours", "3 hours to less than 5 hours", "5 hours to less than 7 hours",

and “7 hours or more”. Due to its distribution in the analysis sample the variable was collapsed into the following four categories based on established methods for this dataset [276]: “Less than 1 hour”, “1 to less than 3 hours”, “3 to less than 5 hours”, and “5 or more hours”.

6.3.2.3 *Confounders*

To address confounding when estimating the effect of social media use on change in BMI z-score I used propensity score matching. The aim of propensity score matching in observational research is to mitigate the potential bias of a treatment effect being found as a result of participants being characteristically different (as opposed to due to the influence of the exposure) by emulating the desired uniform sociodemographic distribution of individuals in randomised controlled trials treatment and control groups [354]. Participants with the same propensity score are assumed to have the same probability of being assigned exposed/control group based on measured covariates. Under these circumstances, a stronger case can be made for an effect being found as a result of the exposure variable. In this study, I matched participants by their propensity score to identify subsamples of adolescents based on their social media use who have a comparable distribution of observed covariates. This emulated a randomised controlled trial, with respect to variables included in the propensity score model, where participants are categorized into treatment groups based on their social media use. However, adjusting for propensity score does not account for unmeasured confounders which is the key limitation of the approach which does not replace the need for randomised controlled trials [355]. Participants with the same propensity score are assumed to have the same probability of being assigned to each treatment group [356] (social media use categories e.g. 0 to <1 hour, to 5+ hours). Potential covariates were selected based on previous research findings (e.g. ethnicity, and income’s relationship with adiposity [128]; however, I also made some theoretical assumptions about the relationship between primary carer age and social media use due to the limited research available. Covariates used to derive propensity scores were: ethnicity, family income, family structure, sleep, depressive symptoms, body weight satisfaction, self-esteem, wellbeing, and primary carer age (all from age 14 data).

Participants self-reported their ethnicity from 19 response options and responses were collapsed into the following 8 categories: “White”, “Mixed”, “Indian”, “Pakistani”, “Bangladeshi”, “Black Caribbean”, “Black African”, and “Other Ethnic group (including Chinese)”. Family income, a marker of participant’s socioeconomic status, was reported by parents in categories and collapsed into quintiles. Participants self-reported their parent(s)/carer(s) in their household from 17 response options (e.g., “Natural Mother”, “Adoptive Father”, and “Sibling”). Family structure was then dichotomised as: “Two parents/carers”, and “One parent/carers”. Sleep (duration) was derived from self-reported time going to bed and waking up on a school night (“About what time do you usually go to sleep on a school night?”, and “About what time do you usually wake up in the morning on a school day?”). The five response options for bed time ranged from “Before 9pm”, to “After midnight” and for time waking up from “Before 6am”, to “After 9am”. These were used to estimate sleep duration which was collapsed as: “7 hours or less”, “8 hours”, “9 hours”, and “10 hours or more” as per previous methods in this dataset (4).

Depressive symptoms was derived from 13-item Mood and Feelings Questionnaire (Short Version)[331] which has good diagnostic accuracy and sensitivity to change in adolescents [333]. Questionnaire items asked how frequently participants experienced a range of negative feelings, such as “didn’t enjoy anything”, “tired”, and “lonely”. Response options were: “Not true”, “Sometimes”, and “True”. Responses were summed and a cut off score of ≥ 28 was used to differentiate between participants living with depressive symptoms (7). Higher scores denoted worse depressive symptoms.

Body weight satisfaction was derived from three questionnaire items (“Which of these do you think you are?” (underweight, about the right weight, slightly overweight, and very overweight), “Have you exercised to lose weight or to avoid gaining weight?” (yes/no), “Have you ever eaten less food, fewer calories, or foods low in fat to lose weight or to avoid gaining weight?” (yes/no). A body weight satisfaction variable (satisfied vs. dissatisfied) was derived (8). Participants were considered body dissatisfied if at least two out of three items were in support of dissatisfaction with body weight.

Self-esteem was derived from the 5-item Rosenberg self-esteem scale [334] which has good construct validity in British adolescents [357]. Questionnaire items asked participants on a 5-point Likert (strongly agree to strongly disagree) to what extent they agreed with five statements, e.g. “On the whole, I am satisfied with myself”, and “I feel I have a number of good qualities”. Responses were summed (range 0 to 15) and higher responses denoted worse self-esteem.

Wellbeing was derived from six questionnaire items which examined adolescents’ overall happiness with their life. Questionnaire items asked “On a scale of 1 to 7, where 1 means completely happy and 7 means not at all happy, how do you feel about the following parts of your life?” – “schoolwork”, “the way you look”, “your family”, “your friends”, “the school you go to”, and “your life as a whole”. Items were summed (range 6 to 42) with higher scores denoting lower wellbeing. Primary carer age was self-reported in years by primary carers. Age, sex, ethnicity, family income, and household characteristics at age 14 years served as descriptors. Sex at age 14 years was also used to explore sub-group differences in effect. Age (descriptor only) was calculated from participant’s birth date and the date of measurement. Sex (descriptor and effect modifier) was self-reported by participants. Ethnicity, family income, and household characteristics have been described in this chapter previously (section 6.3.2.3).

6.3.3 Statistical methods

First, propensity scores were estimated using multinomial logistic regression with social media use serving as the outcome variable and the nine aforementioned covariates (from Age 14 data) serving as exposures. The estimate from this analysis served as the propensity score. In line with best practice, a caliper (a predefined maximum discrepancy in propensity score for participants to be matched which limits the possibility of “bad” matches [354]) of 0.2 of the standard deviation of the logit of the propensity score was set to ensure good matches [358]. Next, the association between social media use (hours/day) as the exposure and change in BMI Z-score as the outcome was explored using multivariable regression analyses adjusting for the propensity score and all nine confounders. The

rationale for adjusting for both propensity score and also all nine confounders was to both reduce the effects of confounding (adding covariates to the model), and emulate a randomized controlled trial, with respect to measured confounders but not unmeasured confounders, in the context of an observational study (adding propensity scores to the model) [355]. Outputs were beta coefficients describing the difference in association between the reference and the category of interest. Due to the suggested difference in response to social media use between boys and girls [353], an a-priori decision was made to stratify the analysis by sex. Analyses were performed in Stata (version 16.1) accounting for relevant survey weights at each wave in both deriving of propensity scores and analyses. I did not explore potential explanatory pathway variables between time spent on social media and change in BMI z-score as per Chapter 5 (e.g. cyberbullying, wellbeing) due to the unavailability of change data from age 14 to age 17 for these variables either through new scales being adopted to record variables (e.g. Warwick Edinburgh Mental Wellbeing scale, perception of weight) or variables being dropped from data collection (e.g. cyberbullying). The goal of these analyses was also to provide the strongest possible evidence of the relationship between social media use and change in BMI z-score using observational data rather than, for example, exploring potential explanatory pathway variables between the potential relationship.

6.4 Results

6.4.1 Descriptive data

The analysis sample includes 3,987 boys and 4,037 girls. Participants excluded from the sample (26.1%) did not have both social media use at age 14 years and/or change in BMI z-score from age 14 to 17 years (most important reason for drop out). Characteristics of the analysis sample are displayed in Table 13. BMI z-score reduced from age 14 to 17 years for boys and girls. The most common social media use category at age 14 years was 0 to <1 hours/day for boys, and 1 to <3 hours/day for girls. Both boys and girls were predominantly of White ethnicity, and had a two parent/carer family structure. Characteristics of participants excluded from the sample are displayed in Table 14.

Participants excluded from the analysis (boys and girls) were also predominantly of White ethnicity, and had a two parent/carer family structure.

Table 13: Descriptive statistics of the analysis sample (n=8,024)

	Boys	Girls
	n=3987	n=4037
	Mean (SD)	Mean (SD)
Age at baseline (years)	13.8 (0.5)	13.8 (0.4)
BMI Z-score at baseline	0.66 (1.21)	0.69 (1.14)
Change in BMI Z-score)	-0.13 (0.73)	-0.11 (0.69)
Weight Status (Age 17y, UK90 thresholds)	N (%)	N (%)
Adolescents living with underweight	99 (2.5)	56 (1.3)
Adolescents living with healthy weight	2507 (62.9)	2465 (64.8)
Adolescents living with overweight	552 (13.8)	561 (14.1)
Adolescents living with obesity	829 (20.8)	775 (19.8)
Social Media Use (hours/day) at 14 years of age	N (%)	N (%)
0 to <1h	1834 (46)	928 (23)
1 to <3h	1316 (33)	1332 (33)
3 to <5h	359 (9)	727 (18)
5h+	478 (12)	1050 (26)
Ethnicity		
White	3190 (80.0)	3270 (81.0)
Mixed	227 (5.7)	202 (5.0)
Indian	100 (2.5)	89 (2.2)
Pakistani or Bangladeshi	199 (5.0)	218 (5.4)
Black or Black British	167(4.2)	161 (3.9)
Other Ethnic Group	104 (2.6)	97 (2.4)
Family Income		
Quintile 1 (Low)	630 (15.8)	641 (15.9)
Quintile 2	691 (17.3)	726 (18.0)
Quintile 3 (Medium)	779 (19.6)	826 (20.5)
Quintile 4	912 (22.9)	864 (21.4)
Quintile 5 (High)	975 (24.5)	980 (24.3)
Family Structure		
Two parents/carers	2962 (74.3)	2979 (73.8)
One parent/carers	1025 (25.7)	1058 (26.2)
Note: SD = Standard Deviation		

Table 14: Descriptive statistics of participants excluded from the analysis sample (n=2,674)

	Boys	Girls
	n=1,301	n=1,373
	Mean (SD)	Mean (SD)
Age at baseline (years)	13.8 (0.4)	13.8 (0.4)
	n=1,184	n=1,076
BMI Z-score at baseline	0.75 (1.2)	0.89 (1.2)
Change in BMI Z-score)	n/a	n/a
Weight Status (Age 17y, UK90 thresholds)	n = 514 (100%)	n = 625 (100%)
Adolescents living with underweight	(3.0)	(0)
Adolescents living with healthy weight	(28.8)	(31.0)
Adolescents living with overweight	(18.1)	(11.5)
Adolescents living with obesity	(50.1)	(57.6)
Change in BMI z-score by weight status	n/a	n/a
Social Media Use (hours/day) at 14 years of age	n = 1,301 (100%)	n = 1,373 (100%)
0 to <1h	(35.6)	(18.2)
1 to <3h	(32.2)	(27.3)
3 to <5h	(13.3)	(19.2)
5h+	18.(9)	(35.3)
Ethnicity	n = 1,301 (100%)	n = 1,373 (100%)
White	(80.4)	(84.5)
Mixed	(5.7)	(4.2)
Indian	(2.0)	(1.3)
Pakistani or Bangladeshi	(3.0)	(4.2)
Black or Black British	(6.1)	(3.4)
Other Ethnic Group	(2.8)	(2.4)
Family Income	n = 1301 (100%)	n = 1,373 (100%)
Quintile 1 (Low)	(22.4)	(25.1)
Quintile 2	(23.8)	(24.2)
Quintile 3 (Medium)	(23.5)	(20.4)
Quintile 4	(18.0)	(16.7)
Quintile 5 (High)	(12.3)	(13.7)
Family Structure	n = 1,301 (100%)	n = 1,373 (100%)
Two parents/carers	(64.6)	(62.9)
One parent/carers	(35.4)	(37.1)
Note: SD = Standard Deviation		

6.4.2 Association between social media use and change in BMI z-score

Table 15 shows estimation of the association between social media use and change in BMI z-score for boys and girls. For boys, greater social media use was associated with a lower change in BMI z-score at the 3 to <5 hours/day (vs. 0 to <1 hours/day) range (β [95%CI]) (-0.55 [-1.00,-0.09]). For girls, higher social media use was associated with lower change in BMI z-score at the 1 to <3 hours/day range (-0.11 [-0.18, -0.04]). There was no evidence of any other associations.

Table 15: Association of change in BMI Z-score with daily social media use, stratified by sex

Daily Social Media Use (closed scale – 0 to <1h, 1 to <3h, 3 to <5h, .5h)	Beta Coefficient (95% CI) after adjusting for propensity scores* and covariates**
Boys (n=3987)	
0 to <1h (reference) (n=1834)	
1 to <3h (n=1316)	-0.02 (-0.08, 0.05)
3 to <5h (n=359)	-0.55 (-1.00, -0.09)
>5h (n=478)	-0.45 (-0.91, 0.01)
Girls (n=4037)	
0 to <1h (reference) (n=928)	
1 to <3h (n=1332)	-0.11 (-0.18, -0.04)
3 to <5h (n=727)	0.16 (-0.16, 0.48)
>5h (n=1050)	0.17 (-0.15, 0.49)

Notes: Beta coefficients indicate the difference in change in BMI Z-score per 1-unit change in social media use. Beta coefficients with 95% CI not containing the value 0 are denoted in bold. *Propensity scores were derived from ethnicity, family income, family structure, sleep, depressive symptoms, body weight satisfaction, self-esteem, wellbeing, and primary carer age. ** Ethnicity, Family Income, Family Structure, Sleep, Depressive Symptoms, Body Weight Satisfaction, Self-esteem, Wellbeing, and Primary carer age.

6.5 Discussion

6.5.1 Main findings

In this chapter, I aimed to examine the association between social media use at age 14 years and change in BMI from age 14 to 17 years in boys and girls. I undertook this research study due to the previously identified lack of research exploring these associations over time identified in Chapter 4, section 4.9.3.2. I showed a longitudinal limited negative associations between self-reported daily social media use and change in measured BMI z-score in a nationally representative sample of adolescents. Associations were small. I found that for boys, greater social media use was associated with lower change in BMI z-score at the 3 to <5 hours/day range (vs. 0 to <1 hours/day). For girls, however, greater social media use was associated with lower change in BMI z-score at the 1 to <3 hours/day range (vs. 0 to <1 hours/day). There was no evidence of a dose-response relationship between social media use and change in BMI.

6.5.2 Strengths and Limitations

This study presents rigorous prospective analyses based on data from a nationally-representative cohort over an important developmental time period. The use of measured BMI, and propensity score matching are further strengths. An important limitation of this work relates to how and when the exposure variable was measured. Social media is a fast-moving industry with new platforms emerging regularly. Social media use in the Millennium Cohort study was measured in January 2015 to April 2016, and findings may not be as relevant to the current social media landscape today due to shifting preferences in social media platforms and/or differences in how adolescents may have interacted with social media. The self-reported nature of the social media use measure is not able to capture differences in use cases (e.g. active vs. passive use) or account for potential self-report biases. Additionally, there was no contextual information to explore how social media is used (e.g. device - mobile vs. computer), where social media is used (e.g. inside or outside the home environment, in bed), or when social media is used (e.g. weekend vs. weekday, day vs. night time) to interpret these findings. Low-to-medium-sized positive correlations have been found between retrospective social

media use measurements and in situ social media use measurements (which differ by platform) [220]. Although my study has the opportunity cost of not exploring the relationship between device-measured social media use and BMI in a smaller sample; despite the limitations of self-reported social media use, this analyses is the strongest to date due to the large, nationally representative sample, and the use of measured BMI. Although physical inactivity is a risk factor for high BMI z-score [359], physical activity was not included in this study in derivation of propensity scores due to high missingness of data. Residual confounding, i.e. the distortion that remains after controlling for confounding in the study design, from excluding additional confounding factors (e.g. physical activity), and/or not adjusting for additional potential confounders at the age 17 years wave could leave room for spurious findings. Social desirability bias relating to the outcome change in BMI z-score, and potentially also the exposure social media use, may have reduced the analyses sample size. This missing data may have led to a loss of power, and/or a reduction in the precision of estimates.

6.5.3 Interpretation

The analyses reported here provide evidence, within the confines of available data, of a limited association between social media use and BMI z-score. Associations must be interpreted with caution given non-conformity with three of Bradford Hill's criteria for determining causality - strength of association, biological gradient, and consistency of associations [134]. For example, observationally a dose-response relationship was not seen in boys and only a weak association was found in girls which is suggestive of there being an increased risk of findings being due to chance, bias, misclassification, or confounding [134]. Associations found in this study have also not been observed elsewhere in other national population samples. No other longitudinal studies were identified using measured BMI z-score. I previously undertook a cross-sectional examination of the relationship between social media use and BMI z-score at Age 14 in the same cohort (Millennium Cohort Study) which is discussed in Chapter 5. I identified that, in girls, high social media use (5+ hours/day) was associated with increased BMI z-score and the association was partially explained by sleep duration, depressive symptoms, body weight satisfaction, and wellbeing. No associations were found in boys. I previously identified in

Chapter 5 that only two other studies have explored the relationship between social media use and BMI. The negative associations in this study are specific to self-reported time spent on social media only. Other related behaviours of social media use could be more strongly associated with a greater change in BMI z-score, for example, exposure to food advertising. Acute exposure to food advertising has been shown to be related to increased food intake in children [344]). However, there is an expected correlation between social media time use and exposure to food advertising which may be captured in the measure of time use I used in this study.

There is much concern surrounding the relationship between social media use and mental health which has also been challenged in the existing literature base with strong methodological approaches showing limited conclusive evidence of a negative association [343]. As data collection efforts in social media research improve, further investigation will improve the validity of the relationship between social media use and physical and mental health outcomes by supporting stronger inference to a potential association with a device-measured method. There is also the potential to explore dose-response relationships.

I found a limited negative association for adolescents who may be considered “moderate users” of social media (1 to <5 hours/day). There are several potential reasons for this. First, social media use has replaced the use of legacy media (e.g. books, movies, and television). For example, the percentage of adolescents in the USA aged 17 to 18 years self-reporting visiting social media “almost every day” in 2008 vs. 2016 was 52% vs. 82% with a comparable change found for adolescents aged 13 to 16 years [360]. Alongside this increased social media use, in the same study over the same timeline, adolescents reported spending less time using legacy media [360]. Second, social media facilitates the continued participation in activities supportive of maintaining a healthy weight (e.g. social support for sport participation) [361]. Third, greater social support is associated with increased adolescent physical activity and certain types of social support for physical activity may be more important for boys (e.g. co-participation), and girls (e.g. encouragement) [167]. However, few studies have

investigated which types of social support for physical activity translate to social media. The hypothesis that a large impact of social media use on change in BMI z-score was not found because social media facilitates increased participation in physical activity and prevents weight gain is contingent on a negative association between physical activity and weight gain during adolescence of which there is little evidence [20]. And finally, 'being on social media' is a behavioural norm for adolescents and their primary method of communication with friends. Adolescents who use social media at "normal" levels (relative to population averages) may not be at risk but small sample sizes of adolescents at the extremes (e.g. "abnormal" levels of social media use such as <1 hours/day and/or 5+ hours/day) may be concealing risk levels. Further research, both at the population level and within sub-groups (e.g. "abnormal" levels) could help explain how adolescents use social media within the context of maintaining a healthy weight.

6.5.4 Policy and research implications

The findings reported here suggest that the association between social media use and adolescent BMI z-score may be limited. These results alone are not strong enough to support policy intervention on adolescent social media use to prevent increased BMI z-score. The proposed need for policy intervention to protect adolescent health has also been questioned within the adolescent wellbeing [362] and mental health [343] literature with little evidence supporting substantial negative associations with social media use. However, adolescents use social media for comparatively large amounts of their waking day. As social media continues to evolve, there is growing potential to embrace novel research methods and approaches to investigating potential health, developmental, and academic consequences. For example, future research could pursue longer-term follow-up as adolescents' transition to adulthood, given that small but sustained negative effects on BMI z-score may translate into changes at the population level. There is also the potential that future research could harness adolescent's engagement in social media to improve population health through social media-enabled obesity prevention interventions. I also found that BMI z-score reduced between age 14 and 17 years in the analysis sample which appears to be as a result of a comparatively large

reduction in BMI z-score for adolescents living with underweight. At the population level, we would expect to see an increase in BMI during adolescence (e.g. due to growth). Our findings may have been as a result of the suggestion that change in BMI z-score may be less sensitive in detecting changes in adiposity in children living with obesity versus other measures [363]. Future research examining how and why associations between social media use and BMI z-score may differ by sex (e.g. through body image concerns, different usage patterns) may also be important.

6.6 Conclusions

The research reported here has shown a longitudinal negative associations between a summary variable of self-reported daily social media use and change in measured BMI z-score in a nationally representative sample of adolescents from age 14 to 17 years. For boys, higher social media use was associated with lower change in BMI z-score at the 3 to <5 hours/day range (vs. 0 to <1 hours/day). For girls, higher social media use was associated with lower change in BMI z-score at the 1 to <3 hours/day range (vs. 0 to <1 hours/day). Overall, this suggests social media use is not strongly and directly linked to BMI z-score change across adolescence. It is likely that stronger potential physical health consequences may arise from other associated behaviours (e.g., snacking of high in fat, salt, and sugar foods, increased sedentary time, disrupted sleep). Findings must be interpreted with the understanding that associations were small, observationally did not demonstrate a dose-response curve, and are not consistent with the few studies completed to date. In my next chapter, the general discussion, I expand upon the potential next steps for this research area that this study underpins.

7 Chapter 7: Discussion

7.1 Introduction

Childhood obesity remains a key public health challenge, and prevalence rates in the UK continue to rise. Suboptimal health behaviours such as energy dense diets that are high in fat, sugar and salt as well as physical inactivity in adolescence are implicated as key targetable risk factors in the onset of adolescent obesity. Schools are considered key settings for intervening to improve adolescent health but existing school-based strategies have not been effective in achieving desired improvements, potentially as a result of a lack of consideration for the broader school environment. This has also driven focus toward environments beyond the school (e.g. the digital environment, including social media). To date, little is known about respective relationships between the school environment and physical activity, and social media use and relationships with adiposity during adolescence. I have addressed this knowledge gap in the UK context in my thesis.

The overall aim of this thesis was to explore relationships between the obesogenic environment and adolescent weight status and physical activity. Given the important gaps in the literature on the offline and online environments for adolescent physical activity and obesity, the specific objectives of this thesis were:

- (1) To explore associations between the school policy, social and physical environment and change in adolescent physical activity to test many potential predictors of change as a hypotheses-generating exercise. In this study I also ascertain how sex and socioeconomic status (SES) modify the relationship between the school policy, social and physical environment and change in adolescent physical activity. These objectives were addressed in Chapter 3.
- (2) To examine the sex-specific cross-sectional association between social media use and measured BMI z-score at age 14 years, and potential explanatory pathway variables of this association (dietary intake, sleep duration, depressive symptoms, cyberbullying, body weight satisfaction, self-esteem, and wellbeing). These objectives were addressed in Chapter 5.

- (3) To explore the prospective association between social media use at age 14 years and change in BMI z-score from age 14 to 17 years in boys and girls. These objectives were addressed in Chapter 6.

These objectives were addressed in three analytical data chapters. The analytical chapters were secondary data analyses drawing data from the GoActive study (Chapter 3), and the UK Millennium Cohort Study (Chapter 5, and 6). Results from individual analytical chapters were interpreted, contextualised within the existing literature, appraised for strengths and limitations, and recommendations for future research were made. Discussions of individual analytical chapters included a deeper focus on analysis-specific factors. For example, why school physical, and policy factors may not be as important for change in physical activity during adolescence as social environment factors (e.g. friendship support for physical activity) (Chapter 3); why the identified association between social media use and BMI z-score in girls was attenuated by sleep, depressive symptoms, body weight satisfaction, and wellbeing (and why an association may not have been found for boys (Chapter 5); and a discussion of potential other related social media use behaviours with BMI z-score (e.g. food advertising) (Chapter 6). These chapter specific discussions are not repeated in this general discussion chapter.

This chapter summarises the main findings of the analytical chapters, discusses overarching methodological strengths and weaknesses, provides an overview of implications for public health policy and practice, and makes recommendations for future research.

7.2 Summary of main findings

7.2.1 Chapter 3: “The school policy, social, and physical environment and change in adolescent physical activity: An exploratory analysis using the LASSO”

Using data from the GoActive study and applying novel LASSO analyses, I showed a potential positive association between friendship support for physical activity (i.e. participants asking a friend to do physical activity and a friend asking a participant to do physical activity) and change in accelerometer-

measured physical activity during adolescence [364]. These findings were found by assessing the predictive value of school policy or physical environment features with change in average daily minutes of MVPA over 10 months in a sample of adolescents (n=1,765) that were participating in the GoActive trial in the East of England, UK. For every unit increase in change in participants asking a friend to do physical activity and change in a friend asking participants to do physical activity, an increase in MVPA of 2.78 (1.55,4.02) and 1.80 (0.48,3.11) min/day was predicted respectively.

A previous systematic review of 75 observational, and experimental studies (if they reported baseline results) exploring the relationship between physical activity and social support (any type) also identified that social support for adolescent physical activity is important. Based on their findings, the authors recommended that integration of social support for adolescent physical activity may provide a tangible target for physical activity interventions [167]. However, the novel statistical methods used in Chapter 3 (LASSO regression) was uniquely able to discern that friendship support for physical activity may be one of the most important potential predictors of change in physical activity relative to over 250 other potential predictors from the wider school policy, social, and physical environment. Factors such as the school policy environment (e.g. presence of school Physical Education uniform policy), and the school physical environment (e.g. specific activity settings such as basketball courts) were not associated in change of physical activity levels. It follows, that efforts would therefore be better placed on resources to support positive friendships rather than investing in tangible, physical activity equipment and/or the development of new physical activity policies at the school-level. Key strengths of this work were the longitudinal, device-measured measurements of MVPA and relatively large representative sample size. Key limitations were the subjective teacher-reported measurements of school environment features, and only being able to measure social environment features (and not policy or physical environment features) longitudinally. To summarize, my exploratory analyses intended to test many potential predictors of change to adolescent physical activity in the school policy, social, and physical environment. Findings suggested that out of over 250 wider environmental factors, only friendship support was significantly associated with change over the observed 10 month

period, and therefore support for physical activity could possibly be harnessed to increase adolescent physical activity levels.

7.2.2 Chapter 5: “Social media use and BMI z-score: a cross-sectional explanatory pathway analysis of 10,798 14-year-old boys and girls”

Chapter 5 presented cross-sectional analyses of the association between self-reported social media use (hours/day) and BMI z-scores in a sample of adolescents from the UK Millennium Cohort study (n=10,798). On average, adolescents reported using 1 to <3 hours of social media per day. For girls (49% of the sample), social media use at ≥ 5 hours/day (vs. 0 to <1 hours/day) was associated with increased BMI z-score ($\beta=0.15$ [95%CI 0.06, 0.25]) and this association was partially explained by sleep duration, depressive symptoms, body weight satisfaction, and wellbeing. No associations were found for boys. In previous studies of adolescents using self-reported height and weight, similar associations have not been demonstrated. The findings provide evidence for a limited or non-significant cross-sectional relationship between social media use and BMI z-score at age 14 years in a UK sample. Due to the cross-sectional study design, it was not possible to infer causality or mediation (or lack of causality or mediation) of the observed relationships. This points to the need for prospective data to disentangle the longitudinal association.

7.2.3 Chapter 6: “Social media use and BMI z-score: a longitudinal propensity score matching analysis of 8,024 14 to 17 year olds”

Chapter 6 presented longitudinal analyses of the association between social media use and change in adolescent BMI z-score. These analyses were undertaken in the same sample as Chapter 5 (the Millennium Cohort Study, n=8,024). The longitudinal findings extend beyond a snapshot of the association gained during my cross-sectional study and show that greater social media use was associated with a higher decrease in change in BMI z-score at the 1 to <3 hours/day range (vs. 0 to <1 hours/day) for boys (β [95%CI] (-0.55 [-1.00, -0.09])), and at the 1 to <3 hours/day range (vs. 0 to <1 hours/day) for girls (-0.11 [-0.18, -0.04] (50% of the sample)). Overall, this suggests that medium use

of social media in early adolescence is associated with a greater decrease in BMI z-score than in low users. These analyses, within the confines of social media use characterised by quantity alone, only show a small association between social media use and BMI z-score. A search of the published literature suggests that no other longitudinal studies on the association of social media use and BMI, using objectively measured BMI z-scores, exist. From cross-sectional investigations using self-reported height and weight to characterise BMI, greater social media use was found to be associated with higher BMI in Iranian adolescents (aged 12-17 years, n = 1,860) [121] and boys (but not girls) in a Canadian cohort (n=4,991, mean age = 15.1 years) [310]. Notably, no dose-response gradients were apparent for social media use and adiposity in Chapter 6. This could be a true finding or attributable to measurement issues. Key strengths of this chapter are the analyses are based on data from a nationally representative cohort over an important developmental time period, the use of objectively-measured BMI z-score, and the application of advanced statistical analysis which involved propensity score matching. Key limitations are the self-reported nature of social media use which was recorded in between January 2015 and April 2016. This means that findings may not be as relevant to the current social media landscape today due to differences in how adolescents may interact with social media, i.e. the devices that adolescents use to access social media, and the type of social media platforms that are popular continually evolve. I identified longitudinal negative associations between a summary variable of self-reported daily social media use and change in measured BMI z-score from age 14 to 17 years.

7.2.4 Summary of main findings overview

In summary, my analytical chapters showed that friendship support is likely to be most the important factor within the school environment for change in physical activity and that quantity of social media only shows small associations with (change in) BMI z-score in adolescents in the UK. In the next section I will discuss the main overarching methodological strengths and weakness of the work presented in my thesis.

7.3 Methodological considerations

This section provides an overview of methodological strengths and weaknesses relevant to the overall thesis. Methodological strengths and weaknesses specifically relevant to the analyses presented in the analytical chapters have been presented within respective chapters.

Two factors are key to consider to appraise validity of findings, where validity refers to how closely observations correspond to the actual state of affairs [365]. First, internal validity (e.g. study design, confounding, multiple testing and the potential of chance findings, and error and bias in measurement), and second, external validity (e.g. generalisability) of the findings derived in this thesis will be discussed.

7.3.1 Internal validity

Internal validity is defined as the extent to which the observed results are correct for the particular group of people being studied [366]. Within observational research, internal validity is important because it determines the strength of inferences that can be made from the findings [367] (i.e. whether the observed changes can be attributed to the exposure and not to other factors). I will focus on the following factors relating to internal validity: study design, confounding, multiple testing and the potential for chance findings, and error and bias in measurement).

7.3.1.1 Study design

All three analytical chapters used observational methods. Observational studies are beneficial when evidence is insufficient to justify the high costs of randomized controlled trials, or if there is a need for greater timeliness of evidence creation [368]. Observational studies also occur in natural surroundings, as opposed to in settings which have been manipulated (e.g. through experimental methods). However, there are also a number of weaknesses of observational methods which require adjustment including an increased risk of bias (e.g. through confounding, information bias, or selection bias [369]), and a restriction to inferring correlations between an exposure and an outcome rather than causation.

Cross-sectional methods (Chapter 3), although useful as a snapshot of an association at a single-time point to substantiate further longitudinal analyses, do not facilitate the exploration of causality or potential mediators. This is a key limitation of Chapter 3. Nevertheless there were key reasons to use the cross-sectional data for my first Millennium Cohort study (Chapter 5). First, there was only one wave of data with social media use available at the time of analyses (September 2020). I explored UK data available to address this research question and evaluated their strengths against the evidence available at the time. Key strengths of the MCS dataset in relation to the stated research question were national representativeness with good representation of ethnic and socio-economic groups, measured BMI z-score, and the ability to study adiposity from an ecological perspective (e.g. through the consideration of how social factors, i.e. social media use, relate to health [323]). I therefore concluded that the cross-sectional analyses using MCS data would have value in the context of what was known about the subject to date. These analyses however were interpreted bearing in mind that no firm conclusions regarding the direction of association could be derived. This meant that reverse causality cannot be ruled out. For example, it remains plausible that adolescents with higher adiposity may report higher levels of social media use. While there is no evidence to support reverse causality, social media use is predominantly a sedentary behaviour. Systematic review level evidence of the temporal sequencing of effects of sedentary behaviour and adolescent adiposity are weak [370], this means that reverse causality cannot be ruled out. Longitudinal studies in population representative samples will be essential to gain better insights into whether social media use is a cause or consequence of increases in adiposity, or both.

Two of three presented analyses applied longitudinal methods (Chapter 3, and 6) which is a key strength. The benefits of using longitudinal methods include the potential for establishment of causal inference through temporality, gaining insight into the order in which events occur, reducing recall bias (e.g. provision of information from participants about their current circumstances, or since the last data collection sweep), and the ability to explore how individual behaviours change over time. While both investigations as longitudinal studies can better support the establishment of causal

relationships through temporality and specificity, to better determine the independent, actual effect of social media use on prospective adiposity development, alternative estimation strategies (e.g. experimental or trial data) are required. However, relevant experimental data were not available for these investigations and their application is possibly better suited to explore the acute effect of social media on behaviours/health, rather than longer term effects. In light of this, Table 16 shows the extent of agreement with each of Bradford Hill's criteria for causation for each of the analytical chapters of this PhD [134]. Based on my research, there is insufficient evidence to infer a causal relationship between any of the exposures and outcomes investigated. Further weaknesses of longitudinal observational studies include their susceptibility to non-response bias, and inability to explore temporality

Table 16: Extent of agreement with Bradford Hill’s criteria for causation for each analytical chapter

Bradford Hill Criteria for causation	Chapter 3: School environment Paper	Chapter 5: Cross-sectional social media use paper	Chapter 6: Longitudinal social media use paper	Rationale
Strength of association	Moderate	Low	Low	The school environment paper had a finding which may almost be clinically significant at the population level
Consistency	High	Low	Low	The school environment paper finding is consistent with the literature base with convincing evidence suggesting the association may be valid
Specificity	Moderate	Low	Low	For the school environment paper, although the sample size was relatively large; there were few adolescents who reported to have no friends to allow comparison
Temporality	Moderate	Low	Low	The school environment paper does not allow the disentangling of selection and influence processes in friendships’ influence.
Biological gradient	Low	Low	Low	I did not investigate dose-response relationships, and none were observationally present

Plausibility	High	High	High	Based on the knowledge of today, all investigated relationships are plausible
Coherence	High	Low	Low	For the school environment paper, findings do not conflict with presumed relationships (given friendships have been consistently identified in the literature base as being influential)
Experiment	Low	Low	Low	All studies were observational in nature. Only experimental evidence would allow agreement with this criteria
Analogy	Low	Low	Low	Exposures are social factors and are therefore not comparable (e.g. to similar drugs being compared for a specific indication)

Colour Code:

- Low = Red
- Moderate = Amber
- High = Green

7.3.1.2 *Confounding*

A limitation that further warrants consideration is the presence of confounding, which may infringe upon internal validity. Confounding is “a mixing of effects of extraneous factors (e.g. confounders) with the effect of interest” [371]. This can occur when a third variable influences both the outcome and exposure variables. The estimated effects of exposures on outcomes can be biased if confounding factors are not appropriately adjusted for [372]. For example, this may falsely obscure or accentuate potential relationships (e.g. spurious associations) [373]. Residual confounding, defined as confounding that remains despite addition of covariates to models, may also result in bias in findings. Residual confounding may arise due to error in measurement of confounders which can lead to incomplete removal of the effect of the confounding variable [374]. For example, certain confounders are imperfect due to being self-reported (e.g. Chapter 6 - dietary intake), and/or have not been reviewed for reliability, and validity in adolescent populations (e.g. Chapter 6 – wellbeing [overall happiness with life]). Given the observational nature of the analyses presented in this thesis, imperfect adjustment for confounding could be weaknesses of these studies. This may have brought rise to inflation of observed associations, or dilution of effects. However, steps were taken to reduce the potential impact of confounding in analytical chapters including the use of multivariable models, directed acyclic graphs, and propensity score matching.

To reduce risk of confounding, multivariable models were used in all analyses. Multivariable models allow adjustment for multiple potential confounders in the same model which facilitates the assessment of the potential independent effect of exposures. In all analyses, potential confounders were selected based on existing research and data of potential relationships between exposures and outcomes.

Unmeasured confounders are variables that are related to both the exposure and the outcome which may present a risk of bias [375]. Certain potential confounders (unmeasured confounders) were unable to be adjusted for due to variables either not being collected as part of the dataset (e.g. Chapter 5, and 6 (social media use and BMI z-score): parental social media use, genetic variation, relationships

with parents, number of friends, social media use cases, locations, and times), or due to high levels of missing data (e.g. Chapter 5, and 6: physical activity).

Measurement error in confounding may also limit internal validity. Random error (i.e. misclassification) in confounders jeopardizes the control of their effect and increases the potential for residual confounding [376]. Given poor measurement of some confounders (e.g. diet), it is only possible to assert adjustment for these confounders within the context of how they were measured. Directed acyclic graphs (DAGs) were also used as a method to identify confounding variables which is a strength. DAGs are a method of identifying confounding variables that require adjustment [377]. The key benefit of using DAGs is to increase transparency on decisions made relating to confounders. I chose to use DAGs to clearly state my assumptions and facilitate external critical appraisal of my studies. Although this approach increases transparency, it is contested whether DAGs increase accuracy and reliability of estimates [377]. For example, a chance of bias remains in each study through excluding certain unmeasured potential confounders. However, best efforts were made to be exhaustive in the addition of these through consideration of what is known about existing relationships between exposures, and outcomes.

In Chapter 3, I used the LASSO variable selection approach to identify potential predictors of change in adolescent physical activity from the school environment. The LASSO approach overcomes some limitations of conventional regression methods when it comes to control of collinear confounders by reducing the risk of residual confounding when collinear variables are not able to be added to traditional regression models (e.g. by reducing the magnitude of their coefficients through regularization) [378].

In Chapter 6, I adjusted for propensity scores to reduce the potential effects of confounding in the longitudinal relationship between social media use and BMI z-score. This is a key strength of the analyses. When adjusting for propensity score (derived from ethnicity, family income, family structure, sleep, depressive symptoms, body weight satisfaction, self-esteem, wellbeing, and primary carer age [all from age 14 data]), the distribution of observed baseline covariates will be similar for treated and

untreated individuals (e.g. adolescents at each level of social media use) which imitates certain attributes of randomisation in intervention methods using observational datasets [355]. Although propensity scores are useful in situations where many potential confounders are relevant, their use is not a substitute for randomized controlled trial research due to only bringing rise to balance in measured, and not unmeasured or poorly measured confounders (as is best in such trials) [379, 380].

7.3.1.3 Multiple testing and the potential of chance findings

Multiplicity in epidemiology can increase in type one error rate as a result of multiple testing [381]. Type one errors occur when the null hypothesis is rejected when it is actually true [382]. The probability of false-positive conclusions were reduced by limiting the number of hypotheses I tested in each study by having a clear, and focussed research question. I also made the a priori decision to split my analyses by sex which slightly increases the probability of a false-positive. However, there is logic in support of not correcting for multiple testing given that power is reduced when doing so (e.g. by Bonferroni correction which increases risk of type two error, meaning the null hypothesis is not rejected when it is actually false) [383].

The risk of chance findings is also diminished as a result of all analyses being conducted in relatively large, and representative samples. This meant that my reported confidence intervals in estimates were narrower than if I had undertaken the analyses in a smaller sample size. Reporting of confidence intervals allows for more accurate interpretation of whether estimates were statistically significant (e.g. when the value of zero effect are not included) [384]. This method may be preferable to traditional p-value-based thresholds for significance because p-values do not enable inference of the direction or size of a difference between groups [384].

7.3.1.4 Error and bias in the measurement of outcomes and exposures

Due to available data, it was not possible to undertake analyses using the most reliable and valid measurement methods for both the outcomes and exposures. This represents a key limitation, of the work presented in this thesis. The measurement approaches of outcomes (change in accelerometer-

assessed physical activity, measured BMI z-score, and change in measured BMI z-score) were prioritised in this thesis which means that outcome measures were the best currently available in terms of validity and reliability in free-living conditions. However, exposure variables were the second concern (i.e. not the best currently available measures in free-living conditions) which means that there is an increased risk of error and bias in their measurement.

In terms of outcomes, the benefits of device-measured physical activity (vs. other methods e.g. self-reported, and criterion measures) were highlighted in the General Introduction (Chapter 1, section 1.3.2). Briefly, physical activity measured by accelerometers reduces measurement error, eliminates self-report biases, and is currently best practice for quantification of physical activity in free-living conditions [56]. However, it may be possible that adolescents with low levels of physical activity would be more inclined to reject collection of their physical activity as they may feel shame or embarrassed about their activity levels. This could potentially increase negative bias in the analytical sample (i.e. the analytical sample is not representative of the sample recruited which is discussed in more detail in section 13.2.2). The benefits of using (change in) measured BMI z-score as the outcome measure in Chapter 5, and 6 include high specificity and sensitivity, and facilitation of comparison at the population level and over time (as discussed in Chapter 1, General Introduction, section 1.4.2). However, it is possible that BMI z-score may incorrectly classify adolescents with high lean mass as living with overweight or obesity despite having low body fat percentage. As discussed in Chapter 1 section 1.3.2, this is rare and due to the high economic cost, organisational cost, and participant burden of objective body composition measurement (e.g. DEXA), BMI z-scores provide a pragmatic alternative.

In terms of exposures, in Chapter 3, the school environment variables were predominantly self-reported which are imperfect measures due to potential subjectivity. School environment surveys were also undertaken by study contact teachers in schools who may not be as skilled in recording school environment features as trained research staff. There may also be social-desirability bias

present in collection of these measures given teachers are stakeholders in a school's success and have an active interest in the school being viewed favourably. This could have led to under-reporting on faults within schools (e.g. graffiti), or embellishing on features within schools (e.g. quality of sports facilities or equipment) which may have caused a type two error in my conclusions.

Chapter 5 and 6 use a self-reported measure of social media use collected as part of the MCS age 14 years data collection. Although useful given that no other data on social media use was available, it was an imperfectly measured exposure variable. Datasets with objectively-measured social media use (vs. self-reported) and measured BMI z-score are limited. Considering this limitation, I initially explored use of other datasets after completing my second analyses (Chapter 5) to gain access to these data. I identified the Study of Cognition and Adolescent Mobile Phone use (SCAMP) study [385]. I pursued using this dataset to analyse the relationship between device-measured social media use (e.g. hours per day drawn from adolescent smartphone use rates) and 1-year change in BMI z-score. Unfortunately, it transpired that these data were unavailable for analysis, due to already planned analyses, and the proposed analysis had to be dropped.

The limitations of social media use defined by quantity alone has been briefly addressed already (see Chapter 4). Social media use characterised by quantity alone does not account for the many multidimensional ways in which social media is used. Social media use can comprise a range of different activities (e.g. actively communicating with friends, passively consuming content), consumed on different devices, in different contexts and in various ways (e.g. consuming videos, posting images, writing posts, etc.). The relationship between social media use and BMI z-score may be dependent on how social media is used (e.g. active vs. passive) or which content is consumed. To assess the effect of social media on adolescent health it may be necessary to differentiate between use cases. Active use is defined as “engaging in social media activities that facilitate interaction with others (e.g. chatting, or broadcasting information)”, whereas passive use comprises “monitoring information on social media without engaging in direct exchanges with others” [386]. It has been suggested that active social media use may elicit support and feedback, whereas passive social media use may trigger

upward social comparison, or envy) [387]. Research on the potential consequences of active vs. passive use is most advanced in the area of wellbeing. However three separate meta-analyses in adults (collectively including 413 studies) comparing time spent on active and passive social media use and the relationship with wellbeing have had mixed findings. Together they suggest that active social media use is not, or is only weakly positively, associated with wellbeing, and that passive social media use is not, or is only weakly negatively, associated with wellbeing [388, 389] [390] [391]. Further research is necessary in the area of adolescent adiposity to identify the potential relationship between active, and passive social media use.

In the previous section I discussed internal validity and the extent to which my observed results are correct for the particular group of people being studied [366]. As a result of the mitigating actions discussed to reduce bias, I have substantial certainty that findings are correct within the context in which they were undertaken. However, it is also important to consider the external validity of these findings.

7.3.2 External validity

External validity, or generalisability, is defined as the extent to which the results of a study applies to people not in the study [366]. External validity is important to identify whether findings may translate to other setting and with other populations. In relation to this thesis, key strengths of all analytical chapters were the reasonably large sample sizes which increases the likelihood that results may hold for other persons, settings, times, or places [392]. For example, the GoActive study (n=2,862 vs. n=1,765 adolescents in my analysis sample) is one of the largest adolescent physical activity interventions to have consecutive device-based measures of physical activity worldwide. There are many levels of comparison relevant here, of which one is the schools from which the participants were drawn. However, it is also important to consider how representative the school population is to the wider population, how representative the recruited sample is of the school sample, and how representative the analytical sample is of the recruited sample. The region in which the GoActive study

took place (East of England, UK) has substantial socioeconomic diversity and includes both urban, and rural areas. Given the study recruited an entire year group in a relatively large number of schools (n=16 schools, 84% of eligible students included), and eligibility criteria for schools were both state-run and non-fee paying, it is likely that findings are representative of the East of England and may also be representative of other schools in the UK. However, given the east of England is not very ethnically diverse, findings may not be generalizable to the wider UK population, particularly with regards to ethnicity.

My second data source for the thesis is the Millennium Cohort study (MCS). The MCS has been set up to be nationally representative of British adolescents. It was launched in the year 2000 and follows around 19,000 adolescents from birth onwards with the most recent data collection wave taking place at age 22 years (which was collected in 2022 and is not currently available as of January 2023). National representativeness will decrease selection bias by not placing a restriction on the population of interest which could decrease representativeness. However, selection bias may occur as a result of the unequal probabilities of selection that result from the stratified cluster sample design. In an effort to overcome this, I applied relevant sample design weights in both analyses in this dataset. Attrition bias is defined as the systematic differences in the way participants are lost from a study and this is particularly relevant to consider in the context of a cohort study [393]. Chapter 5 and 6 used BMI z-score as the outcome measure, which is a potentially sensitive metric for adolescents. It may have been likely that adolescents with socially less desirable BMI z-scores declined to engage with this measure. Furthermore, the Millennium Cohort study waves suffered from participant attrition between the Age 14 and 17 waves which meant the sample size for the longitudinal study (Chapter 6) was comparatively smaller versus the cross-sectional study (Chapter 5). As adiposity increases during adolescence, this may have led to sample bias where the analytical sample did not comprise of adolescents who gained more adiposity (vs. less). It is challenging to identify the implications of participants lost to follow-up due to not being able to collect data from these participants. However,

best practice was followed regarding sensitively collecting weight-related data which increases the likelihood that the number of participants lost to follow-up for these reasons were minimised.

7.4 Implications for public health policy and practice

The findings described in this thesis have several implications for public health policy and practice given that adolescent physical inactivity and obesity is a priority and a challenge worldwide.

7.4.1 Encouraging harnessing of friendship support for physical activity in policy, and practice

Friendship support for physical activity was identified as potentially more important for change in physical activity relative to the school policy, and physical environment factors explored. There is convincing evidence that social support for physical activity from friends is beneficial for adolescent physical activity, particularly for girls [115]. Widespread adoption of harnessing friendship support for physical activity in the practice sphere may support change in the policy sphere. For example, ensuring that physical activity initiatives/programmes are specifically open to dyads or friendship groups, both at the school-level and beyond may support physical activity promotion.

7.4.2 The potentially limited impact of social media use on BMI z-score may provide opportunities for harnessing high adolescent engagement for health improvement

The potentially limited negative impact of social media use on BMI z-score suggests that high adolescent engagement with social media could be harnessed for population health improvement. Adolescents' heavy engagement with social media offers additional opportunities for population health improvement through surveillance, intervention delivery, recruitment to trials, data collection, and dissemination [394]. Exploration of the potential of population health improvement via high adolescent engagement with social media was beyond the scope of this thesis, (in line with the behavioural epidemiology framework (outlined in Chapter 1, General Introduction), given the relative infancy of the research base.

7.4.3 Need for transparent collaborations with industry researchers for increased social media use data access

A key limitation of Chapter 5 and 6 was that data collected on adolescents' social media use behaviours was from seven years earlier prior to analyses in 2022. Although my studies were the first to analyse the cohort's social media use patterns in the context of adiposity; social media use behaviours may have changed since the data was collected (e.g. due to switching platform preferences as discussed in Chapter 4, section 4.7.3). To prevent social media use from becoming a lagging indicator, it is important to consider targeting improved collaboration between researchers and technology companies. Fellowships to support research are available (e.g. the Meta Research PhD Fellowship) which allow approved access to Meta (formerly Facebook's) data stores. The recently launched (November 1st, 2022), EU Digital Services Act which will come into action from the 1st of January 2024 has also created a set of rules to support regulated data access for social media companies to share data with vetted researchers. The limitations of my research (e.g. self-reported social media use from the year 2015) highlights a need for this initiative to overcome the imperfect measures of social media use currently available.

7.5 Recommendations for future research

The key implications for research were presented in each chapter. They include further investigation of sex differences in friendships' influence on physical activity, and the relationship between device-measured social media use and adolescent adiposity. The following four additional research directions are recommended based on my overall thesis: network-based physical activity interventions, social environmental moderation of physical activity intervention effectiveness, the harnessing of heavy adolescent engagement in social media use for obesity prevention, and an investigation of adolescent social media use cases.

7.5.1 Network-based physical activity interventions

Future research is needed to better understand the school social environment, in particular exploring how friendships during adolescence influence physical activity via social network analysis. This type of research would provide insight into how to prevent the decline in physical activity during adolescence. Further identification of pertinent friendship network characteristics (e.g. friendship support for physical activity) should guide network-based interventions aimed at improving physical activity during adolescence. Network-based interventions aim to identify and leverage influential individuals within friendship networks to generate a desired outcome and operate under the assumption that when influential individuals “stimulate and spread” a behaviour (such as physical activity), the behaviour will turn into a group norm and support long-term behaviour change [395]. Using network characteristics to “inform targeting of interventions” has been shown to outperform random selection, and selection of high-risk individuals or “vulnerable contexts” [396] (e.g. adolescents living in areas with a low socioeconomic status, or adolescents living with overweight or obesity) [396]. Selecting individuals who influence the other members of the network the most has been found to bring rise to the biggest increase in physical activity across the network; although the magnitude of effect vs. random selection was modest and may not be clinically meaningful and more research is necessary [397]. Although in practice, this is not straight forward given the requirement to first survey e.g. a school class for individuals within the classroom who are influential, or undertake social network analysis over at least two time points, which is challenging statistically, to identify which individuals influence physical activity within the classroom. This approach may also be challenging to scale up. However, harnessing friendship support for physical activity in network-based interventions is worth exploring in future research. On the back of my findings, an appropriate next step would be to understand the types of friendship support for physical activity that are key to change in physical activity and how these behaviours can be encouraged in interventions.

7.5.2 Social environmental moderation of physical activity intervention effectiveness

Another promising future research direction involves exploring whether the school social environment (e.g. friendship support for physical activity) may moderate physical activity intervention effectiveness. Moderators are factors that modify the direction or strength of a relationship [398]. A moderator will produce different estimates of an association at different levels of the variable [398]. Investigation of potential moderators may provide insight into who the intervention was most effective for. Moderation analysis can also facilitate intervention modification to tailor to sub-groups of the population who may benefit the most. Whilst effect modification by demographic characteristics such as age, sex and socioeconomic position is often investigated in physical activity intervention trials, there is limited exploration of the modifying effect of environmental features. Chapter 3 showed that social environment features - and not the policy or physical environment - were potential predictors of change in physical activity. This suggests that social environment features may be comparatively more important for physical activity interventions and could be prioritised in moderation analyses of intervention effectiveness. This may support the identification of new and possibly more effective intervention targets to support adolescent physical activity.

7.5.3 The potential of population health improvement via adolescent engagement with social media

Adolescents' heavy engagement with social media offers additional opportunities for population health improvement through surveillance, intervention delivery, recruitment to trials, data collection, and dissemination [394]. Exploration of the potential of population health improvement via high adolescent engagement with social media was beyond the scope of this thesis, given the relative infancy of the research base. There remains a need to better understand the relationship between how social media use during adolescence can be leveraged to be protective against adolescent adiposity (e.g. whether health information is available on social media, and where, and how adolescents can be supported to engage with this).

7.5.4 Social media use cases

Evolving social media platform preferences (e.g. change from Facebook to more video-based platforms such as Youtube or Tiktok) suggests that adolescents are using social media for additional reasons other than engaging with friends. Given that Youtube, and Tiktok are primarily content-based platforms, there is a need to explore what content is being consumed by adolescents, and why, to better assess implications for behaviours and health. These data could be derived initially from cross-sectional, qualitative study to generate themes of use cases/content to inform population-based, recurring (i.e. longitudinal) quantitative data collection throughout adolescence. Social norms of social media use are important to consider both in terms of what is “normalized” on social media (e.g. content), and may become normalized off social media, perhaps through direct or indirect peer pressure processes (e.g. an adolescent viewing something on social media, feeling like this is what they should be doing as their friends or idols are, and it becoming adopted into their life). Novel approaches of reviewing popular Youtube videos in Malaysia for advertisements targeting adolescents have identified that food and beverage advertisements are common [245] but it is still unclear which adolescents are viewing these types of videos (e.g. geography, BMI z-score, wellbeing, etc.), and what the implications are on their consumer behaviours, let alone their body weight and growth. Given that Tiktok advertising revenue is amongst the highest of companies worldwide [399] and Tiktok is heavily used by adolescents there would be value in further research in this area to identify the prevalence of food and beverage focussed advertisements targeting children. Several approaches may facilitate this including a broad approach of reviewing social media use analytics platforms (e.g., socialblade.com) to identify the most popular TikTok videos based on number of views, or a targeted approach of collecting a specific adolescent populations opinion on favourite TikTok creators before reviewing and thematically coding these videos for number and type (e.g., visual vs. overlay) of food and beverage adverts.

7.6 PhD Reflections

Before providing an overall conclusion, in the following couple of pages I reflect on my learnings during my PhD, what I would do differently, and how my thinking has progressed.

7.6.1 Learnings

I particularly enjoyed doing a PhD for the three years of almost complete autonomy over my personal and professional development. This led to me being able to develop many general and specific skills/learnings across both curricular (i.e. relating to my PhD), and extracurricular activities (e.g. short-term, team-based projects where I explored my interests in Technology). In general, in my PhD I valued learning skills in project management, data analysis, critical thinking, conflict resolution, and storytelling. I believe these skills are highly transferable and relevant to most professions. Relating to extracurricular activities, I particularly enjoyed leading teams and learning that leaders need to be both skilled in resource allocation, and decisive based on the best available evidence to be successful.

7.6.2 What I would do differently

With regard to my PhD, I hope that it is clear to readers that I tried to use novel methods throughout my thesis. It is my opinion, innovation is generally underrepresented in the adolescent obesity and physical activity research area and it is important to try new things to close this gap. However, there were likely inefficiencies in this approach as I perhaps overreached in my attempt to bring new approaches from other fields. For example, only 1 out of the 4 proposed studies in my First Year report were included in this thesis. When I look at the 15,000 + word "Thesis Deleted Bits" document, and the similarly combined size of assorted additional analysis plans, data request forms, and Gantt charts; it is difficult not to think about the hours/days/weeks of work which did not end up contributing to this thesis. However, they did contribute to my overall learning and skill development. Ultimately, despite several shifting of focusses during my PhD, I appreciated the challenges, and creative freedom to explore my interests.

If pandemic-related restrictions had not prevented it, I would have like to do an overseas institutional visit and international collaboration in the USA. I started my PhD with a clear desire to have a global training experience and had hoped that international exposure would also give me access to new ideas and methodologies beyond what is capable via digital means. Unfortunately, this was not possible, but I did have a successful and very insightful internship in the NHS which advanced my development (see section Appendix 1, Learning and Skill Development) which may have not been possible in conjunction with an overseas institutional visit.

In light of reflecting on “what I would do differently” I think I would recommend three key things to current or aspiring PhD students. First, it is ok to divert from your original plans. Second, “in writing you must kill all your darlings”. And finally, there is more to be gained from a PhD than “just” completing a thesis.

7.6.3 How my thinking has progressed

My favourite thing about doing a PhD, particularly in Cambridge, was the opportunity to speak to a diverse range of people across sectors; many of whom I would not have had the opportunity to meet if I had either not done a PhD, or had done a PhD elsewhere. This underpinned my most important learning from my PhD which is that lasting change to population health will likely be achieved through effective large-scale collaboration and aligning incentives with sectors beyond healthcare. Having spent some time working in the NHS in Covid recovery via an internship, when interacting with Managers and Directors who did not have a background in healthcare or research I recognized how important it was to be able to “speak other languages” and effectively work with individuals who viewed things differently to me. This also means challenging long-held beliefs, even at the institutional level. In research I often feel that I am pushing against an open door, but my internship helped me realise that there is often a mismatch between what may be common knowledge or undeniable for researchers, but is not a widely-held belief out with these circles. This experience helped me define the next step after my PhD.

During my First Year Viva, I was asked “what type of researcher did I want to be?”. The question was posed to help narrow down my overall PhD focus given that I had proposed several studies in the areas of behavioural epidemiology, network analysis, and public health modelling. When reflecting on this question in a literal sense I realised that I had increasingly begun to view a PhD in Medical Science, not as the first step towards a career in research, but as an opportunity to develop skills in science and storytelling which I could harness and use to champion healthcare in settings beyond Universities. Following my PhD, I will leave academia. My next step is to pursue a goal of becoming as skilled as possible at collaborating with people from different backgrounds and sectors. Although this approach may be a less well-trodden path towards impact, I believe it is the right path for me.

7.7 Conclusion

Overall this thesis contributes evidence on the role of the school and digital environment in adolescent physical activity and adiposity. Friendship support was shown to be particularly important for maintaining physical activity in boys during adolescence. Crucially, friendship support was the only factor of over 250 wider aspects of the physical, and social school environment to be significantly associated with change in physical activity over the course of a year, indicating that more research to better leverage these existing social dynamics is needed. Moreover, I showed that the association between social media use and adiposity in adolescence is small, cross-sectionally as well as prospectively. The evidence presented in this thesis demonstrates a need for further research to better understand the potential influence of the school and wider digital environment on adolescent health behaviours and health.

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Appendices

- Appendix 1: Learning and skill development
- Appendix 2: Supplementary Materials

Appendix 1: Learning and skill development

Peer reviewed first-author publications

- Foubister, C., et al. (2021). "The school policy, social, and physical environment and change in adolescent physical activity: An exploratory analysis using the LASSO." *PLoS One* **16**(4): e0249328.
- Social media use and BMI z-score: a cross-sectional explanatory pathway analysis of 10,798 14-year-old boys and girls (In press, *Pediatric Obesity*)
- Social media use and BMI z-score: a longitudinal propensity score matching analysis of 8,024 14 to 17 year olds (In submission)

Conference presentations

- International Society for Behavioural Nutrition and Physical Activity conference, New Zealand, 2020 (Virtual due to the Covid-19 pandemic): The school policy, social, and physical environment and change in adolescent physical activity: An exploratory analysis using the LASSO (Chapter 3)
- European Childhood Obesity Group conference, Budapest, 2021 (cancelled due to the Covid-19 pandemic): Social media use and BMI z-score: a cross-sectional explanatory pathway analysis of 10,798 14-year-old boys and girls (Chapter 5)

Awards

- ISBNPA 2020 Top 10 oral presentation: The school policy, social, and physical environment and change in adolescent physical activity: An exploratory analysis using the LASSO
- NIHR Academy Member's conference Poster Prize Winner: The school environment and adolescent physical activity

Co-authorship

During my PhD I participated in some additional research investigations as a co-author. These are listed below. For publications marked with a "*", some of my contribution occurred prior to beginning my PhD.

- E. R. Lawlor, K. Ellis, J. Adams, R. Jago, L. Foley, S. Morris, T. Pollard, C. Summerbell, S. Cummins, H. Forde, **C. Foubister**, et al. (2022). "Stakeholders' experiences of what works in planning and implementing environmental interventions to promote active travel: a systematic review and qualitative synthesis." Transport Reviews: 1-24
- *A. O. Werneck, E. M. Winpenny, **C. Foubister**, J. M. Guagliano, A. G. Monnickendam, E. M. F. van Sluijs, et al. (2020). "Cohabitation and marriage during the transition between adolescence and emerging adulthood: A systematic review of changes in weight-related outcomes, diet and physical activity." Prev Med Rep **20**: 101261.
- S. T. Jong, C. H. D. Croxson, **C. Foubister**, H. E. Brown, C. Guell, E. R. Lawlor, et al. (2020). "Reach, Recruitment, Dose, and Intervention Fidelity of the GoActive School-Based Physical Activity Intervention in the UK: A Mixed-Methods Process Evaluation." Children (Basel) **7**(11).
- *K. Corder, S. J. Sharp, S. T. Jong, **C. Foubister**, H. E. Brown, E. K. Wells, et al. (2020). "Effectiveness and cost-effectiveness of the GoActive intervention to increase physical activity among UK adolescents: A cluster randomised controlled trial." PLoS Med **17**(7): e1003210.
- *E. M. Winpenny, M. Smith, T. Penney, **C. Foubister**, J. M. Guagliano, R. Love, et al. (2020). "Changes in physical activity, diet, and body weight across the education and employment transitions of early adulthood: A systematic review and meta-analysis." Obes Rev.
- *K. Corder, E. M. Winpenny, **C. Foubister**, J. M. Guagliano, X. M. Hartwig, R. Love, et al. (2020). "Becoming a parent: A systematic review and meta-analysis of changes in BMI, diet, and physical activity." Obes Rev.
- K. Corder, A. O. Werneck, S. T. Jong, E. Hoare, H. E. Brown, **C. Foubister**, et al. (2020). "Pathways to Increasing Adolescent Physical Activity and Wellbeing: A Mediation Analysis of Intervention Components Designed Using a Participatory Approach." International Journal of Environmental Research and Public Health **17**(2): 390.

- *K. Corder, S. J. Sharp, **C. Foubister**, H. E. Brown, S. T. Jong, E. K. Wells, et al. (2019). "Effectiveness of the GoActive intervention to increase physical activity in adolescents aged 13–14 years: a cluster randomised controlled trial." The Lancet **394**: S34.
- S. T. Jong, C. H. D. Croxson, C. Guell, E. R. Lawlor, **C. Foubister**, H. E. Brown, et al. (2019). "Adolescents' perspectives on a school-based physical activity intervention: A mixed method study." Journal of Sport and Health Science.

Internship in NHS

During the third year of my PhD, I undertook a 9 month internship in the NHS supporting Covid Recovery and Restoration in the East of England Healthcare Public Health team. The role involved engaging in multidisciplinary processes for addressing NHS key priority areas (e.g. Covid-19, Digital, Inequalities). I also developed an understanding of core public health competencies (e.g. Needs Assessment, Equality Health Impact Assessment, and Health Equity Audit) and gained professional leadership skills in Healthcare. I wrote about my experience in collaboration with a colleague and this is published as a blog post via the NIHR SPHR and can be found in supplementary material (section Supplementary Material 1).

Key achievements/outputs

- Assurance of Elective Recovery submissions (supporting £1.6B funding allocation)
- Long Covid Rehabilitation – population health management (Regional Lead for Long Covid in the East of England)
- Covid-19 Vaccine Uptake: Evidence Review
- Learning Disabilities: Mortality Review

Writing group

During the second year of my PhD I set up a writing group in collaboration with a fellow PhD student from the MRC Epidemiology Unit. The group was for members of the MRC Epidemiology Unit, and although had a focus on attracting PhD students, some Postdoctoral Researchers also attended. The

format of Writing Group sessions involved two researchers being paired to provide feedback on each other's work approximately once per month. Each researcher came from different teams within the MRC Epidemiology Unit, and had complementary backgrounds to encourage demystifying of assumed knowledge, and further the sharing of ideas, and expertise between fields. As one of two Writing Group hosts, I facilitated sessions to support best practice in provision of feedback and also reviewed each of my colleagues work during the session.

Key achievements/outputs

- Facilitated 10+ Writing group sessions
- Received 1 additional co-authorship of a publication

Journal club

During the First year of my PhD, I set up a Journal club in collaboration with a fellow PhD student from the MRC Epidemiology Unit. The goal of the Journal club was to develop critical appraisal skills, to provide opportunities to discuss new and seminal literature, to generate debate and improved understanding of the literature, and to stimulate novel ideas for further research. The Journal club adopted a traditional format (e.g. an article was selected, individually reviewed by members of the Journal club ahead of the session, and the article was critically appraised as a group during a, typically monthly session. We also hosted the occasional session using a novel format (e.g. debates).

Key Achievements/outputs

- Facilitated 10+ Journal club sessions during the first year of my PhD

Public Engagement/Dissemination Activities

- MRC Epidemiology Unit Away Day talk, presenting on how Patient and Public Involvement groups can assist with dissemination (December 2019)
- MRC Epidemiology Unit science communication event at Life Lab, Ely Cathedral (September 2019)

- Public Engagement event at Arbury Community Centre, MRC Epidemiology Unit Science Bus (June 2019)
- Presented findings of GoActive study at 16 schools across Cambridgeshire and Essex (April/May 2019)
- Developed script alongside Public and Patient Involvement group and assisted with filming a dissemination video for the results of the GoActive study (April 2019)

Courses

- University of Cambridge Researcher and Professional Development: Introduction to Machine learning
- University of Cambridge Researcher and Professional Development: Introduction to Structural Equation Modelling
- University of Cambridge Researcher and Professional Development: Network analysis

Appendix 2: Supplementary Materials

S1: Table 1: GoActive school environment study Exposure Variables

S2: Table 2: Studies included in narrative review of social media use and mental, and physical health

S3: NHS Internship blog post: “Public Health in practice – our fellowship at NHS England and Improvement

S4: School environment paper: GoActive School Environment Survey

S1: Table 1: GoActive school environment study

Exposure variables

Variable Description	Response Categories	How data treated
Job role of respondent	Headteacher = 1; Deputy Headteacher =2; PE Lead = 3; Year 9 Lead = 4; Other = 5	Categorical
Start time of school day	Free text e.g. 8am = 0800	Continuous
End time of school day	Free text e.g. 3.20pm = 1520	Continuous
Start time of morning break	Free text e.g. 11am = 1100	Continuous
Duration of morning break (minutes)	Free text e.g. 15 minutes = 15	Continuous
Start time of lunch break	Free text e.g. 12.15pm = 1215	Continuous
Duration of lunch break (minutes)	Free text e.g. 30 minutes = 30	Continuous
Have any events occurred during the measurement period that may have influenced the level of physical activity of Year 9 students (e.g. sports day)?	No = 0; Yes =1	Dichotomous
Presence of planted beds containing flowers/shrubs/small trees	None = 0; Some = 1; A lot =2	Categorical

Presence of trees for shade	None = 0; Some = 1; A lot =2	Categorical
Presence of loud ambient noise (e.g. traffic, trains, industry)	None = 0; Some = 1; A lot =2	Categorical
Presence of litter	None = 0; Some = 1; A lot =2	Categorical
Presence of murals/outdoor art	None = 0; Some = 1; A lot =2	Categorical
Presence of graffiti	None = 0; Some = 1; A lot =2	Categorical
The grounds are shielded from the surrounding area by hedges/trees/fences	Strongly disagree = 1; Disagree = 2; Neither agree nor disagree = 3; Agree = 4; Strongly agree = 5	Categorical
The grounds are generally well maintained	Strongly disagree = 1; Disagree = 2; Neither agree nor disagree = 3; Agree = 4; Strongly agree = 5	Categorical
The grounds are generally free of vandalism	Strongly disagree = 1; Disagree = 2; Neither agree nor disagree = 3; Agree = 4; Strongly agree = 5	Categorical
Number of pupils in Year 9	Free text e.g. 240 pupils in year 9 = 240	Continuous
Number of pupils in the whole school	Free text e.g. 1300 pupils in the whole school = 1300	Continuous
Number of boys in Year 9	Free text e.g. 124 boys in Year 9 = 124	Continuous
Number of boys in the whole school	Free text e.g. 700 boys in the whole school = 700	Continuous
Number of girls in Year 9	Free text e.g. 116 girls in Year 9 = 116	Continuous

Number of girls in the whole school	Free text e.g. 600 girls in the whole school = 600	Continuous
Percentage of students in Year 9 for whom receive Pupil Premium	Free text e.g. 16.5% of students in Year 9 receive Pupil Premium = 16.5	Continuous
Percentage of students in whole school for whom receive Pupil Premium	Free text e.g. 17% of students in whole school receive pupil premium = 17	Continuous
Does your school have access to a specific indoor hall for gym or sports?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to a shared indoor facility used for sports activities?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to a sports or football field/pitch on school grounds?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to an athletics track (grass or hard surface)?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to courts (e.g. tennis, basketball including half court, netball, multicourt area)?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to a recreational area on school grounds?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical

Does your school have access to a wildlife garden?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to bright or fluorescent markings on play surfaces (e.g. hopscotch, animals)	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to playground equipment (e.g. swings, slide)?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to benches?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to picnic tables?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to drinking fountains?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to uncovered cycle parking?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to covered cycle parking?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to an assault course?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical

Does your school have access to a formal garden or quiet space?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to an outdoor teaching space?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to a vegetable or fruit garden?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to playing fields or a local park off school grounds, which you can use?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to purpose-built changing facilities?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Does your school have access to sports equipment (e.g. gymnastics equipment)?	No = 0; Yes, high quality = 3; Yes, medium quality = 2; Yes, low quality = 3	Categorical
Are the school grounds generally suitable for sport (organised or not)?	Very = 3; Somewhat = 2; Not at all = 1	Categorical
Are the school grounds generally suitable for informal games (kickabout, Frisbee etc)?	Very = 3; Somewhat = 2; Not at all = 1	Categorical
Are the school grounds generally suitable for general play?	Very = 3; Somewhat = 2; Not at all = 1	Categorical

How many hours of physical education do pupils in Year 9 usually have per week?	Free text e.g. 2 hours of PE per week = 2	Continuous
Does your school or any other organisation provide any extracurricular physical activity or sports programmes available to Year 9 before school?	No = 0; Yes =1	Dichotomous
Does your school or any other organisation provide any extracurricular physical activity or sports programmes available to Year 9 during lunch breaks?	No = 0; Yes =1	Dichotomous
Does your school or any other organisation provide any extracurricular physical activity or sports programmes available to Year 9 after school?	No = 0; Yes =1	Dichotomous
Does your school or any other organisation provide any extracurricular physical activity or sports programmes available to Year 9 at weekends?	No = 0; Yes =1	Dichotomous
Availability of rounders as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of cricket as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of table tennis as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of gymnastics as extracurricular activity?	No = 0; Yes =1	Dichotomous

Availability of boxing as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of volleyball as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of swimming as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of archery as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of martial arts as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of dodgeball as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of fencing as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of handball as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of Ultimate Frisbee as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of yoga as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of Zumba as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of Pilates as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of badminton as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of dance as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of running as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of trampolining as extracurricular activity	No = 0; Yes =1	Dichotomous

Availability of tennis as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of hockey as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of football as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of netball as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of rugby as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of athletics as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of other sports as extracurricular activities?	No = 0; Yes =1	Dichotomous
Availability of basketball as extracurricular activity?	No = 0; Yes =1	Dichotomous
Availability of cheerleading as extracurricular activities?	No = 0; Yes =1	Dichotomous
My school considers it important to encourage pupils to be physically active at school (for example, during school breaks)?	Strongly disagree = 1; Disagree = 2; Neither agree nor disagree = 3; Agree = 4; Strongly agree = 5	Categorical
My school considers it important to encourage pupils to do physical activity outside of school	Strongly disagree = 1; Disagree = 2; Neither agree nor disagree = 3; Agree = 4; Strongly agree = 5	Categorical
My school considers it important to educate pupils about the risks of inactivity	Strongly disagree = 1; Disagree = 2; Neither agree nor disagree = 3; Agree = 4; Strongly agree = 5	Categorical
My school considers it important to provide information on how to be physically active in a safe manner	Strongly disagree = 1; Disagree = 2; Neither agree nor disagree = 3; Agree = 4; Strongly agree = 5	Categorical

My school considers it important to encourage pupils to use active transport to school (e.g. walking, cycling)	Strongly disagree = 1; Disagree = 2; Neither agree nor disagree = 3; Agree = 4; Strongly agree = 5	Categorical
Which of the following statements best describes your rules relating to where Year 9 pupils can go during breaks (including lunchtime)?	It is compulsory for all Year 9 pupils to go outside, irrespective of the weather = 1; When the weather allows, it is compulsory for all Year 9 pupils to go outside. However, all Year 9 pupils are kept inside in bad weather = 2; When the weather allows, it is compulsory for all Year 9 pupils to go outside. However, if the weather is bad, they are allowed inside or outside = 3; The Year 9 pupils are allowed to go both inside and outside, irrespective of the weather = 4; It is compulsory for all Year 9 pupils to stay inside, irrespective of the weather = 5	Categorical
Are the Year 9 pupils allowed to use a computer during breaks?	Yes, always = 1; Yes, in bad weather = 2; No, never = 3;	Categorical
Are the Year 9 pupils allowed to watch TV or videos during breaks?	Yes, always = 1; Yes, in bad weather = 2; No, never = 3;	Categorical
Are the Year 9 pupils allowed to use the school's sports equipment during breaks?	Yes, always = 1; Yes, in bad weather = 2; No, never = 3;	Categorical

Are the Year 9 pupils allowed to play ball games indoors during breaks?	Yes, always = 1; Yes, in bad weather = 2; No, never = 3;	Categorical
Are the Year 9 pupils allowed to play ball games outdoors during breaks?	Yes, always = 1; Yes, in bad weather = 2; No, never = 3;	Categorical
Does your school have a policy to promote PA among Year 9 pupils?	Yes, a written policy = 1; Yes, an informal policy = 2; No = 3	Categorical
During a normal week how often do the following things happen? My friends do physical activity or play sports with me.	1 = Never or hardly ever; 2 = Once or twice a week; 3 = Nearly every day; 4 = Every day;	Categorical
During a normal week how often do the following things happen? I ask my friends to do physical activities or play sports with me.	1 = Never or hardly ever; 2 = Once or twice a week; 3 = Nearly every day; 4 = Every day;	Categorical
During a normal week how often do the following things happen? My friends ask me to do physical activities or play sports with them.	1 = Never or hardly ever; 2 = Once or twice a week; 3 = Nearly every day; 4 = Every day;	Categorical
Number of pupils 2016-2017	Free text e.g. 1000 pupils = 1000	Continuous
Number of pupils 2016-2017	Free text e.g. 100 teachers = 100	Continuous
School total expenditure 2016-2017 (£)	Free text e.g. £6.2m = 6200000	Continuous

Staff total expenditure 2016-2017 (£)	Free text e.g. £4.38m = 4380000	Continuous
Premises total expenditure 2016-2017 (£)	Free text e.g. £415k = 415000	Continuous
Occupation total expenditure 2016-2017 (£) e.g. the costs associated with occupying the school building (energy, water, sewerage, rates, insurance, and catering)	Free text e.g. £616k = 616000	Continuous
Supplies and services total expenditure 2016-2017 (£)	Free text e.g. £950k = 950000	Continuous
Cost of finance expenditure 2016-2017 (£)	Free text e.g. £175k = 175000	Continuous
Special facilities expenditure 2016-2017 (£)	Free text e.g. £3.75k = 3750	Continuous
Teaching staff expenditure 2016-2017 (£)	Free text e.g. £3.23m = 3230000	Continuous
Supply staff expenditure 2016-2017 (£)	Free text e.g. £184k = 184000	Continuous
Education support staff expenditure 2016-2017 (£)	Free text e.g. £744k = 744000	Continuous
Administrative and clerical staff expenditure 2016-2017 (£)	Free text e.g. £746k = 746000	Continuous
Other staff costs expenditure 2016-2017 (£) e.g. this includes cost of other staff, indirect employee expenses, staff development and training)	Free text e.g. £283k = 283000	Continuous
Premises staff expenditure 2016-2017 (£)	Free text e.g. £189k = 189000	Continuous
Cleaning and caretaking staff expenditure 2016-2017 (£)	Free text e.g. 106k = 106000	Continuous

Maintenance and improvement expenditure 2016-2017 (£)	Free text e.g. 146k = 146000	Continuous
PFI charges 2016-2017 (£)	Free text e.g. £0 = 0	Continuous
Energy expenditure 2016-2017 (£) e.g. all costs related to fuel and energy	Free text e.g. £107k = 107000	Continuous
Water and sewerage expenditure 2016-2017 (£)	Free text e.g. £17k = 17000	Continuous
Other occupation costs expenditure 2016-2017 (£) e.g. rents for premises, refuse collection, hygiene services)	Free text e.g. \$16k = 16000	Continuous
Other insurance premiums expenditure 2016-2017 (£) e.g. premises related insurance, vehicle insurance, school trip insurance)	Free text e.g. £36k = 36000	Continuous
Catering expenditure 2016-2017 (£)	Free text e.g. £163k = 163000	Continuous
Rents and rates expenditure 2016-2017 (3) e.g. business rates, national non-domestic rates)	Free text e.g. £50k = 50000	Continuous
Administrative supplies expenditure 2016-2017 (£)	Free text e.g. £255k = 255000	Continuous
Educational supplies expenditure 2016-2017 (£)	Free text e.g. £474k = 474000	Continuous
Bought in professional services expenditure 2016-2017 (£) e.g. educational consultancy, auditor costs)	Free text e.g. £116k = 116000	Continuous

Total income 2016-2017 (£)	Free text e.g. £6m = 6000000	Continuous
Grant funding total 2016-2017 (£)	Free text e.g. £5m 5000000	Continuous
Self-generated funding total 2016-2017 (£)	Free text e.g. £349k = 340000	Continuous
In year balance 2016-2017 (£)	Free text e.g. £220k = 220000	Continuous
Revenue reserve 2016-2017 (£)	Free text e.g. £444k = 444000	Continuous
Direct grants 2016-2017 (£) e.g. DfE/EFA revenue grants, pre-16 funding	Free text e.g. £5.3m = 5300000	Continuous
Community grants 2016-2017 (£)	Free text e.g. £370k = 370000	Continuous
Targeted grants 2016-2017 (£)	Free text e.g. £240k = 240000	Continuous
Income from facilities and services 2016-2017 (£) e.g. income from meals provided to external customers, income for consultancy, training courses and examination fees	Free text e.g. £150k = 150000	Continuous
Income from catering 2016-2017 (£)	Free text e.g. £220k = 220000	Continuous
Donations and/or voluntary funds 2016-2017 (£)	Free text e.g. \$£100k = 100000	Continuous
Receipts from supply teacher insurance claims 2016-2017 (3)	Free text e.g. £1k = 1000	Continuous
Investment income 2016-2017 (£)	Free text e.g. £9k = 9000	Continuous

Other self-generated income 2016-2017 (£)	Free text e.g. £57k = 57000	Continuous
School workforce full time equivalent 2016-2017 (Full time equivalent)	Free text e.g. 101FTE = 101	Continuous
Total number of teachers 2016-2017 (full time equivalent)	Free text e.g. 62FTE = 62	Continuous
Teachers with qualified teacher status 2016-2017 (5)	Free text e.g. 99% = 99	Continuous
Senior leadership 2016-2017 (full time equivalent)	Free text e.g. 8FTE = 8	Continuous
Teaching assistants 2016-2017 (full time equivalent)	Free text e.g. 11FTE = 11	Continuous
Non-classroom support staff excluding auxiliary staff 2016-2017 (full time equivalent)	Free text e.g. 31TE = 31	Continuous
Auxiliary staff 2016-2017 (full time equivalent)	Free text e.g. 13FTE = 13	Continuous
School work force head count 2016-2017	Free text e.g. 148	Continuous
OFSTED Rating	1 = Outstanding; 2 = Good; 3 = Requires Improvement; 4 = Inadequate	Categorical
Number of pupils 2016-2017	Free text e.g. 1000 pupils = 1000	Continuous
Number of teachers 2016-2017	Free text e.g. 100 teachers = 100	Continuous
School total expenditure 2017-2018 (£)	Free text e.g. £6.2m = 6200000	Continuous

Staff total expenditure 2017-2018 (£)	Free text e.g. £4.38m = 4380000	Continuous
Premises total expenditure 2017-2018 (£)	Free text e.g. £415k = 415000	Continuous
Occupation total expenditure 2017-2018 (£) e.g. the costs associated with occupying the school building (energy, water, sewerage, rates, insurance, and catering)	Free text e.g. £616k = 616000	Continuous
Supplies and services total expenditure 2017-2018 (£)	Free text e.g. £950k = 950000	Continuous
Cost of finance expenditure 2017-2018 (£)	Free text e.g. £175k = 175000	Continuous
Special facilities expenditure 2017-2018 (£)	Free text e.g. £3.75k = 3750	Continuous
Teaching staff expenditure 2017-2018 (£)	Free text e.g. £3.23m = 3230000	Continuous
Supply staff expenditure 2017-2018 (£)	Free text e.g. £184k = 184000	Continuous
Education support staff expenditure 2017-2018 (£)	Free text e.g. £744k = 744000	Continuous
Administrative and clerical staff expenditure 2017-2018 (£)	Free text e.g. £746k = 746000	Continuous
Other staff costs expenditure 2017-2018 (£) e.g. this includes cost of other staff, indirect employee expenses, staff development and training)	Free text e.g. £283k = 283000	Continuous
Premises staff expenditure 2017-2018 (£)	Free text e.g. £189k = 189000	Continuous
Cleaning and caretaking staff expenditure 2017-2018 (£)	Free text e.g. 106k = 106000	Continuous

Maintenance and improvement expenditure 2017-2018 (£)	Free text e.g. 146k = 146000	Continuous
PFI charges 2017-2018 (£)	Free text e.g. £0 = 0	Continuous
Energy expenditure 2017-2018 (£) e.g. all costs related to fuel and energy	Free text e.g. £107k = 107000	Continuous
Water and sewerage 2017-2018 (£)	Free text e.g. £17k = 17000	Continuous
Other occupation costs expenditure 2017-2018 (£) e.g. rents for premises, refuse collection, hygiene services)	Free text e.g. \$16k = 16000	Continuous
Other insurance premiums expenditure 2017-2018 (£) e.g. premises related insurance, vehicle insurance, school trip insurance)	Free text e.g. £36k = 36000	Continuous
Catering expenditure 2017-2018 (£)	Free text e.g. £163k = 163000	Continuous
Rents and rates expenditure 2017-20178 (3) e.g. business rates, national non-domestic rates	Free text e.g. £50k = 50000	Continuous
Administrative supplies expenditure 2017-2018 (£)	Free text e.g. £255k = 255000	Continuous
Educational supplies expenditure 2017-2018 (£)	Free text e.g. £474k = 474000	Continuous
Bought in professional services expenditure 2017-2018 (£) e.g. educational consultancy, auditor costs)	Free text e.g. £116k = 116000	Continuous

Total income 2017-2018 (£)	Free text e.g. £6m = 6000000	Continuous
Grant funding total 2017-2018 (£)	Free text e.g. £5m 5000000	Continuous
Self-generated funding total 2017-2018 (£)	Free text e.g. £349k = 340000	Continuous
In year balance 2017-2018 (£)	Free text e.g. £220k = 220000	Continuous
Revenue reserve 2017-2018 (£)	Free text e.g. £444k = 444000	Continuous
Direct grants 2017-2018 (£) e.g. DfE/EFA revenue grants, pre-16 funding	Free text e.g. £5.3m = 5300000	Continuous
Community grants 2017-2018 (£)	Free text e.g. £370k = 370000	Continuous
Targeted grants 2017-2018 (£)	Free text e.g. £240k = 240000	Continuous
Income from facilities and services 2017-2018 (£) e.g. income from meals provided to external customers, income for consultancy, training courses and examination fees	Free text e.g. £150k = 150000	Continuous
Income from catering 2017-2018 (£)	Free text e.g. £220k = 220000	Continuous
Donations and of voluntary funds 2017-2018 (£)	Free text e.g. \$£100k = 100000	Continuous
Receipts from supply teacher insurance claims 2017-2018 (3)	Free text e.g. £1k = 1000	Continuous
Investment income 2017-2018 (£)	Free text e.g. £9k = 9000	Continuous

Other self-generated income 2017-2018 (£)	Free text e.g. £57k = 57000	Continuous
School workforce full time equivalent 2017-2018 (Full time equivalent)	Free text e.g. 101FTE = 101	Continuous
Total number of teachers 2017-2018 (full time equivalent)	Free text e.g. 62FTE = 62	Continuous
Teachers with qualified teacher status 2017-2018 (5)	Free text e.g. 99% = 99	Continuous
Senior leadership 2017-2018 (full time equivalent)	Free text e.g. 8FTE = 8	Continuous
Teaching assistants 2017-2018 (full time equivalent)	Free text e.g. 11FTE = 11	Continuous
Non-classroom support staff excluding auxiliary staff 2017-2018 (full time equivalent)	Free text e.g. 31TE = 31	Continuous
Auxiliary staff 2017-2018 (full time equivalent)	Free text e.g. 13FTE = 13	Continuous
School work force head count 2017-2018	Free text e.g. 148	Continuous
Change in number of pupils between 2016-2017 and 2017-2018	Free text e.g. -50 pupils = -50	Continuous
Change in number of teachers between 2016-2017 and 2017/2018	Free text e.g. 5 teachers = 5	Continuous
Change in school total expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £-200k = -200000	Continuous

Change in staff total expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £-14k = -14000	Continuous
Change in premises total expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £11k = 11000	Continuous
Change in occupation total expenditure between 2016-2017 and 2017-2018 (£) e.g. change in the costs associated with occupying the school building (energy, water, sewerage, rates, insurance, and catering)	Free text e.g. £10k = 10000	Continuous
Change in supplies and services total expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £65k = 65000	Continuous
Change in cost of finance expenditure 2016-2017 and 2017-2018 (£)	Free text e.g. £19k = 19000	Continuous
Change in special facilities expenditure 2016-2017 and 2017-2018 (£)	Free text e.g. £-9k -8000	Continuous
Change in teaching staff expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £-26K = -26000	Continuous
Change in supply staff expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £-10K = -10000	Continuous

Change in education support staff expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £-41k = 41000	Continuous
Change in administrative and clerical staff expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £-28K = -28000	Continuous
Change in other staff costs expenditure between 2016-2017 and 2017-2018 (£) e.g. change in the cost of other staff, indirect employee expenses, staff development and training)	Free text e.g. £-148K = -148000	Continuous
Change in premises staff expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £-61K = -61000	Continuous
Change in cleaning and caretaking staff expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £1k = 1000	Continuous
Change in maintenance and improvement expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £5k = 5000	Continuous
Change in PFI charges between 2016-2017 and 2017-2018 (£)	Free text e.g. £59K = 59000	Continuous
Change in energy expenditure between 2016-2017 and 2017-2018 (£) e.g. all costs related to fuel and energy	Free text e.g. £40K = 40000	Continuous
Change in water and sewerage between 2016-2017 and 2017-2018 (£)	Free text e.g. £4k = 4000	Continuous

Change in other occupation costs expenditure between 2016-2017 and 2017-2018 (£) e.g. rents for premises, refuse collection, hygiene services)	Free text e.g. £3k = 3000	Continuous
Change in other insurance premiums expenditure between 2016-2017 and 2017-2018 (£) e.g. change in premises related insurance, vehicle insurance, school trip insurance)	Free text e.g. £7k = 7000	Continuous
Change in catering expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £36k = 36000	Continuous
Change in rents and rates expenditure between 2016-2017 and 2017-2018 (3) e.g. change in business rates, national non-domestic rates)	Free text e.g. £4k = 4000	Continuous
Change in administrative supplies expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £77k = 77000	Continuous
Change in educational supplies expenditure between 2016-2017 and 2017-2018 (£)	Free text e.g. £-47k = -47000	Continuous
Change in bought in professional services expenditure between 2016- 2017 and 2017-2018 (£) e.g. educational consultancy, auditor costs)	Free text e.g. £750 = 750	Continuous
Change in total income between 2016-2017 and 2017-2018 (£)	Free text e.g. £85k = 85000	Continuous

Change in grant funding total between 2016-2017 and 2017-2018 (£)	Free text e.g. £111k = 111000	Continuous
Change in self-generated funding total between 2016-2017 and 2017-2018 (£)	Free text e.g. £-10k = 10000	Continuous
Change in in year balance between 2016-2017 and 2017-2018 (£)	Free text eg. £100k = 100000	Continuous
Change in revenue reserve between 2016-2017 and 2017-2018 (£)	Free text e.g. £-21k = -21000	Continuous
Change in direct grants between 2016-2017 and 2017-2018 (£) e.g. change in DfE/EFA revenue grants, pre-16 funding	Free text e.g. £88k = 88000	Continuous
Change in community grants between 2016-2017 and 2017-2018 (£)	Free text e.g. £-20k = 20000	Continuous
Change in targeted grants between 2016-2017 and 2017-2018 (£)	Free text e.g. £6k = 6000	Continuous
Change in income from facilities and services between 2016-2017 and 2017-2018 (£) e.g. change in income from meals provided to external customers, income for consultancy, training courses and examination fees	Free text e.g. £5k = 5000	Continuous

Change in income from catering between 2016-2017 and 2017-2018 (£)	Free text e.g. £32k = 32000	Continuous
Change in donations and/or voluntary funds between 2016-2017 and 2017-2018 (£)	Free text e.g. £-10k = 10000	Continuous
Change in receipts from supply teacher insurance claims between 2016-2017 and 2017-2018 (3)	Free text e.g. 0	Continuous
Change in investment income between 2016-2017 and 2017-2018 (£)	Free text e.g. £400 = 400	Continuous
Change in other self-generated income between 2016-2017 and 2017-2018 (£)	Free text e.g. £-47k = 47000	Continuous
Change in school workforce full time equivalent between 2016-2017 and 2017-2018 (Full time equivalent)	Free text e.g. 18.7FTE = 18.7	Continuous
Change in total number of teachers between 2016-2017 and 2017-2018 (full time equivalent)	Free text e.g. 4.4.	Continuous
Change in teachers with qualified teacher status between 2016-2017 and 2017-2018 (%)	Free text e.g. 3.3	Continuous
Change in senior leadership between 2016-2017 and 2017-2018 (full time equivalent)	Free text e.g. -1	Continuous

Change in teaching assistants between 2016-2017 and 2017-2018 (full time equivalent)	Free text e.g. -1.4	Continuous
Change in non-classroom support staff excluding auxiliary staff between 2016-2017 and 2017-2018 (full time equivalent)	Free text e.g. 1	Continuous
Change in auxiliary staff between 2016-2017 and 2017-2018 (full time equivalent)	Free text e.g. 2	Continuous
Change in school work force head count between 2016-2017 and 2017-2018	Free text e.g. 10	Continuous

S2: Table 2: Studies included in narrative review of social media use and mental, and physical health

Study	Design	Population	Outcome	Exposure	Main Findings
Alonzo, R., et al. (2021). "Interplay between social media use, sleep quality, and mental health in youth: A systematic review." <u>Sleep Med Rev</u> 56 : 101414.[253]	Systematic review. N=42 studies (36 cross-sectional, mixed geographies)	Youth aged 16-25 years	Various measures of sleep, and mental health metrics (e.g. Pittsburgh Sleep Quality Index, the Beck Depression Inventory)	Various, predominantly self-reported, measures of "active social media use" (e.g. hours of mobile phone use, internet use)	In longitudinal studies, frequent social media use was a risk factor for both poor mental health (n=6 studies), and poor sleep outcomes (n=5 studies)
Barry, C. T., et al. (2017). "Adolescent social media use and mental health from adolescent and parent perspectives." <u>J Adolesc</u> 61 : 1-11. [254]	Cross-sectional	113 adolescents in the USA (aged 14 to 17 years, 55 males, 51 females, 7 unreported)	Anxiety, and Depression (Parent-reported from the Diagnostic and Statistical Manual of Mental Disorders survey) FOMO (Fear of missing out) and loneliness (adolescent-reported)	Frequency of checking social media accounts (Scale = never, to more than ten times per day)	Moderate positive association between social media use, anxiety, and depression, fear of missing-out, and loneliness
Barthorpe, A., et al. (2020). "Is social media screen time really associated with poor adolescent mental health? A time use diary study." <u>J Affect</u>	Cross-sectional	4,032 adolescents in the UK (age 14, Millennium Cohort study)	Self-harm (Dichotomous), Depressive symptoms (SMFQ), Self-esteem (Rosenberg scale)	Social media time use diaries	Positive association with increased risk of self-harm, depression, and lower self-esteem

Disord 274 : 864-870.[255]					
Beeres, D. T., et al. (2021). "Social Media and Mental Health Among Early Adolescents in Sweden: A Longitudinal Study With 2-Year Follow-Up (KUPOL Study)." <u>J Adolesc Health</u> 68 (5): 953-960. [256]	Longitudinal (3 years)	3,501 adolescents aged 14 to 15 years (51% female) in Sweden	Mental health problems (Strengths and Difficulties Questionnaire, SDQ)	Social media use (self-reported, hours per day)	Adolescents with higher use of social media use report more symptoms of mental health problems, but there is no evidence for a longitudinal association between increased use and mental health problems
Berryman, C., et al. (2018). "Social Media Use and Mental Health among Young Adults." <u>Psychiatr Q</u> 89 (2): 307-314. [257]	Cross-sectional	467 undergraduate students in the USA (335 female, 120 male, 2 unreported), Mean age 19 years	General mental health symptoms, suicidal ideation, loneliness, social anxiety, decreased empathy	Social media use (self-reported hours per day)	"Social media use was not predictive of impaired mental health functioning"
Boer, M., et al. (2021). "Social media use intensity, social media use problems, and mental health among adolescents: Investigating	Longitudinal	2,109 adolescents in the Netherlands (Mean age 13 years)	Depressive symptoms (6-item Depressive Mood List)	"Social media use problems" (assesses nine symptoms of addiction to social media use)	Social media use was associated with decreased mental health one year later (unidirectional)

directionality and mediating processes." <u>Computers in Human Behavior</u> 116 . [258]					
Braghieri, L., et al. (2022). "Social Media and Mental Health." <u>American Economic Review</u> 112 (11): 3660-3693. [259]	Natural Experiment	430,000 college students in the USA	Overall index of poor mental health	Before vs. after Facebook was rolled out at respective colleges. No indicator of whether an individual student had a Facebook profile	The rollout of Facebook at a college had a negative impact on student mental health
Coyne, S. M., et al. (2020). "Does time spent using social media impact mental health?: An eight year longitudinal study." <u>Computers in Human Behavior</u> 104 . [260]	Longitudinal	500 adolescents (age 13 at baseline, age 20 at follow-up) in the USA	Depression (20-item Centre for Epidemiologic Studies Depression Scale for Children). Anxiety (6-item generalized anxiety disorder sub-scale from the Spence Child Anxiety Inventory)	Social media use (self-reported, hours per day)	Increased time spent on social media was not associated with increased mental health issues across development
de Calheiros Velozo, J. and J. E. A. Stauder (2018). "Exploring social media use as a composite construct to understand its relation to mental health: A pilot study on adolescents."	Cross-sectional	N = 72 adolescents (35 girls) aged 13 to 16 years in the Netherlands	Mental health (Strengths and difficulties questionnaire, 25-item) – reported by parents	Social media use (self-reported hours per day) and time spent socializing, playing games, shopping, music/videos, posting pictures, videos, or status updates	Adolescents who spent more time on social media socializing, shopping, and those who followed more people they did not know in real life were more likely to exhibit conduct problems such as aggressive behaviour, stealing, and lying

Children and Youth Services Review 91: 398-402. [261]				– reported by adolescents	
Deepa, M. and K. Priya (2020). "Impact of social media on mental health of students." <u>International Journal of Scientific & Technology Research</u> 9(3). [262]	Cross-sectional	N = 90 MBA University students in India, top two deemed Universities in Chennai (no further information provided)	Self-reported (by survey) health-related issues such as difficulty in sleeping and eating, depression, and anxiety (no further information provided)	Social media use (self-reported time spent [on social media])	"More usage of social media is affecting the students mental health such as depression and anxiety"
Dibb, B. (2019). "Social media use and perceptions of physical health." <u>Heliyon</u> 5(1): e00989. [263]	Cross-sectional	N=165 individuals (55 males) over the age of 18 years (Mean age = 31 years) in the UK	Self-esteem, depression, anxiety, life satisfaction, and physical health	Facebook use, Facebook social comparison	Downward social comparison on Facebook was not associated with physical symptoms. Upward comparison was not associated with physical symptoms
Easton, S., et al. (2018). "Young People's Experiences of Viewing the Fitspiration Social Media Trend: Qualitative Study." <u>J Med Internet Res</u> 20(6): e219. [264]	Cross-sectional, qualitative	N=20 individuals aged from 18 to 25 years (14 females) in the UK	Perceived impact on health and wellbeing	"Fitspirational" posts on social media (e.g. "material that purports to motivate and promote healthy lifestyle habits associated with exercise and diet"	<ul style="list-style-type: none"> • (Fitspiration posts is) a tool with the potential to support healthy living • (Fitspirational posts have) negative effects on emotional wellbeing • (Fitspirational posts have) unrealistic, untrustworthy content
Fardouly, J., et al. (2020). "The use of	Cross-sectional	N=528 10 to 12 year olds living in	Body satisfaction (Appearance and	Social media use (self-reported frequency e.g.	Users of Youtube, Instagram, and Snapchat reported more

social media by Australian preadolescents and its links with mental health." <u>J Clin Psychol</u> 76 (7): 1304-1326. [265]		Australia (51% male)	Weight subscales of the Body Esteem Scale. Eating pathology (26-item Children's Eating Attitude Test. Depressive symptoms (Social Phobia subscale of the Spence Children's Anxiety Scale.	Never, vs. Very often, 5-item scale)	body image concerns and eating pathology than non-users but did not differ on depressive symptoms or social anxiety
Gao, J., et al. (2020). "Mental health problems and social media exposure during COVID-19 outbreak." <u>PLoS One</u> 15 (4): e0231924. [266]	Cross-sectional	4,872 participants aged 18 years or older from 31 provinces in China	Depression (the Chinese version of the WHO-Five Well-being index. Anxiety (Chinese version of generalized anxiety disorder scale (7-items)	Social media exposure (How often respondents were exposed to news and information about COVID-19 on social media [never to very often, 5-item scale])	Greater social media exposure (vs. less exposure) was associated with high odds of anxiety and a combination of anxiety and depression during the Covid-19 pandemic
Geirdal, A. O., et al. (2021). "Mental health, quality of life, wellbeing, loneliness and use of social media in a time of social distancing during the COVID-19 outbreak. A cross-country comparative study." <u>J Ment Health</u> 30 (2): 148-155. [267]	Cross-sectional	N=3,810 people living in Norway, UK, USA, and Australia aged 18+ (no mean age provided, largely evenly split by age brackets from 18, to 80+)	Mental health (General health questionnaire 12)	Social media use (self-reported use after the COVID-19 pandemic (several times per day to monthly or less frequently, 5-item scale)	High-frequent use of social media use was associated with worsened mental health

<p>Haddad, J. M., et al. (2021). "The Impact of Social Media on College Mental Health During the COVID-19 Pandemic: a Multinational Review of the Existing Literature." <u>Curr Psychiatry Rep</u> 23(11): 70. [268]</p>	<p>Review</p>	<p>N=6 studies focussed on college students (observational only, primarily cross-sectional)</p>	<p>Anxiety and depression using validated instruments</p>	<p>Social media use data (no further information provided in inclusion criteria)</p>	<p>Social media use appears to be associated with mental health symptoms but the direction of these relations is mixed</p>
<p>Hartas, D. (2019). "The social context of adolescent mental health and wellbeing: parents, friends and social media." <u>Research Papers in Education</u> 36(5): 542-560. [269]</p>	<p>Cross-sectional</p>	<p>Unclear. N reported is Millennium Cohort study Wave 6 (11,884 14 year olds), but analytical sample is not described</p>	<p>Mental health (Short Moods and Feelings Questionnaire (13-item)</p>	<p>Social media use (self-reported, hours per day)</p>	<p>As social media use increased, both boys and girls were more likely to report being less happy overall</p>
<p>Henzel, V. and A. Hakansson (2021). "Hooked on virtual social life. Problematic social media use and associations with mental distress and addictive disorders." <u>PLoS One</u> 16(4): e0248406. [270]</p>	<p>Cross-sectional</p>	<p>N=2,002 individuals from 16 to 80 years in Sweden (1,009 female)</p>	<p>Psychological distress (Kessler Psychological Distress Scale, 6-item)</p>	<p>Social media addiction (Bergen Social Media Addiction Scale (6-item)</p>	<p>Social media use is (positively) associated with mental distress</p>

Hoffner, C. A. and B. J. Bond (2022). "Parasocial relationships, social media, & well-being." <u>Curr Opin Psychol</u> 45 : 101306. [271]	Review	No inclusion criteria or synthesis of studies included	No outcome stated. Broadly focussing on wellbeing	No exposure stated. Broadly focussing on parasocial relationships on social media (defined as "socio-emotional connections that people develop with media figures such as celebrities or fictional characters"	No clear synthesis, all potential benefits and harms listed. In my words, Parasocial relationships on social media can be beneficial (e.g. promotion of healthy attitudes and behaviours) but also disadvantageous (e.g. adversely impacting mental health through negative self-comparisons)
Hong, W., et al. (2021). "Social Media Exposure and College Students' Mental Health During the Outbreak of COVID-19: The Mediating Role of Rumination and the Moderating Role of Mindfulness." <u>Cyberpsychol Behav Soc Netw</u> 24 (4): 282-287. [272]	Cross-sectional	N=439 college students in China	Psychological distress (Kessler Psychological Distress scale. 6-item)	Social media use ("to what extent were [you] exposed to COVID-19 news or information on social media	Social media use exposure to COVID-19-related information did not directly predict psychological distress
Huang, C. (2022). "A meta-analysis of the problematic social media use and mental health." <u>Int J</u>	Meta-analysis	N=133 studies involving 244,676 participants. No list of studies provided	Mental health. Various measures discussed, unclear which method adopted (e.g. anxiety, depression, loneliness)	Problematic social media use. Various methods discussed narratively, unclear which method adopted	The correlations between problematic social media use and various well-being indicators were negative,

Soc Psychiatry 68 (1): 12-33. [273]				(e.g. Bergen Facebook Addiction scale, Social Media Disorder scale)	ranging from small to moderate
Ivie, E. J., et al. (2020). "A meta-analysis of the association between adolescent social media use and depressive symptoms." <u>J Affect Disord</u> 275 : 165-174. [274]	Meta-analysis	N=11 studies (92,371 adolescents aged 11 to 18 years)	Depressive symptoms (continuous measures, no further information provided)	Social media use (time spent using [social media])	Found a small but significant positive correlation between adolescent social media use and depressive symptoms
Karim, F., et al. (2020). "Social Media Use and Its Connection to Mental Health: A Systematic Review." <u>Cureus</u> 12 (6): e8627. [275]	Systematic review	N=16 studies (8 cross-sectional, 3 longitudinal, 2 qualitative, 3 other systematic reviews)	Insufficient information relating to inclusion criteria presented, broadly focussed on anxiety and depression outcomes	Insufficient information relating to inclusion criteria presented, broadly focussed on any measures of social media use	This review found a general association between social media use and mental health issues
Kelly, Y., et al. (2018). "Social Media Use and Adolescent Mental Health: Findings From the UK Millennium Cohort	Cross-sectional	N=10,904 14 year olds in Millennium Cohort study (UK birth cohort)	Depressive symptoms (Mood and Feelings Questionnaire, short-version 13-items)	Social media use (self-reported, hours per day)	Found a (positive) association between social media use and depressive symptoms and this was stronger for girls than for boys

Study." <u>EClinicalMedicine</u> 6 : 59-68. [276]					
Khajeheian, D., et al. (2018). "Effect of Social Media on Child Obesity: Application of Structural Equation Modeling with the Taguchi Method." <u>Int J Environ Res Public Health</u> 15 (7). [121]	Cross-sectional	N=1,860 Iranian adolescents (aged 12-17 years)	BMI (self-reported)	Social media use (self-reported, hours per day)	Greater adolescents' social media use was associated with higher BMI
Lee, D. S., et al. (2022). "Social Media Use and Its Link to Physical Health Indicators." <u>Cyberpsychol Behav Soc Netw</u> 25 (2): 87-93. [277](No access to full paper available, information drawn from abstract only)	Cross-sectional	Young adults	C-Reactive Protein (a measure of chronic inflammation). No further information provided regarding how visits to the doctor or health centre provided in the abstract only	Social media use (self-reported)	Social media use was positively correlated with higher levels of C-reactive protein, and more visits to the doctor or health centres for an illness
Lugito, N. P. H., et al. (2021). "Social media exposure and mental health problems	Cross-sectional	N=220 (121 female) individuals aged 18-56 (Median age = 24)	Depression, anxiety, and stress (Depression Anxiety Stress Scale-21)	Social media use (self-reported, hours per day)	Social media exposure was associated with less depression, anxiety, and stress in the COVID-19 pandemic

during coronavirus disease 2019 pandemic in Indonesia." <u>J Educ Health Promot</u> 10 (1): 200. [278]					
Malaeb, D., et al. (2021). "Problematic social media use and mental health (depression, anxiety, and insomnia) among Lebanese adults: Any mediating effect of stress?" <u>Perspect Psychiatr Care</u> 57 (2): 539-549. [279]	Cross-sectional	N=446 adults in Lebanon (285 female)	Depression (Hamilton Depression Scale, 17-item). Anxiety (Hamilton Anxiety Scale, 14-item). Stress (Perceived Stress Scale, 10-item)	Social media disorder scale (27-items)	Higher problematic social media use was significantly associated with higher depression, anxiety, and insomnia, but not stress
McCrorry, A., et al. (2020). "The relationship between highly visual social media and young people's mental health: A scoping review." <u>Children and Youth Services Review</u> 115 . [280]	Scoping Review	N=25 studies (24% USA, 20% in Australia)	Studies exploring mental health. Studies exploring body image, body dissatisfaction	"Highly Visual social media use (e.g. Snapchat, Instagram, and Facebook – not Twitter"	The relationship and influence of highly visual social media on wellbeing and mental health remains unclear

Ni, M. Y., et al. (2020). "Mental Health, Risk Factors, and Social Media Use During the COVID-19 Epidemic and Cordon Sanitaire Among the Community and Health Professionals in Wuhan, China: Cross-Sectional Survey." <i>JMIR Ment Health</i> 7(5): e19009. [281]	Cross-sectional	N=1,577 adults in China (No further information provided)	Anxiety (Generalized Anxiety Disorder Scale). Depression (Patient Health Questionnaire)	Social media use (self-reported time spent on [social media])	Spending 2 hours or more per day on COVID-19 news via social media were associated with probable anxiety and depression
O'Reilly, M., et al. (2018). "Is social media bad for mental health and wellbeing? Exploring the perspectives of adolescents." <i>Clin Child Psychol Psychiatry</i> 23(4): 601-613. [282]	Cross-sectional, qualitative	N=54 adolescents aged 11 to 18 years in the UK	Mental health and well-being	Perception of social media use	Adolescents perceived social media as a threat to mental wellbeing ... believe (social media use) to cause mood and anxiety disorders for some adolescents ... viewed as a platform for cyberbullying, and framed as a kind of addiction
Ogders, C. L. and M. R. Jensen (2020). "Annual Research Review: Adolescent mental health in the digital age: facts,	Review	Insufficient evidence to replicate. Included narrative reviews, large-scale cohort studies, and	Mental health with a specific focus on anxiety and depression. No inclusion criteria discussed	Social media use. No inclusion criteria discussed	Most research has been correlational, focused on adults versus adolescents, and has generated a mix of often conflicting small positive, negative and null associations

fears, and future directions." <u>J Child Psychol Psychiatry</u> 61 (3): 336-348. [129]		longitudinal, ecological momentary assessment studies. No further information provided			
Petalas, D. P., et al. (2021). "Plurality in the Measurement of Social Media Use and Mental Health: An Exploratory Study Among Adolescents and Young Adults." <u>Social Media + Society</u> 7 (3). [283]	Cross-sectional	N=3,669 adolescents in the Netherlands	Mental health (6-items relating to happiness, confidence, and life satisfaction)	Social media use (self-reported, hours per day)	Some evidence found that greater social media use associates to drops and to increases in mental health
Primack, B. A. and C. G. Escobar-Viera (2017). "Social Media as It Interfaces with Psychosocial Development and Mental Illness in Transitional Age Youth." <u>Child Adolesc Psychiatry Clin N Am</u> 26 (2): 217-233. [284]	Review	Adults (No methods reported)	Depression and anxiety (No methods reported)	Social media use (No methods reported)	Large, cross-sectional, nationally representative studies demonstrate consistent, linear associations between social media use and depression and anxiety among young adults

Richards, D., et al. (2015). "Impact of social media on the health of children and young people." <u>J Paediatr Child Health</u> 51 (12): 1152-1157. [285]	Review	No information provided on search strategy or number of included studies. Papers that referred to adults only were excluded	Search terms included: mental health, cyberbullying, self-image, health, and physical fitness	Search terms: social media, facebook, twitter, youtube, myspace	The health impact of social media on children and young people was greatest on mental health and specifically in the areas of self-esteem and wellbeing
Sadagheyani, H. E. and F. Tatari (2020). "Investigating the role of social media on mental health." <u>Mental Health and Social Inclusion</u> 25 (1): 41-51. [286]	Review	N=50 studies	Studies included a focus on mental health	Studies included a focus on social media	In my words, study presented a narrative review of identified positive and negative effects of social media use on mental health with no critical analysis. Negative effects discussed included increased anxiety and depression among many others. Benefits included access to health information, and emotional support among others
Schoultz, M., et al. (2021). "Mental Health, Information and Being Connected: Qualitative Experiences of Social Media Use during the COVID-19 Pandemic from a Trans-National	Cross-sectional, qualitative	N=1,991 (1,013 UK, 801 USA, 177 Australia), predominantly female	Perceptions of emotional and mental health during the COVID-19 pandemic	Perceptions of social media use during the COVID-19 pandemic	Participants experienced that using social media during the pandemic amplified anxiety, depression, fear, panic, anger, frustration and loneliness

Sample." <u>Healthcare (Basel) 9(6). [287]</u>					
Sharma, M. K., et al. (2020). "Influence of social media on mental health: a systematic review." <u>Curr Opin Psychiatry 33(5): 467-475. [288]</u>	Systematic review	N=16 studies (majority USA, mean age 24 years, sample size varied from 16 to 4,935)	Mental health	Social media use	Studies presented positive, negative, and neutral effects of social media. There is a need for more RCTs to identify social media's role on mental health
Sujarwoto, et al. (2021). "Social Media Addiction and Mental Health Among University Students During the COVID-19 Pandemic in Indonesia." <u>Int J Ment Health Addict: 1-15. [289]</u>	Cross-sectional	N=709 University students in Indonesia (Mean age = 24 years)	Mental health (Centre for Epidemiological Studies Depression scale, 7-items)	Social media addiction (Bergen Social Media Addiction Scale, 6-item)	Students with higher social media addiction scores had a greater likelihood of experiencing mild depression
Sujarwoto, S., et al. (2019). "A Tool to Help or Harm? Online Social Media Use and Adult Mental Health in Indonesia." <u>International Journal of Mental Health and Addiction 17(4): 1076-1093. [290]</u>	Cross-sectional	N=22,423 individuals aged 20 years or older in Indonesia	Mental health (Centre for Epidemiological Studies Depression scale, 10-items)	Social media use (Dichotomous, yes vs. no)	The findings shows that social media use harms adult mental health; an increase of one standard deviation in adults use of social media is associated with 9% increase in depression score

Tao, X. and C. B. Fisher (2022). "Exposure to Social Media Racial Discrimination and Mental Health among Adolescents of Color." <i>J Youth Adolesc</i> 51 (1): 30-44. [291]	Cross-sectional	N=407 "adolescents of color" in the USA (82% female)	Social media racial discrimination (Online Victimization scale). Depressive symptoms (Epidemiologic Studies Depression Scale (20-items). Anxiety symptoms (Generalized Anxiety Disorder Screener (7-items). Alcohol Use Disorder (Alcohol Use Disorders Identification Test). Illicit drug use and problems (Self-reported frequency of use from a list of around 20 options)	Social media use (self-reported, hours per day)	Hours of social media use was associated with increased social media racial discrimination, depressive symptoms, anxiety, alcohol use disorder, and drug use problems
Ulvi, O., et al. (2022). "Social Media Use and Mental Health: A Global Analysis." <i>Epidemiologia (Basel)</i> 3 (1): 11-25. [292]	Systematic review and meta-analysis	N=20 studies (14 focussing on Facebook, spanning many geographies including EMEA, APAC, NA)	Mental Health	Use of social media, Twitter, Instagram, and Facebook	While social media use can create a sense of community for the user, excessive and increased use of social media, particularly among those who are vulnerable, is correlated with depression and other mental health disorders
Valkenburg, P. M., et al. (2022). "Social media use and its impact on adolescent mental	Review of reviews	N=25 reviews (7 meta-analyses, 9 systematic reviews, 9 narrative reviews)	Search terms included: well-being, mental health, or psychopathology	Search terms included: social media, social networking site, Facebook, or Instagram	Most reviews interpreted the associations between social media use and mental health as weak and inconsistent

health: An umbrella review of the evidence." <u>Curr Opin Psychol</u> 44 : 58-68. [293]					
Viner, R. M., et al. (2019). "Roles of cyberbullying, sleep, and physical activity in mediating the effects of social media use on mental health and wellbeing among young people in England: a secondary analysis of longitudinal data." <u>Lancet Child Adolesc Health</u> 3 (10): 685-696. [233]	Longitudinal	N=12,866 adolescents aged 13 to 16 years in England	Mental health (General Health Questionnaire, 12-item). Wellbeing (Life satisfaction, feeling life is worthwhile, happiness, and anxiety)	Social media use frequency (from weekly or less, to very frequent)	Persistent very frequent social media use predicted poorer mental health in boys and girls, and anxiety in girls only. Mental health harms in girls (but not boys) may be due to a combination of cyberbullying, or displacement of sleep or physical activity
Young, L., et al. (2020). "Attachment style moderates the relationship between social media use and user mental health and wellbeing." <u>Heliyon</u> 6 (6): e04056. [294]	Cross-sectional	N=124 people aged 18 or over (mainly Non-Hispanic white or Euro-American females (81%))	General wellbeing (Patient Health Questionnaire, 9-items). Satisfaction with life (Satisfaction with Life Scale, 5-items)	Social media use (self-reported, hours per day)	Negative relationships between problematic social media use and both psychological wellbeing and life satisfaction were observed

<p>Zhao, N. and G. Zhou (2020). "Social Media Use and Mental Health during the COVID-19 Pandemic: Moderator Role of Disaster Stressor and Mediator Role of Negative Affect." <u>Appl Psychol Health Well Being</u> 12(4): 1019-1038. [295]</p>	<p>Cross-sectional</p>	<p>N=512 (62.5% female) college students in China</p>	<p>Covid-19-related psychological outcomes (i.e. depression, and anxiety)</p>	<p>Social media use (self-reported, hours per day)</p>	<p>Higher level of social media use was associated with worse mental health</p>
<p>Zhong, B., et al. (2021). "Mental health toll from the coronavirus: Social media usage reveals Wuhan residents' depression and secondary trauma in the COVID-19 outbreak." <u>Comput Human Behav</u> 114: 106524. [296]</p>	<p>Cross-sectional</p>	<p>N=320 people in China (40% aged 30 to 45 years, 63% female)</p>	<p>Depression (Depression Anxiety Stress Scale, 7-items)</p>	<p>Social media use addiction (with slight revisions from the Facebook addiction scale to focus on the social media platform WeChat)</p>	<p>Social media usage was related to depression</p>

S1: NHS Internship blog post: “Public Health in practice – our fellowship at NHS England and Improvement

By Campbell Foubister and Matt Keeble, SPHR PhD students

The NIHR School for Public Health research is renowned for producing high-quality research. But what happens to that research – where does it go? How is it used? One answer, the one that maybe we all hope for is, “underpinning public health policy”.

We are final year PhD Students in Medical Science based in the MRC Epidemiology Unit at the University of Cambridge. As we move towards the end of our PhD studentships, we’ve spent almost three years working on our research, thinking about what it means for population health and maximising its transferability into practice. Despite this, we had gained little experience of public health in practice. When the chance to spend six months working in NHS England and Improvement (NHS E&I) (formerly Public Health England) in a developmental fellowship role came up, we grabbed a once in a studentship opportunity with both hands.

In 2021, we spent six months working with the Healthcare Public Health team in the NHS E&I East of England regional office. The following blog will provide an insight into our work, how the experience shaped our thinking about careers post-PhD, and some key take away points for others considering similar opportunities.

The aims of our fellowship

The purpose of our fellowship was to learn about public health roles and functions within NHS England, multidisciplinary processes for addressing a wide variety of public health issues (such as disease prevention and control), and ways to improve health and address health inequalities. We also aimed

to gain work experience in priority areas, including mental health, COVID-19 recovery and restoration, and health disparities as well as develop professional leadership skills in the public health field.

What is 'Healthcare Public Health'?

At this point, you might be wondering what 'Healthcare Public Health' is. The Faculty for Public Health have published this definition;

“Healthcare public health is concerned with maximising the population benefits of healthcare and reducing health inequalities while meeting the needs of individuals and groups, by prioritising available resources, by preventing diseases and by improving health related outcomes through design, access, utilisation and evaluation of effective and efficient health and social care interventions, settings and pathways of care”.

Given how broad the remit of the Healthcare Public Health team is, we were confident that we could gain vital experience across many areas. As our fellowship was a developmental role, there was capacity to tailor the opportunity to our specific learning objectives.

Although we're both studying at the same university, we applied for the fellowships separately, and had different experiences during our time with the team....

Campbell

During my fellowship, I was most interested in gaining an insight into population health operations and strategy at a national level. My role broadly involved generating evidence to contribute towards decision making in business planning and policy implementation during the COVID-19 pandemic, such as supporting inclusive recovery and restoration and facilitating equitable vaccine uptake.

The most impactful piece of work I led on was supporting inclusive COVID-19 recovery and restoration via assurance of Elective Recovery Fund submissions. The Elective Recovery Fund is a c. £2Billion/year commitment to tackle the COVID-19 backlog of elective care in the biggest catch-up programme in the NHS's history. It was my responsibility to review funding applications informed by NHS performance reports for the East of England and advise on how resources should be allocated to restore NHS services inclusively. This involved supporting progress towards delineating reporting by ethnicity and index of multiple deprivation to identify disparities in experience, outcome, and access across specialties (e.g., Core20PLUS5).

In the East of England, for a population of more than six million who face distinct health challenges, “progress” can look different depending on the setting. Often our recommendations were tailored to users at a specific level across the organisation (e.g., from frontline staff to board members), and underpinned driving efficiencies, reducing cost and clinical variation, and improving financial and operational activity performance. In practice, a mental model to construct and win buy-in to recommendations was to first use science skills to “build a picture” (i.e., data-driven approaches to identify key priorities for health within the system), and then “create urgency and sell the narrative” by building relationships with stakeholders from diverse backgrounds to find local solutions to product/intervention innovation in limited resource settings, and present an investment case to move the needle. This is a model which could be adopted and applied by members of the SPHR community across work areas (e.g. resiliency, primary care, and children and young people).

Matt

Stepping away from the relative comfort (!) of my PhD studentship seemed daunting at first. But, looking back, I can fully appreciate how my fellowship has shaped my career aspirations. More on that later, but right now let's talk about what I worked on.

During my fellowship, I was responsible for leading a rapid review of published literature to identify approaches to support patients waiting for an elective procedure. This resulted in the publication of short and extended recommendations presented to senior NHS colleagues in multiple large national meetings. This experience was a massively important lesson in honing my communication skills to senior stakeholders and providing information in a concise, yet impactful manner.

I also had the opportunity to collaborate with colleagues to identify areas in the East of England that had poor digital infrastructure and devise ways to mitigate the risk of low COVID-19 vaccine uptake and access to primary and secondary care. To say this was slightly broader than what I'd experienced so far during my PhD studentship would be an understatement.

On top of learning about a broad range of public health topics, I experienced the process of priority setting and multi-department collaboration and negotiation, as well as getting insight into what's considered the "art of public health". A fundamental lesson, in addition to building new research skills, was the need to be adaptable and resilient, and to balance academic rigor with delivering evidence in a timely and insightful way – if it can fit on one page, all the better.

How the fellowship shaped our thinking about careers post-PhD

Before starting our fellowship, we weren't all that sure about what our futures might hold. The beauty of this position was that there was the capacity to tailor it to our developmental needs and interests. Regarding specific roles, together, we strongly feel that we were provided with a unique insight into the role and requirements of Public Health Consultants and embedded researchers, respectively.

Our unique experience will be vital as we move towards the next steps in our research and then future career activities.

What's next?

Campbell "I'm keen to pursue a career involving problem-solving at the global level through a combination of large-scale quantitative analyses, multi-sectoral collaboration and public-facing accountability".

Matt "I see myself working as an embedded researcher where I can split my time between academia and local government. The beauty of this fellowship was the opportunity to learn about the roles and pressures that local authorities face. I feel passionately about making sure that evidence from my research can be applied at a local level, and now feel better equipped to ensure that it is".

Key take-away points for those considering similar opportunities

More roles like ours are planned in the future. For PhD students who might not be sure about their future and want to learn more about public health in practice, we would recommend applying for opportunities when they become available. We can't speak highly enough about our time with the East of England team. You'll be welcomed into a diverse team with wide-ranging knowledge, treated with respect, given autonomy, and encouraged to contribute to multiple areas of work.

There is no upper limit to what you can achieve during a fellowship with the Healthcare Public Health team as ideas trump tenure. The role involves becoming a champion for Healthcare Public Health and contributing novel insights to the team's key priorities. You won't be there to tick boxes and will be challenged out of your comfort zone. You'll be able to widen your expertise and experience a steep learning curve both professionally and personally. You'll gain exposure to policy-relevant methods that are used to inform decisions where nothing less than a recommendation is required.

It's worth mentioning that everything has an opportunity cost. Undertaking a fellowship could be at the expense of a missed conference, a missed extra co-authorship, or even a missed "trying something

completely different” moment. It’s important to have a clear rationale on why you want to do the fellowship and understand both the pros and cons. But for us, the pros outweighed the cons.

We thank Anees Pari, Ally Revell, and the wider team for hosting us and would be happy to speak with any other interested candidates via: [Email addresses redacted]

S4: School environment paper: GoActive School Environment Survey (presented overleaf)



Thank you for agreeing to participate in the GoActive evaluation study.

In this booklet, we will be asking short questions about the physical activity opportunities in your school.

- ✓ Please complete all of the questions in this booklet.
- ✓ Please only select one answer per question or item (i.e. either tick *one* box, or circle *one* response).

Please consider Year 9 in particular when answering this questionnaire.

Your answers will be treated as confidential. If you have any questions, please do not hesitate to contact the study team: goactive@mrc-epid.cam.ac.uk

or Freephone 0800 917 3319

Section 1: School information

1. Name of school _____

2. What is your position?

<input type="checkbox"/>	Head teacher
<input type="checkbox"/>	Deputy head teacher
<input type="checkbox"/>	Physical Education lead
<input type="checkbox"/>	Year 9 lead
<input type="checkbox"/>	Other (please specify) _____

3. What time does the normal school day start? _____ and finish? _____

4. At what time are breaks held, and how long do they last?

	Start time	Duration (minutes)
a. Morning break		
b. Lunchtime		
c. Afternoon break		
d. Other (please specify) _____		

5. Have any events occurred during the measurement period that may have influenced the level of physical activity of Year 9 students (e.g. sports day)?

Your measurement period: _____ to _____

<input type="checkbox"/>	No
<input type="checkbox"/>	Yes (please give details)

.....

.....

.....

.....

Please now think about the area around your school.

6. Please indicate whether the following are present:

None	Some	A lot	
			a. Planted beds containing flowers/shrubs/small trees
			b. Trees for shade
			c. Loud ambient noise (e.g. traffic, trains, industry)
			d. Litter
			e. Murals/outdoor art
			f. Graffiti

7. To what extent do you agree or disagree with the following statements?

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
a. The grounds are shielded from the surrounding area by hedges/trees/fences	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
b. The grounds are generally well maintained	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
c. The grounds are generally free of vandalism	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Section 2: Pupil overview

Please answer the following questions in reference to Year 9 wherever possible.

If Year 9 information is not available, please complete school-level information.

- 8. How many pupils are there in...?
 - a. Year 9.....
 - b. Whole school.....
- 9. How many boys are there in...?
 - a. Year 9.....
 - b. Whole school.....
- 10. How many girls are there in...?
 - a. Year 9.....
 - b. Whole school.....
- 11. What is the percentage of pupils for whom you receive Pupil Premium funding?
 - a. Year 9.....
 - b. Whole school.....

Section 3: Physical activity opportunities at school

12. Does your school have access to...

Please tick all that apply.

If yes, how would you rate their quality?

Please take into account the level of maintenance, cleanliness, accessibility etc.

	No	Yes	High	Medium	Low
a. A specific indoor hall for gym or sports			→		
b. A shared indoor facility used for sports activities			→		
c. A sports or football field/pitch on school grounds			→		
d. Athletics track (grass or hard surface)			→		
e. Courts (e.g. tennis, basketball including half court, netball, multicourt area)			→		
f. A recreational area on school grounds			→		
g. A wildlife garden			→		
h. Bright or fluorescent markings on play surfaces (e.g. hopscotch, animals)			→		
i. Playground equipment (e.g. swings, slide)			→		
j. Benches			→		
k. Picnic tables			→		
l. Drinking fountains			→		
m. Uncovered cycle parking			→		
n. Covered cycle parking			→		
o. An assault course			→		
p. Formal garden/quiet space			→		
q. Outdoor teaching space			→		
r. Vegetable/fruit garden			→		
s. Playing fields or a local park off school grounds, which you can use			→		
t. Purpose built changing facilities			→		
u. Sports equipment (e.g. gymnastics equipment)			→		

13. Are the school grounds generally suitable for....?

Very	Somewhat	Not at all	
			a. Sport (organised or not)
			b. Informal games (kickabout, Frisbee etc.)
			c. General play

14. How many hours of physical education do the pupils in Year 9 usually have per week?

Please round to the nearest half hour.

.....hours per week

15. Does your school or any other organisation provide any extracurricular physical activity or sports programmes available to Year 9?

Please tick your response in each case.

	No	Yes
a. Before school	<input type="checkbox"/>	<input type="checkbox"/>
b. During lunch breaks	<input type="checkbox"/>	<input type="checkbox"/>
c. After school	<input type="checkbox"/>	<input type="checkbox"/>
d. At weekends	<input type="checkbox"/>	<input type="checkbox"/>

16. Which of the following physical activities or sports are available as extracurricular programmes?

Please tick any that apply.

- a. Rounders
- b. Cricket
- c. Table tennis
- d. Gymnastics
- e. Boxing
- f. Volleyball
- g. Swimming
- h. Archery
- i. Martial Arts

Please specify

.....

- j. Dodgeball
- k. Fencing
- l. Handball
- m. Ultimate Frisbee
- n. Yoga
- o. Zumba
- p. Pilates
- q. Badminton
- r. Dance

Please specify

.....

- s. Tennis
- t. Hockey
- u. Football
- v. Netball
- w. Rugby
- x. Athletics

- y. Other

Please specify

.....

Section 4: School rules and attitudes

Please tick the box that best indicates your agreement or disagreement with each of the following statements.

17. My school considers it important to...

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
a...encourage pupils to be physically active at school (for example, during school breaks)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
b...encourage pupils to do physical activity outside of school	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
c...educate pupils about the risks of physical inactivity	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
d...provide information on how to be physically active in a safe manner	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
e...encourage pupils to use active transport to school (e.g. walking, cycling)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

18. Which of the following statements best describes your rules relating to where Year 9 pupils can go during breaks (including lunchtime)?

Please tick one box only.

- It is compulsory for all Year 9 pupils to go outside, irrespective of the weather.
- When the weather allows, it is compulsory for all Year 9 pupils to go outside. However, all Year 9 pupils are kept inside in bad weather.
- When the weather allows, it is compulsory for all Year 9 pupils to go outside. However, if the weather is bad, they are allowed inside or outside.
- The Year 9 pupils are allowed to go both inside and outside, irrespective of the weather.
- It is compulsory for all Year 9 pupils to stay inside, irrespective of the weather.

19. Are the Year 9 pupils allowed to do the following during breaks?

Please tick only one box per statement.

	Yes, always	Yes, in bad weather	No, never
a. Use a computer	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
b. Watch TV or videos	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
c. Use the school's sports equipment	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
d. Play ball games indoors	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
e. Play ball games outdoors	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

20. Does your school have a policy to promote physical activity among Year 9 pupils?

Please tick only one box.

<input type="checkbox"/>	Yes, a written policy
<input type="checkbox"/>	Yes, an informal policy
<input type="checkbox"/>	No

**Thank you very much for
completing this
questionnaire – we really
appreciate your time!**

