Computers & Education 178 (2022) 104400

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

Coding in the cot? Factors influencing 0–17s' experiences with technology and coding in the United Kingdom

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ARTICLE INFO

Keywords:
Early years education
Elementary education
Distributed learning environments
Informal learning

ABSTRACT

In the modern world, digital technology is all around us and our ability to engage with it efficiently and productively has implications for our success as individuals and as a society. The idea that children should hone their digital literacy skills through formal schooling has been recognized by educators and policy makers alike. Before children enter schooling, however, there are now an increasing number of ways for children to begin to learn about computers, robots, and coding. In this research, we present a survey of 729 UK parents (approximately 56% Welsh) of children between 0 and 17 years and asked them to report on whether they and their child had experience with different kinds of digital technology, with a particular emphasis on computer coding. We found that children are outpacing their parents in terms of coding experience before they even turn eight-years-old. Children are generally engaged with digital technology and coding earlier than their parents were as children (e.g., over 70% of two-year-olds use smart devices; nearly 40% of 7-year-olds have experience coding). Logistic regression analyses indicate that boys are significantly more likely to have experience coding than girls and children with parents who have experience coding are significantly more likely to have experience coding themselves. Parents who placed a relatively higher value on STEM education were also more likely to report that their children had experience coding. These findings align with literature on science capital suggesting that there are societal discrepancies in children's exposure to and experiences in STEM subjects. We also found that children with reported experience coding are also reported to show more interest in coding and robotics. This makes the fact that we find differences in exposure to coding prior to formal schooling even more problematic, as the discrepancies seen in early childhood may build up in later years in terms of motivation, engagement, and interest. Taken together, the current research shines light on the positive finding that young children are engaging with coding at early ages, but it also identifies potential problem areas regarding the breadth of exposure and experience. It highlights the need to ensure that the divide between those with and without science capital does not widen, allowing all children the freedom to obtain digital literacy that will help foster a more advanced future.

1. Introduction

It is undeniable that digital technology is omnipresent and rapidly changing in today's world. Parents, educators, practitioners, and

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https://doi.org/10.1016/j.compedu.2021.104400
Received 23 January 2021; Received in revised form 27 September 2021; Accepted 5 December 2021
Available online 8 December 2021
0360-1315/

policy makers have expressed varying degrees of excitement and trepidation regarding the influence of digital technology on children, in terms of both their education and well-being. Objectively, access to different forms of media and digital technology has increased exponentially throughout the past few decades. For example, interviews of 6000 mothers across 10 countries carried out in 2013 found that 3-5-year-old children are more likely to be able to play a game on a computer (66% of children) than tie their own shoes (14%; Child App Use, 2018). A report on media literacy in the UK conducted in 2017 found that over 50% of children as young as 3–4 years of age use the internet (for nearly 8 h per week on average). By 12–15 years, 83% of children own their own smartphone and 99% use the internet (for nearly 21 h per week on average; Office of Communications (Ofcom), 2017, November 29). Computers and other technological devices are increasingly available and relied upon in both school and home settings, starting as early as the preschool years (see, for example, Dore & Dynia, 2020). Moreover, in the past year, because of a global pandemic, many schools have shifted to remote learning, thus forcing both teachers and children to become even more familiar with online platforms for learning.

Although some parents and practitioners worry that exposure to media and screens early in life is harmful for children and takes time away from active play (Twenge, Joiner, Rogers, & Martin, 2018), others note the potential benefits of early exposure in fostering digital literacy and motivating future innovators and developers (Preradović, Lešin, & Šagud, 2016). In 2014, the UK Forum for Computing Education proposed a tiered structure to distinguish the degree and type of digital literacy required in the labour market and in general. “Digital muggles”, who do not require digital skills in their daily lives, only comprise 7% of the workforce (e.g., manual laborers who do not need to use computers). “Digital citizens” (37% of the workforce) need a base level of digital literacy, being able to use technology safely for communication and information gain (e.g., salespeople who have adapted to selling/buying online). More than half of the workforce is comprised of “digital workers” (46%; e.g., analysts or engineers who may do basic programming) and “digital makers” (10%; e.g., computer scientists). These require elementary to advanced levels, respectively, of computer coding[1] knowledge and skills (House of Lords, 2015; UK Digital Skills Taskforce, 2014 , July). Consequently, a fundamental challenge faced by educators, policy makers, and educational scientists is how to best address and integrate digital literacy and computer coding in educational curricula. Central to many approaches has been to introduce digital technology as early as possible (Curzon, Bell, Waite, & Dorling, 2019; Heintz, Mannila, & Färnqvist, 2016; Zhang & Nouri, 2019).

Digital experiences in the early years often take the form of educational games or apps on tablets, smartphones, or computers. The Ofcom report (2017), for example, found that 40% of 3-4-year-olds, 66% of 5-7-year-olds, and 81% of 8–11-year-olds play digital games. Depending on the format, these games can provide opportunities for teaching children both basic educational information (e.g., mathematical or reading skills) and basic skills in how to interact with technological platforms (e.g., how to click a mouse, type, or swipe on a tablet). Although these digital literacy skills might be useful for introducing individuals to digital technology and perhaps increasing motivation to engage with different platforms in the future, they are far removed from developing the coding skills that are drawn upon in the digital economy.

1.1. Coding for children

Researchers and companies have designed apps and robots that allow increasingly younger children to gain experience with computer coding (Geist, 2016). To facilitate children’s ability to create with and understand coding concepts, a handful of graphical languages have been designed using coloured blocks of syntax and drag-and-drop interfaces (e.g. Alice [Cooper, Dann, & Pausch, 2000], Scratch [Resnick, 2008, pp. 18–23], commercial programs: https://codespells.org/, https://www.tynker.com/). For instance, the most frequently used program, Scratch (Price & Barnes, 2015; Wong, Cheung, Ching, & Huen, 2015; Zhang & Nouri, 2019), was created by researchers at MIT and designed for children from the age of 8 (Resnick, 2007; Resnick et al., 2009). ScratchJr followed suit, which was designed for children aged 5 to 7. It uses icons instead of text and a more simplified layout and selection of programming tools (Flannery et al., 2013; Strawhacker, Lee, Caine, & Bers, 2015).

The aim of making coding more accessible to even younger learners and appealing to a broader audience has also given rise to tangible computing systems (Horn & Bers, 2019). These systems entail robots that can be controlled using a range of physical blocks, tokens, or buttons (e.g. KIBO [Bers, 2018]). Some use digital syntax via (tablet-)computer interfaces (e.g. Lego WeDo) that follow basic coding concepts. For example, kick-starter Primo Toys aims to introduce coding from the age of three with their robot Cubetto (https://www.primotoys.com/), whose control board introduces fundamental concepts such as sequences and functions.

Both graphical and tangible coding systems have led to positive learning outcomes in studies with school-aged children (Kazakoff & Bers, 2014; Popat & Starkey, 2019; Sáez-López, Román-González, & Vázquez-Cano, 2016). In their review of empirical studies implementing Scratch in kindergarten through grade 9 (approximately 16 years), Zhang and Nouri (2019) found indications of learning for an array of coding concepts and related thinking skills. However, across the board, the findings and conclusions are limited due to the short durations of such interventions, the focus of these studies on school-aged children in educational contexts, and the extent to which individual differences in prior experience are considered.

[1] In colloquial speech, the terms ‘coding’ and ‘programming’ are used interchangeably. Coding can be seen as a subtask of programming, referring specifically to the writing of syntax, while programming entails the broader process of creating and understanding the problems being addressed with code (Lye & Koh, 2014). The term coding can be more appealing for a general audience because of its secretive tone, associating it with cracking codes (Duncan, Bell, & Tanimoto, 2014; Zhang & Nouri, 2019). Since the term coding was used in the current survey it has been used throughout this paper instead of programming, though these two words could, in the present context, be exchanged.

1.2. Coding exposure

Given the dawn of opportunities for young children to experience coding concepts before and during formal schooling, and the potential importance of this early exposure for learning and motivation, it is surprising that, as far as we are aware, no research to-date has investigated when children first experience coding and what factors relate to individual differences in experience. This means that when and whether children first engage with coding and to what degree they express interest in coding and/or robotics across childhood remains an open question.

1.2.1. Parental factors

With the advent of coding apps and robots that are designed to introduce children to coding concepts prior to and outside of formal schooling, we expected that family dynamics might play an important role in determining parent report of initial exposure to these resources. Potential environmental influences on the propensity to experience coding can be gleaned from literature addressing the factors that alter children's interest in pursuing science-related activities and careers. The concept of *science capital* entails all of the science-related knowledge, attitudes, experiences, and resources to which a child has access and that influence children's experience with and aspiration toward gaining scientific knowledge and skills (Archer, Dawson, DeWitt, Seakins, & Wong, 2015). This includes factors such as social class, the attainment of science qualifications in the family, knowing people with science-related jobs, and parental attitudes towards science. Children with higher science capital tend to have more interest in studying science and aspiring to science-related careers (Archer, Dawson, et al., 2015; DeWitt, Archer, & Mau, 2016).

If similar factors influence experience with coding and digital technology, we might expect, for example, that households with higher incomes would report having children with more coding experiences. Although some evidence indicates that families with lower incomes spend more time engaging with screens and technology than families with higher incomes (Office of Communications (Ofcom), 2017, November 29), this may not transfer to engaging with digital technology for the purpose of learning coding. It is likely that families who have careers or degrees related to coding and other digital literacy skills (e.g., "digital workers", as described above) have higher incomes than those without this form of science capital, thus potentially conflating these variables. Additionally, although some apps and games are free, others that include robots and other tangible components can be costly, meaning they are more likely to be purchased by families with more disposable income.

In line with the science capital theory and evidence (Archer, Dawson, et al., 2015), it is also hypothesized that exposure to role models might increase experience with coding. Parents who have some experience coding themselves might be more likely to introduce their children to coding games earlier. Consistent with this hypothesis, case studies and qualitative evidence have suggested that parents without technical and computing experience express concerns about their ability to engage in coding with their children and help their children improve their coding skills (DiSalvo, Reid, & Roshan, 2014; Roque, Lin, & Liuzzi, 2016; Yu, Bai, & Roque, 2020). Additionally, children with parents who have coding experience may be more likely to express interest in this domain themselves or choose to gain experience with these activities due to either mere exposure (knowing it is a possibility) or interest in emulating a parents' interests and skills. This is not to suggest, of course, that parents who do not have experience with coding would not encourage their children to pursue these games. One might also expect that the more value parents place on the broader field of Science, Technology, Engineering, and Mathematics (STEM), regardless of their own career path, the more likely their child would be to engage with these experiences.

1.2.2. Gender

In addition to variability between home environments based on parental factors, another demographic factor that is commonly thought to influence choices of play is gender. Previous research suggests, for example, that boys are more likely to play video games than girls (Office of Communications (Ofcom), 2017, November 29; Rideout, 2017), but that girls are more likely to use tablets and smartphones to go online than boys (between 8 and 11 years of age). In terms of interest and experience with STEM-related topics, it is frequently noted that females are underrepresented in terms of studying STEM topics and pursuing STEM-related careers. In recent surveys, 21% of American secondary school students taking an Advanced Placement Computer Science Exam were female (Kafai & Burke, 2013) and only 9% of A-level computing students in the UK were female (Kemp, Wong, & Berry, 2016). In addition to potential effects of discrimination, one key reason women seem to be underrepresented in STEM-related fields is because of their decision not to pursue these pathways in the first place (Ceci & Williams, 2010). It has been found that, in adolescence, girls tend to be less interested in coding than boys (Stoilescu & Egodawatte, 2010), have less confidence in their digital abilities than boys (Archer, Dawson, et al., 2015; Lasen, 2010), and are often influenced by stereotypes about computer science and gender when deciding whether to pursue this path (Master, Cheryan, & Meltzoff, 2016). Although most of the research on gender differences in coding and digital literacy focuses on adolescents, newer research with 6-year-olds found that children held stereotypes about boys being better at coding and robotics than girls, and that girls with stronger stereotypes reported less interest and self-efficacy in these areas (Master, Cheryan, Moscatelli, & Meltzoff, 2017). Whether the presence of these stereotypes influences experience with coding in the early years, before formal schooling, is an open question.

1.3. Current research

Here, we present the findings of a UK survey completed by parents of children 0–17 years. Participants were asked about both parent and child use of digital technology, experience with computer coding, and demographic variables. Analysis of survey responses was constrained to families living within the UK for consistency of interpretation (in terms of income, education, and language of survey). A wide age range was sampled in order to measure how experience with coding, as well as the factors that drive it, vary across development. We intentionally oversampled parents of children who are not yet in formal schooling because there is relatively less known about experience in these domains in these age groups, especially as technologies to allow access to coding in these age groups have only emerged in the last decade or two.

2. Methods

2.1. Participants

Participants were asked to complete an online survey between 2017 and 2018 and were recruited through social media, a community research panel of parents in South Wales, and the HealthWise Wales research panel (https://www.healthwisewales.gov.wales/). Although we sought out participants from across the United Kingdom, our research base in Wales meant that the majority of our respondents (approximately 56%) reported that they were from Wales. In the current analyses, we only consider respondents who reside within the United Kingdom, which included 824 adults providing responses for 1167 children between birth and 18 years of age, inclusive. 673 respondents were mothers, 109 were fathers, and 41 indicated that they were other caregivers or relatives (e.g., stepparent, grandparent, foster carer). One respondent did not indicate their relationship to the child. Demographics of the parental respondents, including their ages, household incomes, and highest education level achieved are summarized in Table 1. Parents were asked to respond for one child at a time but could repeat the survey for as many children as they had. 536 parents reported on only 1 child, 238 reported on 2 children, 45 reported on 3 children, and 5 reported on 4 children. Exclusion criteria included missing age for either the responder or the child, missing data for the question "Has your child engaged in coding?", or missing data for parental income. We also excluded reports on 5 children older than 17. After these exclusions, we considered data on 1043 children from 729 parents.

Descriptives are reported for all children, regardless of how many children were reported on for each family (section 3.1). The inferential analyses (section 3.2) only include one child per family so as not to overweight the parental characteristics from families who chose to report on multiple children. We selected the parental report on the oldest child for each family as their experiences seemed less likely to be influenced by other siblings and they seemed more similar to only children; for example, older siblings might drive family activities or cause younger children to be exposed earlier. We note, however, that results are similar if only youngest children are included and all data is available on OSF (https://osf.io/4n93c/).

2.2. Materials

A self-report survey was distributed to parents via Qualtrics. Parents had the opportunity to answer questions regarding demographic characteristics, personal use and attitudes regarding digital technology, and child's use and attitudes regarding digital technology. Each of these variables are described in more detail below and the full survey is available on OSF (blinded link for reviewers: https://osf.io/4n93c/?view_only=3c3786c3d05b4d98a4a33cd1612321fc).

2.2.1. Demographics

The parent completing the survey was asked about their relationship to the child, gender, age, country of residence, and native language. They were also asked about their occupation, yearly household income, number of languages spoken fluently, and highest level of education achieved. All parents had the chance to respond to each of these questions (and subsequent parent-related questions) both for themselves and/or for a second parent. The demographics reported in Table 1 (and data used in analyses) are based on Parent 1's report, since we consistently had this information for all respondents. Demographic questions about the child included age, country of residency, native language, number of languages understood/spoken, and, for those in school, type of school attended (privately funded, government funded, other).

2.2.2. Parents' digital technology use and attitudes

Parents were then asked questions about their own use of computers. Parents were asked to report whether or not they use a laptop/desktop at home and/or at work, at approximately what age they began using computers, and how often they use computers (daily, weekly, monthly, less than once a month). They were then given the following definition of coding (as defined by the authors): "*Coding*

Table 1
Demographic characteristics of parental respondents. Secondary School includes GCSEs and A-levels or other equivalents. Other Certification included professional qualifications specific to certain careers.

Age		Household Income		Highest Education	
16–25 years	18	< £30,000	225	Secondary School	199
26–35 years	178	£30,000–60,000	357	University	293
36–45 years	397	£60,000–90,000	165	Postgraduate	278
46–55 years	178	£90,000 +	60	Other Certification	49
		NA	17		
56 years +	49			NA	5
NA	4				

(also called programming) can be defined in a variety of ways, but it is often thought of as creating directions or instructions for a computer or robot that direct behaviour (events and sequences of events)." They were asked to report whether they had any experience with coding based on this definition. Responses ranged from no experience with coding to a large amount of experience with coding on a 5-point Likert scale. If they reported that they did have experience, they were also asked at what age they started coding, how often they coded, and how they learned to code (work environment, formal education, self-taught, or other). Finally, they were asked whether they consider their occupation to be STEM related (5-point Likert scale from not at all to completely) and how important they thought it was for their child to engage with STEM learning (5-point Likert scale from not at all important to very important).

2.2.3. Child's digital technology use and attitudes

Parents were asked questions about their child's use of a variety of digital devices, including computers, tablets, and smartphones. For each of these devices, they were asked whether the child uses the device at home (and separately whether used at school), at what age they started using the device at home/school, and how often they use the device at home/school (daily, weekly, monthly, less than once a month). They were also asked about whether they place any restrictions on the amount of time the child is allowed to use the device (with an open-ended opportunity to comment on these restrictions). They were asked whether the child most commonly uses the device independently or with others at home/school (always with others, usually with others, equally with others and independently, usually independently, always independently) and how many hours/minutes the child typically spends on the device in a single session. Parents were then given the same definition of coding as above and asked if coding is part of their child's curriculum and whether their child has experienced coding (yes, no, don't know). If reported that the child had experience with coding, parents were asked if the child enjoyed coding (completely, very much, somewhat, not much, not at all, don't know) and what applications, websites, and games the child used for coding at home or at school (see Table S1). They were also asked at what age children started coding and whether they coded independently or with others. Finally, parents were asked how interested their child was in playing with and learning more about coding and/or robots (regardless of whether the child had experienced coding or not).

2.3. Analysis plan

2.3.1. Descriptive overview

Initial analyses summarize descriptive statistics regarding developmental trends in computer and tablet/smartphone use and coding experience. These depictions are intended to both replicate previous surveys demonstrating an increase in access to digital technology across generations (i.e., children use technology much earlier than their parents did) and build upon this to examine trends across a wider age range. As far as we are aware, this is also the first descriptive investigation of when children first gain experience with coding, the social versus independent nature of their coding experiences, and how coding experience relates to interest in coding and robots throughout childhood. For these descriptive analyses, we included multiple children from the same family if parents reported on more than one child.

2.3.2. Factors relating to coding experience

In order to investigate factors relating to individual differences in children's experience with coding across ages, we used logistic regression to assess which factors relate to whether parents affirmed that the child has had experience with coding (thus, a response of "no" is treated the same as "don't know"). We preformed three sequential model tests, with each model including a conceptually related set of predictors. Model 1 included demographic and developmental predictors: child age, child and parent gender, and parent income. We call Model 1 the "Basic" model. Model 2 added predictors related to the parent's career: whether it is in a STEM-related field, and whether the parent has experience coding. We call Model 2 the "+Experience" model. Finally, the third model added a

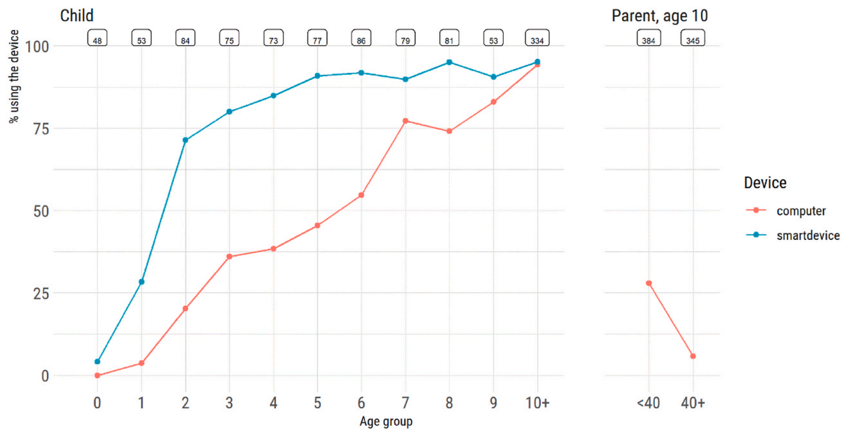

Fig. 1. Children's and parents' computer and smartphone/tablet use before the age of 10. Numbers at the top of the graph represent number of data points in each age group (per year for children, < or >40 years for parents).

predictor related to parental attitudes: whether the parent said that engagement with STEM learning was "very important". We call the third model, including all predictors, the "+Experience + Attitudes" model.

3. Results

3.1. Descriptive overview

Unsurprisingly, children are beginning to use computers much earlier than their parents did. Whereas only 17.40% of parents reported that they first used a computer at or before 10 years of age, parents reported that, for children of this age (or older), 94.31% used computers at home or school. The fast-moving pace of technological advances can be seen when considering parents' ages. Whereas 27.86% of parents under 40 years of age started using computers before 10 years, only 5.80% of parents 40-years-old and older were exposed to computers this early. The percent of children exposed to computers already surpasses both of these rates by 3 years of age, when 36.00% of children are reported as using computers (see Fig. 1). Children are being exposed to tablets and smartphones at even earlier ages, with 28.30% of one-year-olds and 71.43% of 2-year-olds already using tablets or smartphones, with rates increasing beyond these ages (see Fig. 1).

In terms of experience with coding, 36.90% of parents stated that they had experience coding, with only 2.20% of parents learning before the age of 10 years and 14.95% of parents learning by 20 years of age. In contrast, parents report that already 3.57% of 2-year-olds, 6.67% of 3-year-olds, and 13.70% of 4-year-olds have experience coding. By 7 years of age, the percent of children with experience coding (39.24%) already surpasses the percent of parents with experience coding (see Fig. 2).

A trend emerged such that parents were more likely to report that their sons (boys) had experience coding than their daughters (girls). This was true across ages, except in the youngest age range, at which point a floor effect washed out any potential to clearly identify differences between genders (see Fig. 3). Of course, this floor effect is expected as very young children, regardless of gender, are unlikely to code. Across ages, children of parents with the highest incomes were also more likely to have reported experience coding than children of parents with lower incomes, though we note caution in interpreting this given that it appears to be a small effect if present (see Fig. 4). We follow this up more systematically and qualify this conclusion in the logistic models conducted below.

In order to assess whether those children who do code do so socially or alone, we examined parents' responses to whether children's coding tended to occur with others or independently, on a 5-point Likert scale. At younger ages, of those children whose parents reported that they have experience with coding, children tended to largely code with others, and more time coding independently emerged across years (see Fig. 5).

We also examined whether children who did, did not, or had unknown (i.e., parent responded 'I don't know') experience with coding varied in their reported interest in coding/robotics. Parents rated whether children seemed interested in coding and/or robots on a 3-point Likert-like scale. Across ages, parents who reported that their child had experience coding also reported greater child interest in coding and/or robots than children who did not have experience, with children with unknown experience falling in the

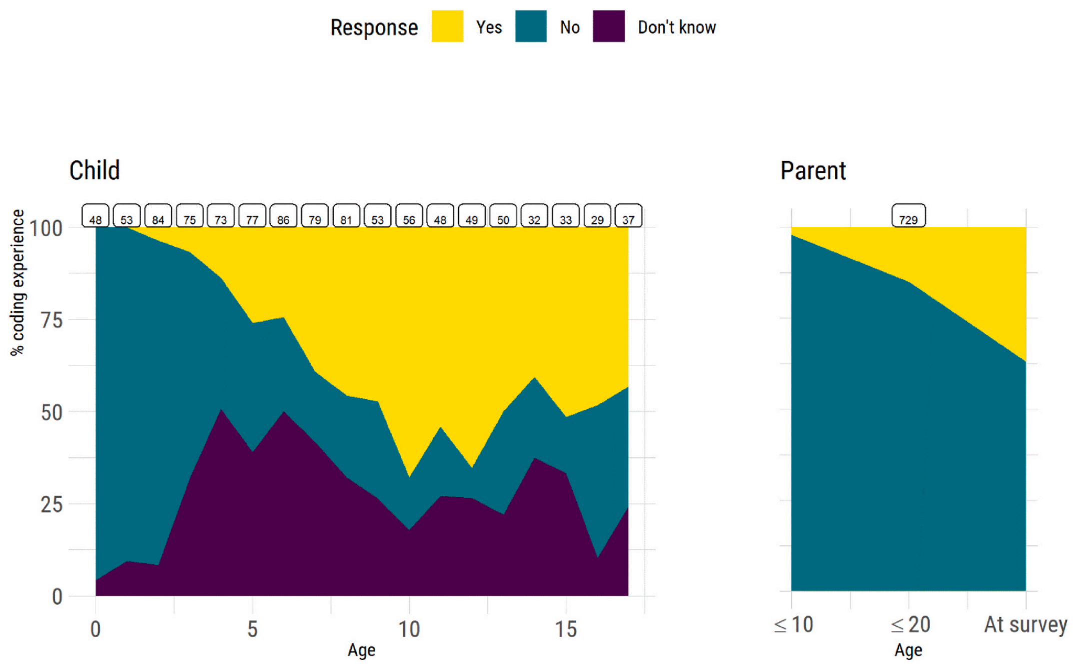

Fig. 2. Percent of children and parents with experience coding at different ages. Numbers at the top of the graph represent number of data points in each age group (per year for children). Parent experience is accounted for at 10 or 20 years of age and at time of survey.

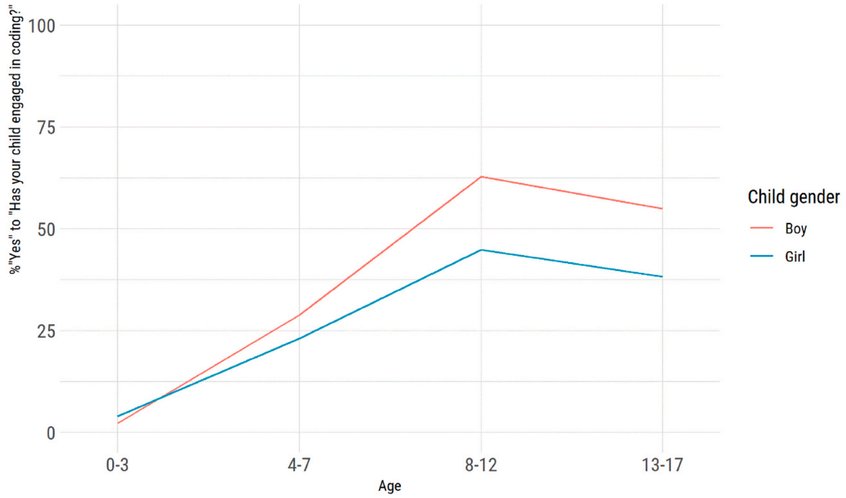

Fig. 3. Reported experience with coding as a function of age and gender revealed a trend for boys to have more reported experience than girls.

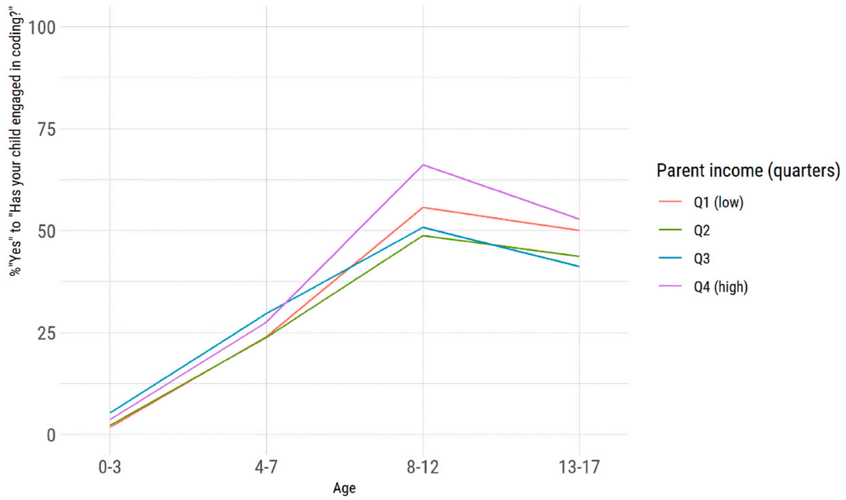

Fig. 4. Reported experience with coding as a function of age and household income revealed a trend for children from households with higher income to have more reported experience with coding. Here, household income is displayed in quartiles.

middle (see Fig. 6). A trend also emerged such that parents of teenagers were less likely to answer the question regarding their children's interest in coding and robotics than parents of younger children.

3.2. *Test of factors relating to coding experience*

We performed a sequence of logistic regressions to test factors related to whether parents affirmed that the child had experienced coding. Although these analyses were informed by previous findings regarding digital media usage (e.g. Office of Communications (Ofcom), 2017, November 29) and science exposure and interest (e.g. science capital; Archer, Dawson, et al., 2015), these analyses explore these potentially influential demographic and parental factors in the related but more specific context of children's coding experience. Therefore, these should be considered exploratory analyses and they involve several data-driven choices about how to express the predictors (which we outline below). Due to the exploratory nature of the analyses and the observational nature of the data, one should interpret reports of statistical significance with caution. We made the following decisions regarding the construction of the logistic regression analysis:

3.2.1. *Outcome*

Parents could answer "yes", "no" or "I don't know" to the question "Has your child engaged in coding?". We chose as the outcome whether parents responded "yes", reasoning that this response is likely to mean they have specific knowledge that the child had, in fact,

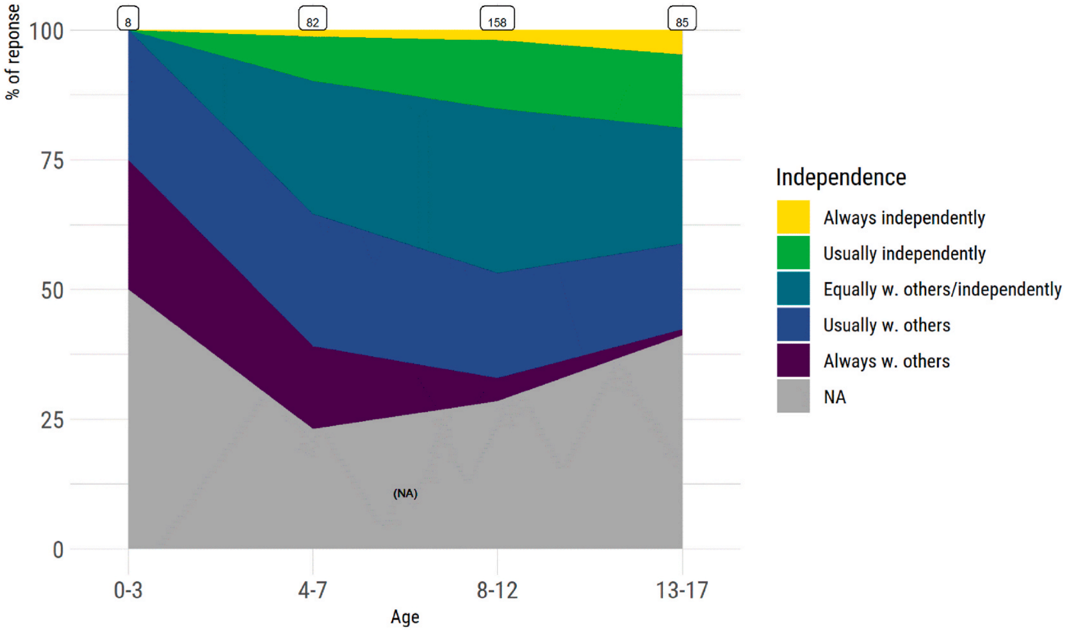

Fig. 5. Ratios of collaborative to independent coding per age for those children with reported experience coding. Numbers at the top of the graph represent number of data points in each age group. Note: This graph only includes children whose parents reported that they had experience coding. NA refers to parents who reported that their child had experience coding but did not respond as to whether their children's experience occurred socially or independently.

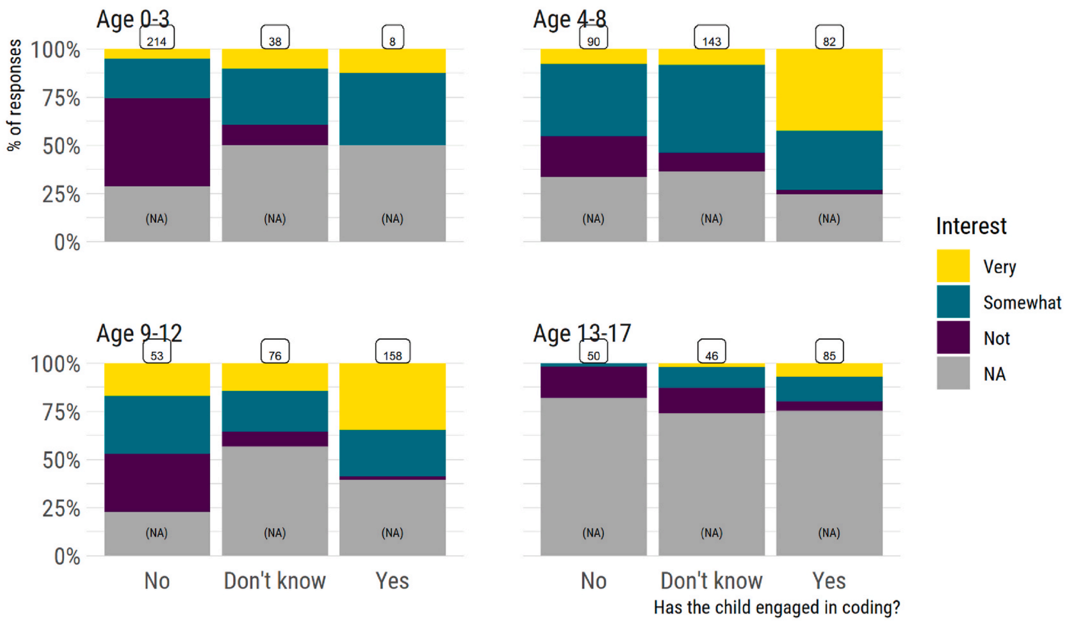

Fig. 6. Children's interest in coding and/or robots as a function of coding experience separated by age groups. NA refers to children whose parents did not report the child's interest.

experience with coding.

3.2.2. Selection of children

Only the oldest child remaining in the data set (after eliminations) per reporting parent was entered into the analysis (see 2.1 Participants). This resulted in the elimination of 314 younger children from the analysis, leaving 729 older children.

3.2.3. Missing/other gender

Of the remaining 730 children, one child's gender was described as "other", and two parents described their own gender as "other". Three children's parents preferred not to respond about their or their child's gender. These six children were not considered in the logistic regression analysis (but data is included in OSF files for completeness and transparency) due to lack of power to address these as separate gender variables and in order to ensure complete information for these variables. This then left 723 children in subsequent analyses.

3.2.4. STEM occupation/coding experience

STEM occupation and coding experience were asked on five-point ordinal scales. Due to the difficulty of interpreting the difference between, say, "some experience" and "a bit of experience" coding and the distribution of data (see Table 2), we dichotomize these two variables into either "none" (occupation is "not at all" STEM related/"I have no experience with coding") or "some" (i.e., all the other responses).

3.2.5. Importance of STEM learning

Responses to the question "Do you think it is important for your child to engage with STEM learning?" were on a five-point ordinal scale. No parent responded "Not at all"; only 9 (1.24% of the logistic regression sample) responded "Not very important" (see Table 2). The majority (423; 58.51%) responded "Very important". The remaining response options ("Somewhat important" and "Important") are difficult to distinguish in meaning. We therefore dichotomize this variable, creating an indicator of whether the parent said that STEM learning was "Very important" or not (i.e., anything rated less than "Very important").

3.2.6. Income

Although the income response options were ordinal, the possible response options increased linearly (in increments of £10,000) except the largest option, which was a catch-all for incomes higher than £100,000. Thus, the reported household income was entered as the logarithm (base 2) of the response. As a result, the regression coefficient for income is interpretable as the effect of a doubling of household income. Furthermore, to ensure the separate interpretability of the linear and quadratic coefficients, household income was centered by subtracting the mean logarithm of the income.

3.2.7. Child age

To ensure separate interpretability of linear and quadratic regression coefficients, child age was centered around the mean age of 8.61.

3.3. Results: basic model

As shown in Table 3, the Basic model contained relevant demographic information about the parent and child: parent and child gender, child age (linear and quadratic), and household income (linear and quadratic). Of these predictors, child age and child gender were significant at the 0.05 level. Confidence intervals on the coefficients are shown in Fig. 7. This model suggests that reported coding experience increased with child age and was greater for boys than girls. Although the descriptive trend for higher income families to report more coding experience was present, this did not reach significance. These results support the general trends described in the descriptive results above. See Table 4 for the correlation matrix between all predictors. Some of these are mildly collinear, which may cause regression coefficients to change when new predictors are added to the model.

Table 2
Number and percentage of parents responding to questions regarding coding and STEM experience and attitudes.

	N	%
Experience coding		
(1) I have no experience with coding	456	63.07%
(2) I have a bit of experience with coding	145	20.06%
(3) I have some experience with coding	82	11.34%
(4) I have quite a lot of experience with coding	25	3.46%
(5) I have a large amount of experience with coding	15	2.07%
STEM occupation		
(1) Not at all	316	43.71%
(2) Not very	97	13.42%
(3) Somewhat	145	20.06%
(4) Very much	69	9.54%
(5) Completely	96	13.28%
Child's STEM learning		
(1) Not at all important	0	0.00%
(2) Not very important	9	1.24%
(3) Somewhat important	80	11.07%
(4) Important	211	29.18%
(5) Very important	423	58.51%

Table 3
Regression coefficient estimates for the three logistic regression models. Values under the estimates are standard errors. Cells corresponding to coefficients that do not exist in a given model are left blank. See Fig. 7 for related 95% confidence intervals.

		Basic	+Experience	+Experience + Attitudes
(Intercept)	–	0.10	−0.38	-.63**
		(0.26)	(0.32)	(0.33)
Age	(child)	0.29***	0.31***	0.31***
		(0.03)	(0.03)	(0.03)
Age^2	(child)	−0.04***	−0.04***	−0.04***
		(0.01)	(0.01)	(0.01)
Gender: girl	(child)	−0.40*	−0.45*	−0.45*
		(0.18)	(0.18)	(0.18)
Gender: woman	(parent)	−0.05	0.26	0.21
		(0.24)	(0.26)	(0.26)
log (Income)	(parent)	0.16	0.14	0.09
		(0.12)	(0.13)	(0.13)
$\log_2(\text{Income})^2$	(parent)	0.04	0.04	0.02
		(0.10)	(0.11)	(0.11)
Job in STEM	(parent)		−0.16	−0.26
			(0.19)	(0.20)
Code experience	(parent)		1.00***	0.96***
			(0.20)	(0.21)
STEM 'v. Important'	(parent)			0.62**
				(0.19)
AIC		780.99	760.04	751.23
BIC		813.08	801.29	797.07
Deviance		766.99	742.04	731.23
Incremental fit (LRT)		–	$p < 0.0001$	$p = 0.001$

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

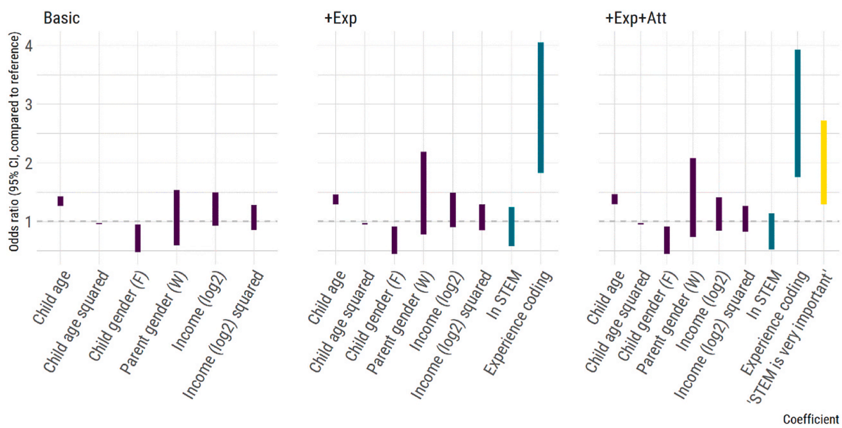

Fig. 7. Estimates of regression coefficients in each of the three models (95% CIs; presented as odds ratios). Odds ratios are interpretable as change from reference group (or change with 1 unit) where other coefficients are held constant at their reference value (gender, experience, attitudes), or mean (age or income).

Table 4
Pearson correlations between the predictors in the regression model. (C) represents child factors. (P) represents parent factors.

	Has coded (C)	Age (C)	Gender (C)	Gender (P)	Income (P)	STEM (P)	Has coded (P)
Age (C)	0.348						
Gender (C)	−0.092	−0.009					
Gender (P)	−0.035	−0.103	0.022				
Income (P)	0.025	−0.044	−0.061	−0.033			
STEM (P)	0.004	−0.024	0.098	−0.200	0.185		
Has coded (P)	0.116	−0.062	0.050	−0.246	0.076	0.270	
STEM important (P)	0.131	−0.003	0.005	-.006	0.169	0.175	0.115

3.4. Results: +Experience model

In addition to the predictors included in the Basic model, the +Experience model adds two more: whether the parent thought of their occupation as STEM related and whether the parent reported having coding experience. As summarized at the bottom of Table 3, the addition of these predictors led to a significant improvement in fit (LRT $\chi^2_2 = 24.95$, $p < 0.001$) and a substantial decrease of 20.95 AIC points (also indicating a better fit). Fig. 7 (middle) shows that the increase in fit is apparently driven by whether the parent reports coding experience: parents with coding experience report that their children have experience with coding at substantially higher rates than those parents who have no experience coding (OR: 2.71, $CI_{95\%}$: [1.82, 4.05]). In contrast, having a STEM-related occupation does not appear to be strongly related to reporting that one's child has experience coding (OR: 0.85, $CI_{95\%}$: [0.58,1.24]).

3.5. Results: +Experience + Attitudes model

On top of the predictors included in the Basic and +Experience models, the +Experience + Attitudes model added the parent's response to the question "Do you think it is important for your child to engage with STEM learning?" ("Very important" vs otherwise). Again, the fit of the +Experience + Attitude model was incrementally better than the +Experience model (LRT $\chi^2_1 = 10.81$, $p < 0.001$), with a substantial decrease of 8.81 AIC points, also indicating a better fit. Parents indicating that STEM learning is very important reported that their children experienced coding at a substantially higher rate than those parents attributing less importance to STEM learning (OR: 1.86, $CI_{95\%}$: [1.28, 2.71]). All variables previously reported as significant remained so.

4. Discussion

Increasingly earlier exposure to digital technology has the potential to foster interests and skills in coding at a young age and thereby give children a head start in the digital economy (Master et al., 2017; Yücel & Rızvanoğlu, 2019). However, the extent to which children are interacting with the array of child-friendly coding systems, at what age children start coding, and importantly, the factors influencing this exposure, are unclear. In order to begin to address this issue, in a UK-based survey, we asked 824 parents about their own and their 1167 children's experiences with coding and digital technology.

4.1. Descriptive findings

Unsurprisingly, the descriptive findings from our research clearly establish that children encounter digital technology earlier than their parents were first exposed to computers and smartphones and/or tablets. The reported use of digital technology starts early and shows a steady increase during the first ten years of life. The rate of increase is particularly sharp for tablet and smartphone use, with nearly three quarters of the respondents' two-year-olds already using these devices. Though computer use is lower in the youngest children, by the age of six, more than half of the children were reported to use computers (consistent with 48% of children 6 and under using computers in Rideout, Vandewater, & Wartella, 2003). Before entering secondary school, computer use is commonplace. Moreover, the percentage of children with experience coding is already approaching that of their parents before children start their formal education careers. This increases steadily across the primary school years and by the time children leave primary education, the majority have come into contact with coding, likely at least partially through school initiatives following new digital literacy education targets (The Royal Society, 2017; WelshGovernment Education Wales, 2018; 2019).

These findings raise questions regarding how children's early learning can best be supported. How can parents, and especially teachers, who have little or no experience within this domain, successfully support children's learning? Both parents and teachers, particularly those teaching in the early years, may lack confidence in their own coding skills or have no experience with the matter themselves (Ertmer, Ottenbreit-Leftwich, Saik, Sendurur, & Sendurur, 2012; Roque et al., 2016). They may therefore feel insecure about encouraging and guiding children's experiences with these activities (DiSalvo et al., 2014; Yu et al., 2020). This would imply that directing resources to helping parents and teachers gain confidence with these basic skills is important for guiding children's learning (see, for example, Govind, Relkin, & Bers, 2020; Relkin, Govind, Tsiang, & Bers, 2020). Promising findings on this front come from primary teacher professionalization research, demonstrating that teachers can quickly improve their coding-related skills, self-efficacy, and pedagogical capabilities (Bower et al., 2017; Jaipal-Jamani & Angeli, 2017).

Descriptive trends in our research indicated that younger children tend to gain experience with coding in social contexts and independent coding experience emerges later in childhood. This is perhaps to be expected given that both play and learning tend to begin in social contexts (Doolittle, 1995). In the current research, we did not disambiguate whether social experiences involved interactions largely with parents, teachers, or peers. We cannot disentangle whether this may also, at least partially, be due to the types of games created for younger versus older children being designed for multi-user or guided learning versus independent learning. These nuances are important to consider in future research. Scaffolding play in early interactions could have knock-on effects in terms of both future motivation and learning in this domain (Bodrova & Leong, 2015).

Parents who reported that their children had coding experience also reported having children who were the most interested in coding and robots. The current findings are unable to distinguish whether children who are interested in coding and robots seek out opportunities to gain experience with them, whether experience engaging with coding increases interest, or whether interest and experience are related due to parental bias in reporting. Importantly, parents who reported that they did not know if their children had any experience and those who reported that their children did not have experience did not consistently report that their children were uninterested in coding and robotics, suggesting that parents were not simply equating a lack of experience with lack of interest. Instead, these findings appear to be in line with recent experimental research showing that girls' interest in coding was higher following an opportunity to code with robots than following control activities (Master et al., 2017). This association between experience and interest warrants further, larger scale research, especially with respect to the potential of using low-threshold experiences as a means of fostering STEM-interest in children with lower science capital or negative-STEM stereotypes.

Although the relation between experience and interest was relatively consistent across ages, we observed a difference in parental reporting across ages that warrants caution in interpreting these findings. Parents of older children, particularly teenagers, were less likely to respond about their child's interest in coding and robotics than parents of younger children. There are several potential reasons that parents may be less likely to report on their child's interest as the child gets older. One possibility is that parents spend less time with their children as they get older and are thus less likely to be in tune with their interests. This is borne out in the above-reported trend that older children are more likely to play and learn independently (e.g., without their parents) than younger children. Another potential explanation is that parents are less confident in assessing the interests of their teenagers than they are of their younger children (Lionetti et al., 2019). Regardless of the reason for this discrepancy, it implies that the relation between experience and interest in older children should be interpreted with caution.

4.2. Demographic and family factors influencing coding experience

A series of logistic regressions described how reported coding experience varied as a function of demographic and family factors. The basic model considered the role of child age, parent gender, child gender, and household income on parent's report of their child's experience with coding. This model indicated significant effects of child age and child gender on reported experience coding. When adding parental experience to the model, we found significant effects of parent's reported experience with coding. In the final model, we also added parent's attitudes regarding STEM learning. This model indicated that parents who reported valuing STEM more were more likely to report that their child engaged in coding.

With regards to child characteristics, we found that, unsurprisingly, older children were more likely to have reportedly gained experience with coding than younger children. This is likely due to increasing opportunities for coding and opportunities for coding experiences within school settings for older children. In terms of gender, boys were more likely to have experience with coding than girls. This finding is disconcerting, given the relation between young children's STEM interest and motivation and the gender gap in STEM careers and degrees, which is particularly evident in technological fields such as computing (Ceci & Williams, 2010; Master & Meltzoff, 2016; Smith, Brown, Thoman, & Deemer, 2015). The situation for coding is even more worrying when considering recent findings that 6-year-olds already hold gender stereotypes for coding but not yet for math and science in general (Master et al., 2017). Thus, the present finding does not bode well for breaking cultural gender stereotypes; tackling the gender gap warrants immediate attention. One possible avenue for overcoming this gap is to offer more opportunities for all children to engage with coding early on. Our descriptive findings that children who have experience coding are reported to be more interested in coding and robotics is consistent with research indicating that introducing young girls to coding in early primary school improves STEM motivation (Master et al., 2017). Thus, avenues for mitigating stereotypes and increasing exposure early in development can have important knock-on effects. This is particularly imperative when considering broader contexts, including government initiatives regarding educational policy (see discussion below).

In considering household demographics, we took into account both the gender of the parent completing the survey and the household income. There was no difference between female versus male parents in terms of their reporting of child experience with coding. This suggests that we did not find a bias in reporting such that mothers or fathers were more likely to report experience with coding than one another. Although the descriptives showed a trend such that children from higher income households were more likely to have reported experience coding, the effect of household income was not significant in the logistic regressions. Direct economic barriers to experience are unlikely to be the sole drivers of differences in experience, as supported by the lack of effect of household income in our models. In contrast, families from higher income families have more science capital and are more likely to be aware of the value and opportunities of engaging with coding (Archer, Dawson, et al., 2015). In line with this, household income was correlated with rated importance of STEM, which was related to reported coding experience of children.

In terms of parental experience, whether or not parents reported having a career in STEM was not significantly related to child's reported experience coding. In contrast, parent experience with coding was related to reports of child coding experience. That is, parents who had any experience coding were more likely to report having children with experience coding than parents who had no reported experience coding. This is consistent with previous research suggesting that science capital is important for influencing children's exposure to relevant experiences for learning in STEM. Science capital research with 11- to 15-year-olds has shown that awareness of the benefits of science experience (e.g., qualifications in scientific fields) and having scientific role models relates to older children's aspirations regarding studying and pursuing science as a career (Archer, Dawson, et al., 2015; DeWitt et al., 2016). The current evidence is consistent with this across a wider age range and in the field of computer coding.

Finally, when parent attitudes about STEM were included in the model, these also had a significant effect on reported coding experience of the child. Although most parents who completed the survey responded that they thought STEM education was important, those who said it was *Very Important* (i.e., the highest response possible on the scale) were more likely to report having children with coding experience. This is also consistent with a science capital perspective, suggesting that parental attitudes toward science influence children's exposure and interest. It is important to note that we only asked parents about their attitudes concerning STEM and did not ask them to report their attitudes about other subject areas. Therefore, we cannot strongly conclude that it is value placed on STEM, rather than value placed on education more broadly, driving this effect. Still, the current research suggests that factors that have previously been related to science capital (such as parental experience and attitudes; Archer, Dawson, et al., 2015) are likewise relevant specifically for coding experience, and this already holds true earlier in life than the ages studied in previous science capital research. This is important to take into account because, as discussed above, early exposure could have long-term implications for motivation, interest, and engagement (Master et al., 2017).

4.3. Limitations

Despite the importance of the findings, methodological limitations warrant caution. The sample was obtained via convenience sampling and was distributed online, meaning that only digitally literate parents were likely to complete the survey. Further, the sample was biased in terms of oversampling parents with higher incomes (with a majority earning over £30 K) and higher education (majority with university or higher degrees) than average parents in the UK. The majority of the sample was Welsh given the location and resources of the researchers. The current analyses addressed demographic factors that we thought were theoretically interesting as laid out in the introduction, but we did not consider all demographic factors. Information about coding experience in children of different races and in different kinds of schooling (e.g., state versus private funded may have different curriculums) will be important to consider in future research (see, for example, Archer, Dewitt, & Osborne, 2015). Future research should aim to recruit and analyze the differences between a more diverse and representative sample of families, both within and beyond the UK.

Parental reporting of child behaviour and interest always suffers the possibility of bias. It may be, for example, that parents with more experience coding themselves are more likely to report that their children have experience with coding, not due to their children actually engaging more, but because they are more aware of what coding encompasses. Parents with certain demographic characteristics (e.g., higher income, interest in STEM) might also have viewed experience coding more positively and have thus been more likely to want to portray their children as experienced and interested. Additionally, some parents may be more or less aware of what their children are doing in school, leading to inaccuracies in reporting for certain parents (i.e., if they're unaware their child is exposed to coding in school; Lionetti et al., 2019).

We made several choices when carrying out our analyses about what data to include that could have influences on the reported outcomes. For example, although parents sometimes reported on multiple children within their household, we only reported findings for the oldest child reported in our logistic regressions. We made this decision in order to ensure independence of cases so as not to inflate the importance of parental factors due to the same parental characteristics being reported for multiple children within the same household. Despite the advantages of only reporting on the oldest child, it's possible that excluding younger siblings may have provided an incomplete picture. To check that this approach did not introduce bias, we also ran the logistic regression with youngest siblings, which resulted in a similar pattern of results (all data and code available on OSF). For completeness, we included all children when reporting descriptives.

4.4. Implications and broader context

Notwithstanding the limitations, the current findings are an important starting point for uncovering when children are first exposed to computer coding and how this varies as a function of child and family characteristics. Early exposure to coding may be particularly beneficial for children with lower science capital in order to expose them to low-threshold and engaging coding experiences, potentially motivating them to pursue similar activities in the future (Master et al., 2017).

Although the distribution of the survey solely within the UK (and largely within Wales) represents a limitation in some senses, it is also a strength in that it allows the research to be nestled in a UK context, in which digital literacy and related skills have been given a place in all four curricula of England, Northern Ireland, Scotland, and Wales, though the approaches differ between them (see for an overview Everett, 2019). A recent report on Welsh government standards for digital technology states that they aim to double the number of children gaining computing qualifications each year due to the upward social mobility afforded by these qualifications relative to those in more traditional professions (WelshGovernment Education Wales, 2019). In fact, part of the British Computer Society Royal Charter mandates that "everyone has access to the widest range of educational opportunities necessary to become creative, empowered, capable, and safe citizens in a digital society. And that means that everyone, regardless of gender, ethnic or social group, has the fundamental right to a computing education." British government reports also emphasize the importance of bridging the gender gap in digital literacy and computer science more specifically (The Royal Society, 2017). They note that targeting this gap early in childhood is important for overcoming early stereotypes. In the past few years, the Welsh Government has introduced a new Digital Competence Framework (WelshGovernment Education Wales, 2018; 2019) that enforces exposure to a wide range of computing curriculum topics at the earliest ages possible. They recognize the importance of giving all children equal access to opportunities to learn in this domain early in life due to its implications for later achievement and even note that this learning must begin at home, in addition to within schools (Feinstein, Duckworth, & Sabates, 2008). Our findings echo this call and demonstrate, for the first time, that children are beginning to gain experience with coding before they begin school, and that there are already meaningful discrepancies in who has early access to coding experience. They highlight the need for intervention to bring equal access, particularly to girls and children with lower science capital, in order to provide early opportunities for all children to experience coding.

Although childhood coding experience is in line with government interests and mandates, exposure to screens and digital media has often been discouraged by health authorities and governments for children under two years of age (American Academy of Pediatrics Committee on Public Education, 2001). Our research indicated that digital technology use, particularly smartphone or tablet use, was quite high in the first few years of life (i.e., 69.61% of 2-year-olds are using smartphones or tablets). This is consistent with research conducted in 2003 indicating that 68% of children under two years of age were exposed to screen media (Rideout et al., 2003) and 63%

of children under two watched television daily (Vandewater, Rideout, Wartella, Huang, Lee, & Shim, 2006). Guidelines have since been updated to indicate that children under two should only use digital media for videochatting and parents should use media with children and use should be moderate (Council on Communications and Media, 2016). In our research, we did not distinguish whether digital technology was used for videochatting or other functions. The survey was also distributed prior to the Covid-19 pandemic, during which videochatting with family members and online learning likely increased the prevalence of screen use (Parents Together Foundation, 2020). In assessing coding experience, we included both coding that could happen on screens (e.g., tablets or computers) and in hands-on play (robots and other toys; see Table S1). The balance of the potential advantages and disadvantages of early digital technology adoption should be considered in future investigations.

4.5. Conclusions

In conclusion, the current research highlights the early exposure to digital technology in young children in modern society. It suggests that the youngest generation are exposed to coding within their first few years of life at rates higher than their adult parents. Family characteristics play an important role in individual differences concerning when children first experience coding. These findings align with research regarding science capital, suggesting that parent attitudes and experience play important roles in children's experience within this domain. Unfortunately, digital literacy disadvantages emerge early for children with lower science capital (e.g., children from lower income families, children with parents who are not interested or experienced in STEM), not solely because of issues with access, but because parent values and experiences shape children's behaviour. Relatedly, the gender gap in digital literacy also starts early, with girls already engaging with coding less than boys before school starts. This implies that interventions are needed to encourage equal experience before schooling begins. Taken together, the current research shines light on the positive finding that young children are engaging with coding at early ages, but it also identifies potential problem areas regarding the breadth of exposure and experience. It highlights the need to ensure that the divide between those with and without science capital does not widen, allowing all children the freedom to obtain digital literacy that will help foster a more advanced future.

Credit author statement

Sarah Ashley Gerson: conceptualization, methodology, investigation, writing **Richard Morey:** formal analysis, data curation, writing, visualization **Johanna van Schaik:** conceptualization, methodology, investigation, writing.

Acknowledgements

We express our gratitude to all of the parents who participated in this research. We also thank Healthwise Wales and PrimoToys for helping distribute the survey widely.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compedu.2021.104400.

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