



*Citation for published version:*

Maras, K, Sweiry, A, Villadsen, A & Fitzsimons, E 2024, 'Cyber offending predictors and pathways in middle adolescence: Evidence from the UK Millennium Cohort Study', *Computers in Human Behavior*, vol. 151, 108011. <https://doi.org/10.1016/j.chb.2023.108011>

*DOI:*

[10.1016/j.chb.2023.108011](https://doi.org/10.1016/j.chb.2023.108011)

*Publication date:*

2024

*Document Version*

Peer reviewed version

[Link to publication](#)

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# **Cyber offending predictors and pathways in middle adolescence: Evidence from the UK Millennium Cohort Study**

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## **Acknowledgements**

The Millennium Cohort Study is core funded by the Economic and Social Research Council (ESRC), and co-funded by a consortium of UK government departments. This work was carried out under an ESRC Policy Fellowship with the UK government's Home Office, awarded to the first author (Grant Ref: ES/W008114/1). For the purpose of open access, the author has applied a 'Creative Commons Attribution (CC BY) licence to any Author Accepted Manuscript version arising.

## **Keywords**

Cyber crime, Hacking, Offending, Deviancy, Adolescence, Millennium Cohort Study, Longitudinal data

# **Cyber offending predictors and pathways in middle adolescence: Evidence from the UK Millennium Cohort Study**

## **Abstract**

Despite the pervasiveness of cyber crime victimisation, knowledge is limited regarding the prevalence, characteristics and pathways of offenders. The present study examines predictors of self-reported engagement in cyber crime in middle adolescence in a large (N=13,277) longitudinal dataset from the UK Millennium Cohort Study. We adopted an ecological systems approach to examine a range of multicausal, intersecting factors across individual, familial, psychosocial and environmental systems. The overall prevalence of self-reported cyber offending (account hacking or the deployment of viruses) was 5.6% at age 14 and 3.8% at age 17, although persistence over time by the same individuals was relatively low (1.1%). Significant predictors of cyber offending at age 17 were being male, domestic violence between parents, low parental monitoring, low wellbeing, self-harm, exclusion from school, spending more time online gaming, participating in offline leisure activities, and engaging in serious violence (weapon carrying or use), assault, and cyber crime at age 14. Findings indicate that young cyber offenders are often males and those who have experienced a range of risk factors that are connected to poorer wellbeing and engaging in multiple risky/offending behaviours. Implications for theory, policy and practice are discussed.

## **Keywords:**

Cyber crime, Hacking, Offending, Adolescence, Millennium Cohort Study, Longitudinal data

## **1. Introduction**

### **1.1. What is cyber crime and how common is it?**

Cyber crime is a relatively new but quickly evolving crime type. It is defined in the UK under the Computer Misuse Act 1990 (CMA) as gaining unauthorised access or causing damage to computers, networks, data and other digital devices, or the information held on those devices. Also referred to as ‘cyber-dependent’ offending, examples include hacking or unauthorised access into online accounts (such as banking, email or social media accounts), denial of service attacks (DDoS), or infecting devices with a virus or malicious software (including ransomware). In the year ending December 2022, there were an estimated 764,000 cyber offences in England and Wales against 557,000 adult victims (Office for National Statistics, 2023). These attacks cost the UK economy around £1.1 billion per year and compromise national security and infrastructure, while also significantly impacting on individual victims personally (Home Office, 2018).

### **1.2. Overview of current research landscape on cyber offenders**

Despite the pervasiveness of cyber crime victimisation and the detrimental impact it has on individuals, businesses and states, we know relatively little about the prevalence of cyber offending, the nature of offenders or their offending trajectories. These evidence gaps collectively limit the development of suitable and effective interventions to deter, desist and divert would-be domestic cyber offenders onto positive legal pathways. For example, there is little robust empirical evidence on the characteristics of cyber offenders and how these compare to ‘traditional’ (offline) offenders. Compounding this problem, most research does not distinguish between cyber-enabled offences (traditional offences that can be committed online or offline, such as online fraud) and cyber-dependent computer misuse offences (offences that can only be committed using Information Communication Technology, such as

DDoS attacks). Indeed, a recent systematic review found that the vast majority of longitudinal studies on risk factors for cyber deviance have focussed on cyber bullying, sexting and cyber dating abuse, with little attention on cyber-dependent offences such as hacking and use/deployment of malware (Virgara & Whitten, 2023). Understanding is also limited around the volume of cyber crime offenders, as evidence is often derived from law enforcement and court data (i.e., only those who have been caught)<sup>1</sup>, or inferred based on the number of computer misuse incidents that are reported by victims.

One of the few consistent findings from the extant research to date is that individuals who engage in cyber offending are more likely to be male, with most research studies generally estimating that males constitute between 60% and 90% of cyber offenders (for reviews see Edwards et al., 2019; Gekoski et al., 2021). This largely mirrors the male-dominated pattern seen in delinquency and offending more generally (Rokven et al., 2018; Ruiters & Bernaard, 2013). However, other individual and environmental factors in cyber offending are inconsistently reported and poorly understood. For example, cross-sectional self-report data from 1365 Dutch juvenile delinquents indicates that, while juveniles with a higher 'risk' profile (e.g., low self-control, alcohol use, gaming, positive attitudes towards delinquency, negative familial, peer, and school factors) were more likely to commit both offline and online offences overall, there were few significant associations with the risk and protective factors for *cyber-dependent* offenders specifically (Rokven et al., 2018). That is, cyber-dependent offenders reported more protective factors and fewer risk factors compared to both cyber-enabled and offline offenders and were the group least likely to also commit offline offences. As Rokven et al. (2018) acknowledge, however, the variables included in this study were not comprehensive; for example, they did not encompass mental health,

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<sup>1</sup> In the year ending June 2022 there were just 34 convictions in the UK where CMA was the principle offence (Ministry of Justice, 2022)

online and offline activities, or family socioeconomic background. The cross-sectional nature of the data also precluded inferences about temporal relationships and cause and effect.

### **1.3. Key theoretical accounts of offending and their applicability to cyber offending**

Key theoretical accounts of traditional offending span those from the macro (e.g., the societal context) to the micro level (e.g., group influences and individual differences). For example, according to Differential Opportunity Theory (Cloward & Ohlin, 1960), an individual is likely to be channelled in a direction determined by what is available to them in society. In deprived neighbourhoods, for instance, gang cultures are more likely to flourish due to lack of opportunity in education and employment coupled with the support and boost to self-esteem and self-worth that is provided by gang membership (Wood, 2014). At the group level, Differential Association Theory (Sunderland & Cressey, 1970) posits that exposure to individuals who hold antisocial attitudes about offending behaviours results in a greater likelihood of breaking the law oneself, while according to Social Learning Theory (Akers et al., 1979) crime is learned through the processes of imitation and differential reinforcement from social interactions. There is support for the role of differential association (i.e., having friends who engage in delinquent behaviours) in criminality generally and cyber offending specifically (see Holt, 2023), although evidence for the reinforcement and imitation aspects of social learning in offending is less consistent (for a meta-analysis, see Pratt et al., 2010).

Other prominent theories such as Routine Activity Theory (Cohen & Felson, 1979), which emphasises the situational and opportunistic aspects of offending, and the General Theory of Crime (Gottfredson & Hirschi, 1990), which highlights the role of low self-control at the individual level, have received substantial empirical support for explaining offending and delinquent behaviours generally (Miller, 2013; Vazsonyi et al., 2017). Routine Activity

Theory and the General Theory of Crime have also been successfully applied to explain various forms of cyber-enabled offending such as digital piracy and online pornography (see Holt, 2023; Holt & Bossler, 2016; Leukfeldt & Yar, 2016). However, the limited research to date that has examined cyber dependent offences specifically (e.g., hacking or use of malware and viruses) provides only weak and inconsistent support for these theories (e.g., Yar, 2005; Bossler & Burruss, 2011), indicating the role of (or interplay with) other factors in cyber offending.

Bronfenbrenner's Ecological Systems Theory (Bronfenbrenner, 1979) adopts a more multicausal approach to understanding human behaviour. Within an ecological model, offending is seen as the result of a multifaceted relationship between different levels and factors: ontogenic development (individual factors or experiences), the microsystem (the immediate context in which the behaviour occurs, such as intimate and family relationships), the mesosystem (interrelations among two or more settings, such as spending more time with peers and less time at home), the exosystem (environmental settings that have indirect effects on the child, such as the media, family friends, neighbours, community supports) and the macrosystem (broader societal structures and cultural norms). The utility of this framework in explaining offending is supported by research suggesting a complex interplay of multiple factors, including individual factors (e.g., age, gender, mental health, substance use, school exclusion), family background (e.g., low family income, domestic abuse between parents, parental monitoring, parent-child relationship), social influences (e.g., association with delinquent peers) and other environmental factors (e.g., education, employment, and cultural context) together increase the likelihood of an individual engaging in delinquent or offending behaviours (e.g., Villadsen & Fitzsimons, 2022; see also Ellis, Beaver, & Wright, 2009). At a simplistic level, for example, in many cultures adolescent males tend to experience less parental monitoring and have lower self-control than their female counterparts, which in turn

is associated with affiliation with delinquent peers and increased likelihood of engaging in a variety of violent and non-violent delinquent behaviours, particularly among individuals from lower socio-economic status backgrounds (e.g., Barrett & Katsiyannis, 2016; Koon-Magnin et al., 2016; Young et al., 2011). Other factors, such as family adversity, clinical disorders such as ADHD, and previous engagement in delinquent behaviours, can serve as further causal or perpetuating mechanisms in offending (e.g., Barrett & Katsiyannis, 2016; Heeramun et al., 2017).

However, there are a number of key differences between cyber crime and general offline offending. These include the potentially reduced effectiveness of guardianship (since cyber offences can be committed inconspicuously from home), a prerequisite degree of cyber skill and interest (particularly for more advanced types of cyber crime), the perception of anonymity online, and often a lack of awareness of the illegality of actions (e.g., Payne et al., 2019, 2020; Xu, Hu & Zhang, 2013). Perhaps partly due to these apparent differences, a view amongst UK law enforcement has been that cyber offenders are a specialist and unique cohort of individuals who are unlikely to engage in offline, traditional offending (National Crime Agency, 2017). There is also a widely held belief that there is an over-representation of autistic individuals committing cyber crime (Ledingham & Mills, 2015), although to date there is mixed empirical support for this notion (Lim et al., 2023; Payne et al., 2019; Seigfried-Spellar et al., 2015).

#### **1.4. The present study**

To our knowledge, previous research has not examined potential explanatory pathways specifically into cyber-dependent offending by looking at multicausal, intersecting factors across individual, familial, psychosocial and environmental systems over time. This is critical for theory as well as policy and practice. Adolescence is a time of significant neurobiological, psychological, and social development, which is reflected in a steep increase



on average in offending behaviours from childhood to adolescence followed by a rapid decline from late teens to early 20s (MacLeod et al., 2012). It is also a pivotal period for offending prevention (Ross et al., 2011). As such, it is key time to examine cyber offending, providing a microcosm of the effect of these developmental changes and risk factors on offending behaviours. To this end, we utilised data from the Millennium Cohort Study (MCS) – a large representative UK population-based cohort study of young people, their families, and wider social contexts – to explore factors spanning individual demographics, family background, mental health and wellbeing, school, peers, activities, delinquency and other types of offending that may contribute to cyber offending. We predicted that being male, having higher cognitive scores (i.e., for the required skillset), lower parental monitoring, lower school connectedness, a diagnosis of autism, spending more time online and online gaming, spending less time in offline leisure activities, and engaging in cyber offending at age 14 would predict cyber offending at age 17, over and above that of predictors of more traditional (offline) offending (such as substance use and socioeconomic status).

## **2. Method**

### **2.1. The Millennium Cohort Study (MCS)**

The Millennium Cohort Study (MCS) is a longitudinal study tracking the lives of 19,243 individuals born in the UK between September 2000 to January 2002. Participants were initially identified from child benefit (a universal benefit) records and selected from a stratified sample of electoral wards, to ensure representation across all four countries and regions of the UK. Children born in ethnically diverse and economically disadvantaged areas were oversampled, to ensure adequate representation of these harder to reach families (Joshi

& Fitzsimons, 2016). For the purposes of the current research, the sample consisted of 13,277 adolescents with available data at age 17, 51.6% of whom were male (Table 1).

### **2.1.1. Procedure**

The initial MCS survey took place when children were 9 months of age, with follow up sweeps at ages 3, 5, 7, 11, 14, and 17 years.

A variety of multidisciplinary data are collected at each sweep from both the individuals and their parents, including environmental factors (e.g., socioeconomic circumstances, family structure, childrearing environment, and parental characteristics) and individual factors (e.g., social, cognitive, behavioural, and physical development, mental and physical health). Since the age 7 sweep, participants have increasingly self-reported their experiences (via questionnaires and home visit interviews) and at the two most recent sweeps (at ages 14 and 17), participants were asked about their involvement in a range of offending behaviours, including cyber crime. Interviews were completed in the home by trained interviewers, who collected responses to questions from respondents via tablets in self-completion mode.

Ethical approval for each sweep of the MCS was granted through the UK National Health Service Research Ethics Committee. Written informed consent was obtained from all participating parents at each survey up to age 14, including from age 11 for their permission for interviewers to approach their child for their own verbal consent. Consent for the current analyses was obtained from the University of Bath's Psychology Research Ethics Committee.

Further details of the study design, procedures, attrition, and available variables can be found elsewhere (e.g., Fitzsimons et al., 2020; Joshi & Fitzsimons, 2016).

## **2.2. Measures included in the current analyses**

### ***2.2.1. Cyber crime***

There were two questions on cyber crime at the age 14 and 17 sweeps of the MCS, broadly pertaining to hacking and virus/malware respectively, as follows (*italics* denotes additions to the questions for the age 17 sweep):

1. ‘In the last 12 months have you accessed, or hacked into, someone else’s *internet-enabled device* (e.g., computer, *tablet*, *mobile phone*, *games console*), e-mail or social networking account without their permission?’ (+ If Yes: ‘How many times in past year?’ not included in the current study).
2. ‘In the last 12 months have you used the internet to send viruses, *spyware* or other harmful software/*malware*, to deliberately damage or infect other computers?’ (+ If Yes: ‘How many times in past year?’ not included in the current study).

A binary variable for cyber crime was created (for each age), which identified those who had engaged in either of these behaviours at the respective age.

### **2.2.2. Predictor variables**

**2.2.2.1. Individual demographics and cognitive ability.** Individual demographic measures included participants’ *Age* (in months at the date of the age 17 sweep interview), *Sex*, and *Ethnicity*. A single composite score of *Cognitive Ability* at age 7 was calculated from word reading and pattern construction from the British Ability Scales (BAS II; Elliot, 1996) and the standardised age score from progress in maths from the National Foundation for Education Research (NfER) Progress in Maths test (as adapted by Hansen et al., 2010).

**2.2.2.2. Family background and environment.** Socioeconomic Status was ascertained from *Household Weekly Income* averaged

across childhood between 9 months and 11 years of age. Measures of family and home environment included *Parental Mental Health Problems*, whether there was *Domestic Abuse Between Parents*, whether the parent was *Ever a Single Parent* when the participant was between 9 months and 11 years of age, and whether there was ever any *Parental Drug Use* up until the participant was 14 years of age. A measure of *Parental Monitoring* when the participant was 14 year of age was also included.

**2.2.2.3. Mental health and wellbeing.** *Childhood Externalising Problems* and *Internalising Problems* were assessed via the parent-reported Strengths and Difficulties Questionnaire (SDQ; Goodman, 1997) when their child was aged between 3 and 11 years. Measures of *Depressive Symptoms* (the Short Moods and Feelings Questionnaire; Messer et al., 1995), *Self-Harm*, and *Wellbeing* at age 14 were also included, as well as whether the participant had received an *Autism Diagnosis* by age 14.

**2.2.2.4. School factors.** Measures relating to school included *School Connectedness* at ages 7 and 11, *Academic Achievement* at age 16 (five or more GCSEs at grades A to C), and whether the participant had ever been *Excluded* or *Persistently Truant from School* between the ages of 11 and 14.

**2.2.2.5. Peer factors.** Measures relating to peers included *Time Spent with Friends in Leisure Time*, whether the participant was the *Victim of Peer Bullying* and whether their *Peers Engaged in*

*Substance Use* (alcohol, cigarettes, cannabis, and/or hard drugs) at age 14.

2.2.2.6. **Online and offline activities.** Measures of online activity included *Time Spent on Social Media* and *Gaming Time* at age 14, while *Offline Leisure Activities* captured frequency of activities such as going to the cinema, watching live sport, reading, attending youth clubs and visiting museums and galleries at age 14.

2.2.2.7. **Delinquency and offending behaviours.** In addition to cyber crime, participants were asked whether they had engaged in other types of offending behaviours at age 14 and age 17, specifically: *Serious Violence* (weapon carrying or use); *Assault*; *Shoplifting*; *Community Crime* (theft from person, breaking and entering); *Criminal Damage* (graffiti and vandalism); and being a *Gang Member*. At age 14, participants also reported *Substance Use* (alcohol, cigarettes, cannabis, and/or hard drugs).

Further details on the measurement of predictor variables are available in the Supplemental Material.

### **2.3. Analyses**

All analyses were carried out using STATA version 17 (Stata Corp, 2019). Engagement in cyber offending was predicted using multivariate logistic regression with a range of potential predictors spanning different domains of participants' lives and all measured before age 17 years. The MCS is extremely rich in the information collected, and

variables measuring similar concepts were streamlined where possible in the prediction model. For instance, household income was chosen over other measures of socioeconomic status as it was the strongest predictor in this domain.

Logistic regression analyses were conducted incrementally, by introducing different predictors in blocks (Models 1-4). This permitted the study of more distal aspects such as family circumstance and environment in childhood, before examining each block of later factors in adolescence such as mental health, school and peers. In the final model, prior delinquent offending behaviours from age 14 are added, including substance use, weapon involvement, assault, shoplifting, community crime, criminal damage and arson, gang membership and cyber crime. We refer to this as the lagged model, and because it controls for prior engagement in the outcome of interest (cyber crime), its coefficients can be interpreted as predictors of *change* in cyber crime between ages 14 and 17.

### **2.3.1. Missing data**

Of the 19,519 families who were initially recruited for the study, 10,757 participants provided any data at age 17, with lower response rates on some specific survey questions. Missing data were dealt with using multiple imputation and weighting. Multiple imputation is an efficient method for replicating population estimates in longitudinal data when sections of data are missing (Mostafa et al., 2021), under the assumption that there is a pattern to the missingness and that this can be predicted by the observed data (Little & Rubin, 2002). A rule of thumb when imputing missing data is to impute up to 50% of missing data, as imputing above this threshold can reduce accuracy and bias estimates (Mishra & Khare, 2014). Therefore, missing data were imputed back to the age 11 survey, creating 30 imputed data sets through multiple chained equations. To improve the accuracy of imputed values and estimates, several auxiliary variables that were not part of the substantive analysis were used

in imputations (Von Hippel & Lynch, 2013), including school readiness at age 3, observed positive and negative child behaviours at age 3, and antisocial behaviours at age 11. To further adjust for attrition or missingness between the initial sweep and age 11, inverse probability weights were used, and estimates were adjusted for the complex sampling design of the initial MCS survey (Mostafa, 2015). The final sample used in the current analyses consists of 13,277 participants.

### **3. Results**

#### **3.2. Rates of self-reported engagement in offending behaviours at ages 14 and 17**

Table 1 displays the overall rates of participants' self-reported engagement in offending behaviours at ages 14 and 17, as well as the percentage of individuals who reported persistently engaging in offences at *both* ages 14 and 17 (descriptive characteristics of all other study variables are available in Supplemental Materials B). At the age 14 sweep, 5.55% of participants reported having carried out a cyber offence in the last 12 months, and this predominately related to hacking (5.17%; versus 1.16% deployment of viruses). This rate is much lower than reported prevalence of assault (31.61%), but higher than community crime (1.56%) and shoplifting (4.21%). Self-reported cyber offending dropped slightly at age 17, to 3.75%. Around 8% of participants reported having engaged in cyber crime at one or both of the survey sweeps, although persistence was low (1.1%), including compared to assault (15.6% persistence across ages).

Table 1. Percentage of participants who self-reported engaging in offending behaviours [95% CIs] ( $N = 13,277$ )

	Age 14 (overall %)	Age 17 (overall %)	% of individuals engaging at <i>both</i> age 14 and 17 (persistence)
Cyber crime overall	5.55% [4.91, 6.18]	3.75% [3.19, 4.32]	1.14% [0.82, 1.47]
Hacking	5.17% [4.57, 5.77]	3.67% [3.12, 4.22]	1.02% [0.72, 1.31]
Virus	1.16% [0.86, 1.47]	1.28% [0.87, 1.69]	0.29% [0.12, 0.46]
Weapon involvement	3.75% [3.23, 4.26]	6.20% [5.39, 7.00]	1.42% [1.04, 1.80]
Assault	31.61% [30.46, 32.75]	26.61% [25.43, 27.80]	15.55% [14.55, 16.56]
Shoplifting	4.21% [3.63, 4.79]	8.50% [7.47, 9.52]	1.34% [1.02, 1.67]
Community crime	1.56% [1.23, 1.89]	2.61% [2.12, 3.10]	0.17% [0.00, 0.02]
Criminal damage	5.71% [5.07, 6.36]	8.55% [7.75, 9.34]	1.78% [1.40, 2.54]
Gang member	1.93% [1.55, 2.30]	2.06% [1.38, 2.75]	0.26% [0.06, 0.46]

### 3.2. Predictors of cyber offending at age 17

Table 2 presents the stepwise results of the regression predicting self-reported engagement in cyber offending<sup>2</sup> at age 17 across Models 1 to 4. Model 1 included individual demographics and cognitive ability together with family background and environment. As shown in Table 2, males had a significantly higher risk than females of engaging in cyber crime at age 17 (OR = 1.77, 95% CI = 1.27-2.45), as did those who had experienced domestic abuse between parents during childhood (OR = 1.50, 95% CI = 1.07-2.09). Parental monitoring served as a protective factor, with those with the highest level of parental monitoring being at a much reduced risk of cyber offending compared to those with the lowest level of monitoring (OR = 0.30, 95% CI = 0.20-0.46).

In Model 2, mental health, wellbeing, and autism diagnosis were added to the regression. Self-harm at age 14 was a risk factor for cyber offending at age 17 (OR = 1.85,

<sup>2</sup> The overall prevalence rates were too low to run separate analyses on each of the two cyber offending questions.



95% CI = 1.18-2.89), while a one standard deviation increase in wellbeing at age 14 was associated with a lower risk of cyber offending at age 17 (OR = 0.73, 95% CI = 0.61-0.88). Model 3 included variables relating to school, peers, and (online and offline) activities at age 14. Exclusion from school (OR = 1.89, 95% CI = 1.03-3.45), spending a lot of time gaming (OR = 2.23, 95% CI = 1.08-5.19) and frequent participation in offline activities (OR = 1.19, 95% CI = 1.01-1.41) all increased the risk of cyber offending.

Finally, in the lagged model (Model 4), delinquency and offending behaviours at age 14 were added as predictor variables. Engagement in serious violence (weapon carrying or use) (OR = 2.16, 95% CI = 1.08, 4.31), assault (OR = 1.79, 95% CI = 1.20-2.66), and cyber offending (OR = 4.28, 95% CI = 2.74-6.69) all increased the risk of cyber offending at age 17. The only other significant variable remaining in the final model was wellbeing (OR = 0.79, 95% CI = 0.65-0.96).

Prevalence rates of cyber offending at age 17 by each of the predictor variables (unadjusted for other covariates) are available in Supplemental Materials C.

Table 2. Results of the multivariate logistic regression predicting self-reported engagement in cyber offending at age 17

	<b>Model 1</b>		<b>Model 2</b>		<b>Model 3</b>		<b>Model 4</b>	
	<b>OR</b>	<b>95% CI</b>	<b>OR</b>	<b>95% CI</b>	<b>OR</b>	<b>95% CI</b>	<b>OR</b>	<b>95% CI</b>
<b>Individual demographics and cognitive ability</b>								
Participant age in months at age 17 survey	1.00	0.97-1.04	1.01	0.97-1.05	1.01	0.97-1.05	1.01	0.97-1.05
Male	<b>1.77***</b>	1.27-2.45	<b>2.33***</b>	1.62-3.35	<b>1.75*</b>	1.14-2.69	1.34	0.85-2.13
Ethnic minority	0.76	0.46-1.27	0.82	0.50-1.36	0.86	0.51-1.44	0.74	0.44-1.26
Cognitive ability (age 7) <sup>a</sup>	1.13	0.95-1.35	1.14	0.96-1.37	1.15	0.95-1.40	1.11	0.91-1.35
<b>Family background and environment</b>								
Household weekly income (average 9 months to 11 years) (ref: 80%-100% highest)								
Lowest 20%	1.01	0.56-1.83	0.92	0.51-1.66	0.82	0.45-1.50	0.81	0.43-1.50
20-40%	0.93	0.54-1.60	0.86	0.50-1.46	0.81	0.48-1.38	0.82	0.47-1.44
40-60%	0.95	0.60-1.50	0.89	0.56-1.42	0.89	0.56-1.41	0.92	0.57-1.49
60-80%	0.97	0.63-1.50	0.95	0.62-1.46	0.94	0.61-1.45	0.94	0.59-1.48
Main parent mental health problems (9 months to 11 years) <sup>a</sup>	1.05	0.91-1.22	0.98	0.83-1.17	0.98	0.83-1.17	1.03	0.86-1.23
Domestic abuse between parents (9 months to 11 years)	<b>1.50*</b>	1.07-2.09	<b>1.46*</b>	1.04-2.06	1.42+	1.00-2.01	1.37+	0.95-1.98
Main parent used recreational drugs (3, 5 or 14 years)	0.91	0.49-1.67	0.85	0.45-1.59	0.80	0.41-1.55	0.75	0.38-1.51
Ever a single parent (between 9 months and 11 years)	1.38	0.93-2.06	1.35	0.90-2.01	1.28	0.86-1.93	1.26	0.83-1.91
Parental monitoring at age 14 (ref: lowest 0-15%)								
15-30%	<b>0.51**</b>	0.32-0.82	<b>0.60*</b>	0.37-0.97	0.66+	0.41-1.07	0.81	0.48-1.35



One type of substance		1.06	0.72-1.57	0.97	0.65-1.45
Two or three types of substances		1.26	0.83-1.91	1.00	0.64-1.57
<b>Activities</b>					
Social media time (age 14) <sup>b</sup>		1.32	0.70-2.52	1.12	0.58-2.16
Online gaming time (age 14) <sup>b</sup>		<b>2.36*</b>	1.08-5.19	2.02+	0.90-4.54
Offline leisure activities (age 14) <sup>a</sup>		<b>1.19*</b>	1.01-1.41	1.18+	0.99-1.41
<b>Delinquency and offending behaviours</b>					
Substance use (alcohol, smoking, drugs) at age 14 (ref: no substances)					
One type of substance				1.16	0.69-1.96
Two or three types of substances				0.62	0.26-1.45
Serious violence (weapons carrying/use) (age 14)				<b>2.16*</b>	1.08-4.31
Assault in past year (age 14)				<b>1.79**</b>	1.20-2.66
Shoplifting in past year (age 14)				1.54	0.84-2.79
Community crime (breaking and entering, theft from person) (age 14)				1.98+	0.94-4.17
Criminal damage and arson (age 14)				1.18	0.65-2.15
Gang member ever (age 14)				0.99	0.45-2.20
Cyber crime (hacking/virus) (age 14)				<b>4.28***</b>	2.74-6.69

Abbreviations: CI, confidence interval; OR, odds ratio.

<sup>a</sup> Predictor variable is standardized (z-score), meaning that the OR coefficient is for one standard deviation increase in the predictor.

<sup>b</sup> Predictor variable is a ridit score, which is a transformation of ordinal scale responses (hourly time-use bands) into a continuous measure. The OR coefficient corresponds to differences between those with the highest time use (e.g., 7 hours or more) compared to those with the lowest (no time spent).

\*\*\* $p < .001$ ; \*\* $p < .01$ ; \* $p < .05$ ; + $p < .10$ .

## **4. Discussion**

### **4.1. Overview of findings and integration with previous research**

The current study aimed to examine rates and predictors of self-reported cyber offending in a large representative sample of UK adolescents. A key finding was that 5.6% of 14-year-olds and 3.8% of 17-year-olds reported engaging in cyber offending in the last 12 months. However, desistance was high for those who had cyber offended at age 14, with just 1.1% of the sample persisting in cyber offending between the ages. Significant predictors of engaging in cyber offending at age 17 were being male, a history of domestic violence between parents, low rates of parental monitoring, low wellbeing, engaging in self-harm, exclusion from school, excessive gaming, frequent participation in offline leisure activities, engaging in serious violence (weapon carrying or use), assault, and cyber crime. However, the only variables that predicted the uptake of cyber offending between ages 14 and 17 in the final lagged model were engagement in other types of offline offending behaviours, whilst wellbeing at age 14 predicted desistance between 14 and 17. That is, although individual demographics and family environment were initial predictors of cyber offending, they did not predict emergent cyber offending between ages 14 and 17. This is likely because these earlier predictors are mediated through these later offending risk factors, especially cyber offending at age 14 which is a particularly strong predictor of reoffending at age 17.

#### **4.1.1. Rates of self-reported cyber offending**

The headline findings that around 5.2% of 14-year-olds said they had hacked somebody's computer at least once in the past 12 months and 1.2% had sent a virus at age 14 are striking. This compares to just 1.6% of participants who reported having engaged in community crime (which encompasses *offline* breaking and entering or theft from a person). This dropped to around 3.8% self-reported cyber offending at age 17, although the figures for

teenage boys were higher than for their female peers, with around 4.9% of boys admitting to cyber crime at age 17 compared to 2.5% of girls (see Supplemental Materials). This is consistent with a previous large multinational study of secondary school age pupils, which reported prevalence rates of 5.4% for hacking, with rates being significantly higher in males (8.3%) than females (2.6%) (Udris, 2016). However, other studies have reported much lower prevalence; for example, in a study in Germany just 0.5% of individuals over 16 years of age reported engaging in cyber-dependent crime within the last twelve months (Mueller et al., 2023), although the older age range may account for this lower reported prevalence rate.

In the current study, the reduced prevalence of participants engaging in cyber crime (from 5.6% at age 14 to 3.8% at age 17) and notable desistance between the sweeps (with just 1.1% persisting at both ages) differentiated cyber offending from most other self-reported offending behaviours. In contrast to cyber offending, serious violence (weapon involvement), shoplifting, community crime (breaking and entering, theft from person) and criminal damage all had higher prevalence at age 17 than at age 14. In addition, while between a third and a half of those engaging in weapon involvement, assault or criminal damage at age 14 reported continued offending at age 17, almost four in five of those engaging in cyber crime at 14 were desisting by age 17. This is in line with previous longitudinal data from Korea, which showed that over a four-year period overall levels of cyber delinquency amongst adolescents decreased, while the level of offline delinquency increased (Nam 2021; but see Logos et al., 2022). Due to the low prevalence rates, it was not possible in the current study to examine the factors which specifically predicted persistence, but this is a logical next step for future research.

#### **4.1.2. Predictors of self-reported cyber offending**

There was a strong relationship between continued engagement and uptake of cyber crime between ages 14 and 17 with engagement in other offending behaviours at age 14. Specifically, alongside cyber offending at age 14 (which was associated with over four times the odds of continuing this behaviour at age 17), serious violence (weapon carrying or use) and assault at age 14 also predicted an increase in cyber offending at age 17. This supports previous reports that risk taking, aggression and anti-social behaviour are associated with other types of offending behaviours, including cyber offending (e.g., Logos et al., 2022; Nam, 2020; Seigfried-Spellar et al., 2017). Previous research has also shown that spending more time on computers and gaming are associated with higher rates of cyber deviancy and offending (see Edwards et al., 2022), and those who hold positive attitudes towards offending more generally are more likely to self-report engaging in cyber delinquency themselves (Chua & Holt, 2016; Rokven et al., 2018; Silic & Lowry, 2021; Udris, 2016; Young et al., 2007). Time spent on computers and/or gaming may act as a pathway to developing the necessary cyber skills and knowledge to carry out cyber offences (Xu et al., 2013) and as a motive and means of opportunity (e.g., carrying out DDoS attacks in retaliation against other gamers), adding some support for the utility of Routine Activity Theory in cyber crime (Cohen & Felson, 1979).

Engagement in offline leisure activities (such as going to the cinema, watching live sport, reading, attending youth clubs and visiting museums and galleries) was also a significant predictor of engaging in cyber offending, but in the opposite direction to that predicted: participating in more offline activities increased the likelihood that an individual would also engage in cyber offending. Although the relationship was modest (OR = 1.19), it is difficult to explain. Speculatively, more individuals with higher technical skills may be more inquisitive and motivated to seek out wider experiences, or perhaps these individuals



have wider peer networks and therefore potential sources of peer influence – although these suppositions require investigation.

Overall, though, there were few significant environmental predictors of cyber offending at age 17 (aside from parental monitoring and domestic violence), in line with Weulen Kranenbarg et al. (2022). For example, in contrast to previous findings regarding various forms of offline and cyber-enabled offending, socioeconomic status did not negatively predict cyber offending. If anything, we expected to find a positive relationship with cyber crime, since higher socioeconomic status is associated with more readily available access to education, skills, equipment and opportunity (Donner et al., 2015; Lee & Holt, 2020; Park et al., 2019; Pontell & Rosoff, 2009). However, it is likely a nuanced association, influenced by other factors such as the technicality and seriousness of the crime and one's motivations for committing it, which were not captured in the present study. Relatedly, we found no evidence that autism was a predictor of cyber offending in the present study, which is in contrast to recent findings (Lim et al., 2021) and anecdotal reports (including among law enforcement) that there is a link between autism and cyber crime (e.g., Ledingham & Mills, 2015). Previous research suggests that autism is associated with higher IT skills, which in turn are a prerequisite for committing certain types of cyber crime (Payne et al., 2019). The lack of positive association between autism and cyber crime in the current study may therefore be related to the broad cyber crime questions asked, which would have also captured lower-level and less skilled cyber offending activity such as password guessing.

We also found no evidence of peer influence in cyber offending. Some previous studies also report no evidence of peer influence in cyber deviancy (Weulen Kranenbarg et al., 2022), or that the relationship between peer delinquency and cyber offending, while significant, is not as strong as it is for offline offending (Weulen Kranenbarg et al., 2019, 2021). However, some studies have reported an increased risk of an individual engaging in

cyber offending or cyber deviancy if their peers also engage (or at least are perceived to engage) in cyber offending or general delinquency (e.g., Donner et al., 2014; Fox & Holt, 2021; Weulen Kranenbarg et al., 2019; Lee, 2018; Louderback & Antonaccio, 2021; Marcum et al., 2014; Nodeland, 2020; Rokven et al., 2018; Weulen Kranenbarg et al., 2021, 2022). In the current study we were not able to examine peer engagement in cyber crime, however this peer dimension may be especially important as individuals may be mirroring their peers when engaging in cyber crime.

#### **4.2. Implications for theory, policy, and practice**

To our knowledge, this is the first longitudinal research examining predictors of cyber-dependent offending within a broader ecological framework. Findings have implications for theoretical accounts of cyber offending, as well as policy and practice in preventing individuals from engaging in cyber offending.

It has been argued that traditional criminological theories such as Routine Activity Theory (Cohen & Felson, 1979), Differential Association Theory (Sunderland & Cressey, 1970) and Social Learning Theory (Akers, 1979) apply equally as well to cyber crime (Grabosky, 2001). However, the lack of peer-related predictors in the present study preclude support for the utility of Social Learning and Differential Association Theory in cyber offending, although we acknowledge the limitation of our measures of peer influence which was limited to substance use. The finding that low parental monitoring and excessive gaming were significant risk factors lend some support for Routine Activity Theory in explaining cyber offending, while findings that other types of offences predicted uptake of cyber crime is consistent with the General Theory of Crime (Gottfredson & Hirschi, 1990). Although self-control was not directly examined in our study it is likely to underpin these other offending behaviours and also cyber crime. Clearly, though, a more multifaceted account is needed

given that there were further significant predictors across different domains, including individual demographics and family environment, mental health and wellbeing, activities, and other offending behaviours. Indeed, findings are more in line with Bronfenbrenner's (1979) Ecological Systems Theory, whereby outcomes are not driven by an individual's characteristics, background, experiences or context alone, but their relative and interactive effects combined (Papachristou et al., 2020). Ecological Systems Theory has been recently applied to explain juvenile delinquency and offending (e.g., Villadsen & Fitzsimons, 2022) but not empirically, until now, to cyber crime.

In terms of policy and practice, the current findings highlight the need for more encompassing interventions that target different areas of a young person's life, including family environment and gaming time, as well as the mental health and wellbeing of young people more broadly. Findings on the declining prevalence of cyber offending between ages 14 and 17, when taken together with the low levels of persistence in offending between the ages, highlight the potential value of primary and secondary prevention intended to avert early onset offending, supplemented with more carefully targeted and tailored interventions which might address the needs of those most likely to persist. The high rates of desistance between ages 14 and 17 also emphasise the need for caution in the design, delivery and timing of interventions for young cyber offenders to avoid risks of unnecessary treatment and to ensure that risks of peer contagion effects are avoided.

#### **4.3. Limitations and future research**

Although the current study has several strengths, including the large nationally representative sample and the availability of measures across ecological systems over time, there are also some important limitations to note. In particular, the two cyber crime questions were relatively broad; the openness of the hacking question in particular meant that low level,

unskilled cyber offending such as accessing a device without permission (e.g., 'shoulder surfing' and low-level password guessing) was included. Thus, caution is warranted in making inferences about the prevalence, characteristics and pathways of persistent and/or serious cyber offenders. It will be important for further research to develop these questions to differentiate more highly skilled, serious forms of cyber offending from low level activities, in order to gain a more nuanced view of the prevalence, pathways and predictors of cyber offending amongst adolescents. Such work should also include potential predictors that were not possible to examine in the present study, such as individuals' understanding of illegality, risk, and consequences, their motivations, and levels of self-control, and peer engagement in cyber crime. Again, these may play a different role in onset and persistence depending on the type, technicality and severity of cyber offending in question.

Further investigation of the mechanisms through which engaging in other types of offending behaviours predicts cyber offending is also an important next step. The current findings suggest there may be a cascading effect of individual and environmental factors (including being male and experiencing discord at home and school) on wellbeing and offending behaviour generally, which in turn predict cyber offending specifically. Potentially this may be mediated through factors such as gaming and normalisation or desensitisation of offending, although a more detailed examination of this is warranted, alongside the question of why participating in more offline activities increases the likelihood that an individual would also engage in cyber offending.

## **5. Conclusion**

The extent to which cyber crime and traditional crime overlap is currently poorly understood. It has previously been suggested that cyber delinquency is similar to traditional

delinquency but is committed using technology in a virtual space. The present findings indicate that cyber offending shares some overlap with traditional (offline) offending in that it is predicted by individual (e.g., gender, mental health) and environmental (e.g., parental monitoring, domestic violence) factors which interact to form a set of causal mechanisms. However, there are also some important differences, including the lack of association with other factors that are established predictors of offline offending, such as socioeconomic status, educational attainment, and peer influence (e.g., Holt 2007; Weulen Kranenbarg et al., 2019).

In sum, contrary to popular stereotypes, there is not an archetypal cyber offender who is distinct from other types of offenders; multiple individual factors may differentially contribute to different types of cyber offending across different individuals. This makes it difficult to apply a 'one size fits all' approach to characterising cyber offenders. However, the current findings highlight the need for interventions that target different areas and time periods of a young person's life, including family environment and gaming time, as well as the mental health and wellbeing of young people to help prevent the onset of offending. By contrast, the low levels of persistent cyber dependent offending through middle adolescence indicated by the study emphasise the need for cautious targeting of tertiary crime prevention.

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## **Supplemental Material A:**

### **Measurement of Predictor Variables**

#### **Individual Demographics and Cognitive Ability**

##### ***Age in Months at Age 17 Survey***

Participant's age in months at the date of the age 17 sweep interview was derived from interview date and birthdate of the participant.

##### ***Sex***

The sex at birth of the participant was reported by the main parent in the initial MCS survey.

##### ***Ethnicity***

Ethnicity of the participant was reported by the main parent in the initial survey using 16 categories. The variable used in the current study is a condensed binary version (white versus other ethnic groups).

##### ***Cognitive Ability (age 7)***

A single composite score of cognitive ability was calculated from three measures: Word reading (standard score) and pattern construction (age-based T-scores) from the British Ability Scales (BAS II; Elliot, 1996) and the standardised age score from progress in maths (developed by the National Foundation for Educational Research);  $\alpha = 0.68$ .

#### **Family Background and Environment**

### ***Household Weekly Income (average between 9 months to 11 years of age)***

The main parent indicated their annual band of income (multiple choice options), from which a continuous income measure was estimated using relevant predictor variables. Income was equivalised using modified OECD scales, which takes account of the household size and composition, thereby factoring in the needs of the family.

### ***Main Parent Mental Health Problems (between 9 months and 11 years)***

The main parent completed the Malaise (Rutter et al., 1970) in the initial birth sweep and the Kessler (Kessler et al., 2003) in subsequent sweeps at age 3, 5, 7, and 11. A composite measure was then created combining parental mental health across childhood.

### ***Domestic Abuse Between Parents (between 9 months and 11 years)***

In all five sweeps from birth to age 11, the main respondent and their partner (where available), were asked: 'People often use force in a relationship – grabbing, pushing, shaking, hitting, kicking etc. Has your partner ever used force on you for any reason?' [yes/no]. If either party responded yes at any sweep this was counted as domestic abuse.

### ***Parental Drug Use (age 3, 5, or 14 years)***

The main parent was asked, 'As you know many people have experimented with drugs at some time. During the past year have you used any recreational drugs like cannabis, cocaine or ecstasy?' [Occasionally, Regularly, Never]. Occasional or regular use was counted as having used recreational drugs.

### ***Ever a Single Parent (between 9 months and 11 years)***

If the main respondent in any sweep between the birth sweep (9 months of age) to age 11 reported having no partner living with them this was counted as having been a single parent.

### ***Parental Monitoring (age 14)***

The participant was asked whether their parents know where they go out, who with, and what they do when they are out [Always, Usually, Sometimes, Never]. Higher scores indicate higher level of monitoring. Internal consistency was good ( $\alpha = 0.81$ ).

## **Mental Health, Wellbeing and Autism**

### ***Childhood Externalising Problems (ages 3-11)***

Parents completed the widely used and validated self-report Strengths and Difficulties Questionnaire (SDQ; Goodman, 1997) about their child. Ten items of the SDQ measure childhood externalising problems: five items relate to conduct problems (e.g., often has temper tantrums; often lies or cheats) and five relate to hyperactivity (e.g., easily distracted; constantly fidgeting or squirming). The items measuring externalising problems showed good internal consistency at age 3 ( $\alpha = 0.78$ ), age 5 ( $\alpha = 0.78$ ), age 7 ( $\alpha = 0.80$ ), and age 11 ( $\alpha = 0.81$ ).

### ***Childhood Internalising Problems (ages 3-11)***

A further ten items of the parent-reported SDQ were used to measure childhood internalising problems: five items assess emotional problems (e.g., often unhappy; worries a lot) and five assess peer-related problems (e.g., solitary; gets on better with adults than with other children). Items showed acceptable interitem reliability at most time points: age 3 ( $\alpha = 0.61$ ), age 5 ( $\alpha = 0.67$ ), age 7 ( $\alpha = 0.72$ ), and age 11 ( $\alpha = 0.77$ ).

### ***Depressive Symptoms (age 14)***

The participant completed the Short Moods and Feelings Questionnaire (Messer et al., 1995), comprising 13 items on affective symptoms in the last two weeks (e.g., felt miserable

or unhappy; felt lonely) from which a summed score (range 0-26) is calculated (higher scores indicate higher levels of depression). Internal consistency is high ( $\alpha = 0.93$ ). Clinical levels of depression are score of 12 or above.

### ***Self-Harm (age 14)***

Participants were asked a single question, ‘In the past year have you hurt yourself on purpose in any way?’ [Yes, No].

### ***Wellbeing (age 14)***

Participants were asked to rate (on a 7-point Likert scale) their psychological wellbeing for their perceived happiness in relation to their appearance, family, friends, their school and schoolwork, and their life as whole. Items are reverse coded such that high scores indicate a higher level of wellbeing. This measure has high internal consistency ( $\alpha = 0.86$ ) (Patalay & Fitzsimons, 2016).

### ***Autism Diagnosis (by age 14)***

Parents were asked, ‘Has a doctor or other health professional ever told you that your child had Autism, Asperger’s Syndrome or other autistic spectrum disorder?’ [yes, no].

## **School Factors**

### ***School Connectedness (age 7 and 11)***

Participants self-reported on five questions relating to school connectedness (e.g., ‘how often do you find school interesting’, ‘how often do you feel school is a waste of time’) [all of the time, most of the time, some of the time, never]. The five items demonstrated reasonable internal consistency (age 7  $\alpha = .67$ , age 11  $\alpha = .71$ ).

### ***Academic Achievement (age 16)***

Participants self-reported their GCSE results at the age 17 sweep. A binary measure was derived whether the individual had attained at least five GCSEs at grades A to C.

### ***School Exclusion (between ages 11 and 14)***

The main parent reported at age 11 and age 14 whether their child had ever been temporarily or permanently suspended from school. A binary measure was derived for experiencing either type of exclusion between the age of 11 and 14. Those who had been excluded already by age 11 were excluded from the analytical sample, meaning that the measure captures new or first-time school exclusion between age 11 and 14.

### ***Persistent Truancy from School (between ages 11 and 14)***

Participants self-reported at age 11 whether they had ever missed school without parental permission, and at age 14 they reported any truancy in the past twelve months. A binary measure was derived that captured truancy between age 11 and 14 (as for exclusion those admitting to truancy by age 11 were dropped from the analytical sample).

## **Peer factors**

### ***Time Spent with Friends in Leisure Time (age 14)***

Participants were asked, 'In the afternoon after school, how often do you spend time with your friends, but without adults or older children, doing things like playing in the park, going to the shops or just 'hanging out'? [Most days, At least once a week, At least once a month, Less often than once a month, Never]. A binary measure was created for "spending time with friends in leisure time on most days".

### ***Victim of Peer Bullying (age 14)***

Participants were asked, 'How often do other children hurt you or pick on you on purpose? [Most days, Once a week, Once a month, Every few months, Less often, Never]. A binary measure was created for the regression analyses whereby No=Never and Yes= Most days, Once a week, Once a month, Every few months, Less often.

### ***Peer Substance Use (age 14)***

Participants were asked three questions pertaining to how many of their friends smoke cigarettes, drink alcohol, and take drugs, respectively [None of them, Some of them, Most of them, All of them]. Responses were converted into a binary measure for each of the three questions (No=Never, Yes=Some, Most, or All of them) and for the regression analysis a single measure of peer substance use was created: None, One type of substance, Two or three types of substances.

## **Online and Offline Activities**

### ***Social Media Time Use (age 14)***

Participants were asked, 'On a normal weekday 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?' [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, 7 hours or more]. The categorical variable was transformed into ridit scores for use in the regression analysis (Jansen, 1984).

### ***Gaming Time (age 14)***

Participants were asked, 'On a normal weekday during term time, how many hours do you spend playing electronic games on a computer or games systems, such as Wii, Nintendo D-S, X-Box or PlayStation? Please remember to include time before school as well as time after school.' [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, 7 hours or more]. The categorical variable was transformed into ridit scores for use in the regression analysis (Jansen, 1984).

### ***Offline Leisure Activities (age 14)***

Participants asked about the frequency with which they took part in various offline leisure activities, including going to the cinema, watching live sport, reading, attending youth clubs and visiting museums and galleries [Most days, At least once a week, At least once a week, A least once a month, Several times a year, Once a year or less, Never or almost never]. Higher scores indicate higher greater frequency of engagement in these activities.

### **Delinquency and Offending Behaviours**

#### ***Substance Use (age 14)***

Participants were asked about the frequency with which they had drunk five or more alcoholic drinks at a time over the past 12 months, whether they were a regular smoker, and whether they had tried cannabis and/or hard drugs ever. For the regression analysis, a single measure of substance use was created: None, One type of substance, Two or three types of substances (cannabis and drugs were combined as 'drugs'; the other types were binge drinking and regular smoking).

#### ***Serious Violence: Weapon Involvement (age 14 and 17)***

Participants were asked, 'In the last 12 months have you used or hit someone with a weapon?' [yes/no]. 'Have you ever carried a knife or other weapon for your own protection because someone else asked you to or in case you get into a fight?' [yes/no]

***Assault (age 14 and 17)***

Participants were asked, 'In the last 12 months have you pushed or shoved/hit/slapped/punched someone?' [yes/no]

***Shoplifting (age 14 and 17)***

Participants were asked, 'In the last 12 months have you taken something from a shop without paying for it?' [yes/no]

***Community Crime: Theft from Person, Breaking and Entering (age 14 and 17)***

Participants were asked, 'In the last 12 months have you stolen something from someone (e.g., a mobile phone, money etc.?)' [yes/no]. 'Have you ever gone into someone's home without their permission because you wanted to steal or damage something?' [yes/no]

***Criminal Damage: Graffiti, Vandalism (age 14 and 17)***

Participants were asked, 'In the last 12 months have you written things or spray painted on a building, fence or train or anywhere else where you shouldn't have?' [yes/no]. 'In the last 12 months have you on purpose damaged anything in a public place that didn't belong to you, for example by burning, smashing or breaking things like cars, bus shelters and rubbish bins?' [yes/no]

***Gang Member (age 14 and 17)***

Participants were asked, 'Are you a member of a street gang? By a street gang, we mean groups of young people who hang around together and: have a specific area or territory;



have a name, a colour or something else to identify the group; possibly have rules or a leader;  
who may commit crimes together.' [yes/no/used to be but not anymore]

## Supplemental Materials B

### Descriptive statistics of study measures (*N* = 13,277)

	% [95% CIs] or mean (SD)
Age at age 17 survey	17.17 years (0.34)
Sex (% male)	51.64%
Ethnicity (%)	
White	84.44% [81.67, 87.16]
Mixed	3.51% [2.99, 4.05]
Indian	2.03% [1.46, 2.61]
Pakistani and Bangladesh	5.04% [3.03, 7.05]
Black or Black British	3.52% [2.29, 4.75]
Other ethnic groups (incl. Chinese)	1.48% [0.94, 2.01]
Cognitive ability z score (age 7)	-0.04 (1.00)
Household weekly income (average 9 months to 11 years)	£365.19 (178.25)
Quintiles	
20% lowest	£150.16 (22.87)
20%-40%	£233.41 (28.13)
40%-60%	£330.35 (29.56)
60%-80%	£438.29 (36.0)
80%-100% highest	£636.47 (111.03)
Main parent mental health problems (average 9 months to 11 years)	3.90 (3.32)
Domestic abuse between parents (9 months to 11 years)	22.32% [21.39, 23.26]
Parental drug use (age 3, 5 or 14 years)	8.61% [7.67, 9.55]
Ever a single parent (9 months to 11 years)	38.55% [36.87, 40.22]
Parental monitoring (age 14)	7.19 (1.97)
Quintiles	
15% lowest	17.44% [64.06, 18.47]
15%-30%	14.51% [13.61, 15.41]
30%-45%	14.05% [13.28, 14.83]
45%-60%	17.58% [16.61, 18.55]
60%-100% highest	36.42% [35.10, 37.74]

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Childhood externalising problems (average age 3 to 11 years)	5.46 (3.14)
Childhood internalising problems (average age 3 to 11 years)	3.00 (2.24)
Clinical levels of depressive symptoms (age 14)	15.90% [14.91, 16.90]
Self-harmed in the past year (age 14)	15.76% [14.78, 16.74]
Wellbeing (age 14)	26.61 (6.73)
Autism diagnosis (by age 14)	4.52% [3.99, 5.05]
School connectedness z score (ages 7 and 11)	-0.05 (1.01)
Academic achievement – at least 5 GCSEs grade A-C (age 16)	56.12% [54.44, 57.80]
School exclusion (ages 11-14)	7.09% [6.31, 7.87]
Persistent truancy from school (ages 11-14)	5.77% [5.06, 6.49]
Spending time with friends in leisure time on most days (age 14)	38.74% [37.32, 40.16]
Victim of peer bullying (age 14)	48.97% [4.75, 50.42]
Peer substance use – alcohol, smoking, drugs (age 14)	
No substance use	37.00% [35.25, 38.75]
One type of substance	26.69 [25.42, 27.96]
Two or three types of substances	36.31% [34.72, 37.90]
Time spent on social media (age 14)	
None	7.95% [7.32, 8.58]
Less than 30 mins	12.03% [11.29, 12.78]
30 mins to 1 hour	13.99% [13.20, 14.77]
1-2 hours	16.72% [15.81, 17.64]
2-3 hours	15.18% [14.25, 16.11]
3-5 hours	14.09% [13.26, 14.93]
5-7 hours	9.91% [9.20, 10.06]
7 hours or more	10.12% [9.26, 10.97]
Gaming time (age 14)	
None	17.59% [16.64, 18.54]
Less than 30 mins	13.02% [12.17, 13.87]
30 mins to 1 hour	12.27% [10.56, 11.99]
1-2 hours	15.30% [14.54, 16.06]
2-3 hours	13.87% [12.94, 14.80]
3-5 hours	13.31% [12.50, 14.11]

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5-7 hours	7.31% [6.63, 8.00]
7 hours or more	8.33% [7.57, 9.09]
Offline leisure activities (age 14)	11.45 (5.21)
Substance use – binge drinking, regular smoking, drugs (age 14)	
None	86.78% [85.84, 87.72]
One type of substance	8.27% [7.50, 9.04]
Two or three types of substance	4.95% [4.33, 5.57]

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*Note:* Descriptives for continuous variables are the raw scores except where measures are composites of measures that have been standardized before being added together (e.g., cognitive ability and school connectedness)

## Supplemental Material C:

### Prevalence of Cyber Offending at Age 17 by Predictor Variables

		<b>Prevalence of cyber offending (age 17) [95% CIs]</b>
<b>Age at age 17 survey</b>		
	Under 17 years	3.57% [2.62, 4.51]
	17-17.3 years	3.86% [2.95, 4.77]
	17.3-17.5 years	3.60% [2.15, 5.04]
	over 17.5 years	3.99% [2.36, 5.62]
<b>Sex</b>		
	Male	4.89% [3.96, 5.83]
	Female	2.54% [1.91, 3.16]
<b>Ethnicity</b>		
	White	3.94% [3.34, 4.53]
	Mixed	3.86% [0.35, 7.38]
	Indian	1.86% [0.19, 3.92]
	Pakistani & Bangladeshi	1.31% [0.31, 2.30]
	Black or Black British	4.88% [1.27, 8.49]
	Other inc. Chinese	N/a
<b>Cognitive ability (age 7)</b>		
	lowest 20%	3.73% [2.17, 5.29]
	20-40%	3.30% [2.12, 4.48]
	40-60%	3.54% [2.32, 4.77]
	60-80%	4.25% [3.17, 5.33]
	highest 80-100%	3.98% [2.90, 5.06]
<b>Household weekly income (9 months to 11 years)</b>		
	20% lowest	4.16% [2.71, 5.62]
	20%-40%	3.89% [2.68, 5.11]
	40%-60%	3.65% [2.44, 4.86]
	60%-80%	3.47% [2.37, 4.57]
	80%-100% highest	3.52% [2.56, 4.48]
<b>Main parent mental health problems (9 months to 11 years)</b>		
	lowest 20%	2.90% [1.86, 3.94]
	20-40%	3.81% [2.75, 4.87]
	40-60%	3.66% [2.54, 4.77]
	60-80%	3.89% [2.60, 5.17]
	highest 80-100%	4.40% [3.04, 5.76]
<b>Domestic abuse between parents (9 months to 11 years)</b>		
	No	3.33% [2.68, 3.97]
	Yes	5.25% [3.94, 6.55]
<b>Parental drug use (age 3, 5 or 14 years)</b>		
	No	3.68% [3.11, 4.24]
	Yes	4.55% [1.94, 7.17]
<b>Ever a single parent (9 months to 11 years)</b>		

No	3.13% [2.56, 3.71]
Yes	4.74% [3.57, 5.91]
<b>Parental monitoring (age 14)</b>	
15% lowest	7.74% [5.84, 9.64]
15%-30%	3.84% [2.38, 5.30]
30%-45%	3.65% [2.31, 4.99]
45%-60%	3.33% [2.18, 4.48]
60%-100% highest	2.06% [1.38, 2.73]
<b>Childhood externalising problems (age 3 to 11 years)</b>	
20% lowest	2.89% [1.88, 3.89]
20-40%	3.22% [2.10, 4.33]
40-60%	3.43% [2.28, 4.58]
60-80%	3.74% [2.44, 5.04]
80-100% highest	5.08% [3.42, 6.74]
<b>Childhood internalising problems (age 3 to 11 years)</b>	
20% lowest	3.54% [2.13, 4.96]
20-40%	3.17% [2.08, 4.26]
40-60%	3.46% [2.29, 4.63]
60-80%	3.94% [2.62, 5.27]
80-100% highest	4.53% [3.07, 5.98]
<b>Clinical levels of depressive symptoms (age 14)</b>	
No	3.31% [2.72, 3.89]
Yes	6.12% [4.37, 7.86]
<b>Self-harmed in the past year (age 14)</b>	
No	3.13% [2.54, 3.71]
Yes	7.09% [5.18, 9.01]
<b>Wellbeing (age 14)</b>	
20% lowest	6.41% [4.69, 8.13]
20-40%	4.38% [3.19, 5.56]
40-60%	3.52% [2.29, 4.74]
60-80%	2.17% [1.32, 3.03]
80-100% highest	1.98% [1.09, 2.87]
<b>Autism diagnosis (by age 14)</b>	
No	3.63% [3.07, 4.20]
Yes	6.28% [2.48, 10.09]
<b>School connectedness (ages 7 and 11)</b>	
20% lowest	6.04% [4.43, 7.65]
20-40%	4.04% [2.78, 5.30]
40-60%	3.44% [2.16, 4.72]
60-80%	2.94% [1.92, 3.96]
80-100% highest	2.09% [1.08, 3.10]
<b>Academic achievement at age 16 – at least 5 GCSEs grade A-C</b>	
No	4.38% [3.14, 5.62]
Yes	3.26% [2.50, 4.02]
<b>School exclusion (ages 11-14)</b>	
No	3.31% [2.77, 3.84]
Yes	9.62% [5.66, 13.58]
<b>Persistent truancy from school (ages 11-14)</b>	
No	3.35% [2.82, 3.88]

Yes	10.30% [5.98, 14.63]
<b>Spending time with friends in leisure time on most days (age 14)</b>	
Yes	4.10% [3.07, 5.12]
No	3.54% [2.88, 4.19]
<b>Victim of peer bullying (age 14)</b>	
No	2.98% [2.23, 3.73]
Yes	4.56% [3.72, 5.40]
<b>Peer substance use – alcohol, smoking, drugs (age 14)</b>	
No substance use	2.42% [1.75, 3.10]
One type of substance	3.07% [2.20, 3.94]
Two or three types of substances	5.61% [4.46, 6.76]
<b>Time spent on social media (age 14)</b>	
None	2.96% [1.17, 4.75]
Less than 30 mins	2.84% [1.46, 4.22]
30 mins to 1 hour	2.82% [1.70, 3.95]
1-2 hours	3.71% [2.57, 4.86]
2-3 hours	4.12% [2.50, 5.75]
3-5 hours	3.82% [2.24, 5.39]
5-7 hours	4.03% [2.18, 5.88]
7 hours or more	5.90% [3.57, 8.22]
<b>Gaming time (age 14)</b>	
None	2.50% [1.42, 3.57]
Less than 30 mins	2.41% [1.17, 3.64]
30 mins to 1 hour	2.34% [0.99, 3.68]
1-2 hours	3.47% [2.15, 4.78]
2-3 hours	3.92% [2.58, 5.26]
3-5 hours	4.38% [2.91, 5.84]
5-7 hours	5.45% [2.99, 7.92]
7 hours or more	8.19% [5.29, 11.09]
<b>Offline leisure activities (age 14)</b>	
20% lowest	4.14% [2.71, 5.57]
20-40%	3.98% [2.70, 5.27]
40-60%	3.60% [2.43, 4.77]
60-80%	3.23% [2.23, 4.23]
80-100% highest	3.94% [2.75, 5.14]
<b>Participant Substance Use – alcohol, smoking, drugs (age 14)</b>	
No substance use	3.06% [2.52, 3.59]
One type of substance	7.04% [4.55, 9.52]
Two or three types of substances	10.50% [5.86, 15.14]
<b>Serious violence – weapon involvement (age 14)</b>	
No	3.14% [2.62, 3.65]
Yes	19.59 [13.28, 25.91]
<b>Assault (age 14)</b>	
No	2.12% [1.57, 2.67]
Yes	7.29% [5.92, 8.65]
<b>Shoplifting (age 14)</b>	
No	3.21% [2.68, 3.74]
Yes	16.16% [10.74, 21.59]

**Community crime (age 14)**

No	3.40% [2.86, 3.94]
Yes	26.01% [16.13, 35.89]

**Criminal damage (age 14)**

No	3.16% [2.67, 3.66]
Yes	13.51% [8.84, 18.18]

**Gang member (age 14)**

No	3.38% [2.86, 3.91]
Yes	12.09% [6.48, 17.69]

**Cyber offending (age 14)**

No	2.77% [2.28, 3.25]
Yes	20.56% [15.59, 25.53]

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