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Cracking the code: exploring student attitudes towards coding in secondary education

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ABSTRACT

Digital skills are beneficial for young people and society, but some individuals, particularly girls, are less likely to choose computing post-compulsory education. Coding is a crucial skill in the school computing curriculum. The authors collected survey data from 4983 secondary-school students (ages 11–16) as well as conducted exploratory factor analysis and created multivariable logistic regression models. Their findings revealed that high coding attitudes were associated with various factors, including student experience in computing lessons, teacher and parent support, perceptions of computer scientists, computing at home and gender. These findings have implications for classroom practice and curriculum design, highlighting the importance of addressing barriers and fostering positive coding attitudes among all students. The authors' findings highlight the need to reconsider the coding content within the computing curriculum in England, as certain groups of young people, including girls, will continue to be less well represented in this subject.

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Gender equality; quality education; decent work and economic growth; digital skills

Introduction and rationale

Over the last century, there has been extensive research on individual attitudes or 'attitudes' in a vast array of contexts, especially in educational psychology (Rüschenpöhler & Markic, 2019). In Science, Technology, Engineering and Mathematics (STEM) subjects, there is now a well-established association between student attitudes and associated expectancy to success (or not) with achievement, subject choice and career aspirations and outcomes (e.g. Archer et al., 2015; Wang & Degol, 2013). However, there is more limited literature on the attitudes of young people in coding, especially within the English secondary computing education system (age 11–16). The need to better understand coding attitudes has been especially pertinent since the curriculum change in England in 2014, where there was a shift in curriculum focus

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from broad Information and Communications Technology (ICT) skills to a curriculum with a greater emphasis on programming and coding (Larke, 2019).

At around 14–16 years of age, young people in English schools can opt in to computing with a General Certificate of Secondary Education (GCSE) 'Computer Science' qualification. GCSE Computer Science is a relatively new qualification that began in 2013, replacing the ICT GCSE which was fully discontinued in 2017. The current computing curriculum and GCSE Computer Science have a greater emphasis on coding and programming as a means of creating a 'rigorous, fascinating and intellectually challenging subject' (Brown et al., 2014; Department for Education, 2012). According to a survey of 100 computing teachers in England, the computing curriculum now contains a greater proportion of time devoted to 'coding, programming and digital making', with the least time spent on data handling and 'citizenship, environmental and ethical issues' (Mee, 2020). Furthermore, teachers surveyed in Mee's study stated that coding dominates the computing curriculum, which left little time for developing digital literacy, student engagement and motivation. Since 2013 there are now fewer young people choosing any computing qualification at GCSE than before the change. More concerningly, the change in the computing curriculum appears to have disproportionately affected some groups of young people more than others, in particular girls, who made up just 22% of the GCSE Computer Science cohort versus 43% of the ICT GCSE in 2017 (Joint Council for Qualifications, 2014, 2017, 2020; Kemp & Berry, 2019). The research presented here advances our understanding of the attitudes of secondary-school age students towards coding. It presents a link between coding attitudes with students' choice to study GCSE Computer Science and suggests which factors are associated with more positive attitudes towards coding. For clarity, computing is understood to refer to the skills and knowledge areas covering computer science, information technology and digital literacy, whereas coding is a narrower topic, covering the activity of writing computer programs in a way that computers can understand, for example to solve problems or to create apps or computer games (e.g. Royal Society, 2012).

Review of the literature

The research presented in this paper draws on three key attitudinal theories: 1) social cognitive theory, which emphasises perceptions of self-efficacy (Bandura, 1977); 2) academic self-concept theory, drawing on how an individual perceives their academic performances (Shavelson et al., 1976); and 3) expectancy-value theory, which highlights the extent that individuals believe they will achieve a particular outcome (Atkinson, 1957). 'Attitudes' is the overarching term sometimes given to different 'self' constructs that include self-efficacy, self-concept and self-esteem (e.g. Valentine et al., 2004). Self-efficacy is described as a person's belief in their ability to influence events that affect their lives (Bandura, 1977), and so these theories connect attitudes and expectancy of success with outcome aspirations and ultimately subject choice and career aspirations. They have been shown to influence a student's academic achievement and career aspirations in numerous domains including science and computing (e.g. Archer et al., 2015; Vandenberg et al., 2021).

Academic self-concept is an individual's self-perceptions of their own academic performance that are developed through interactions with their environment (Hattie, 2014; Shavelson et al., 1976). In students, it is influenced by multiple factors, including parent and teacher encouragement and attributions of the student's own behaviour (Marsh & Scalas, 2011). Higher academic self-concept in a particular domain has often been associated with better domain-specific outcomes (e.g. DeWitt & Archer, 2015).

Outcome expectancy, a concept grounded in expectancy-value theory, is the degree to which someone believes that a particular outcome will occur (Eccles & Wigfield, 2002). For students, this includes how well they believe they are likely to do in any subject, and whether the subject has a high 'value' to them or not. Expectancy-value is rooted in the idea that multiple factors grouped around the social world, cognitive processes and motivational beliefs all have an influence on the perceived likelihood of success. In the computing classroom, these may include things like self-efficacy, classroom and curriculum experiences, as well as teacher and parental support (e.g. Eccles & Wigfield, 2002; Landry, 2003). A review of expectancy beliefs in the US found that overall, students' expectancy beliefs decline from elementary through to high school, with the rate and time at which this occurs varying between subjects (Muenks et al., 2018).

Studies have found that girls generally have lower self-efficacy scores than boys in STEM subjects (He & Freeman, 2010; Kalender et al., 2020), and this is also true for young people from lower socio-economic backgrounds (Kalaycioglu, 2015). In the Programme for International Student Assessment (PISA) studies, girls had an overall lower academic self-concept in science and mathematics than boys, and it was found that the academic self-concept of girls who achieved the same level as boys in their PISA science and mathematics scores were approximately one quarter of a standard deviation lower (OECD, 2015).

Attitudes and expectancy beliefs are complex and interrelated and appear to be influenced by overarching themes including personal interest, perceived ability, parent and teacher encouragement and support, as well as the influence of peers (e.g. Rüschenpöhler & Markic, 2019). This research explores such overarching themes in relation to coding attitudes, and key themes will be discussed within this literature review.

There have been several studies exploring attitudes in relation to computing (e.g. Guggemos, 2021; Mason & Rich, 2020; Román-González et al., 2018; Torkzadeh & Koufteros, 1994). However, studies focused specifically on coding, especially at the secondary-school age, are much more limited.

Attitudes to coding

In 1990, Lips and Temple suggested that girls' computing and mathematical attitudes are correlated to participation in computer science and a statistically significant difference was found between participation and self-efficacy. Vandenberg et al. (2021) confirmed an association between self-efficacy and conceptual understanding in coding, and that female students tended to have a lower self-efficacy than male students. Elsewhere, Blouin (2011) developed the computer science interest survey and found that amongst high-school senior students aged 18 years there was no statistically significant difference between gender and attitude in computing. Mason and Rich (2020) validated an 'Elementary Student Coding Attitudes Survey' in young people aged 9–12 years in the United States. These authors found that gender did not have a significant effect on students' coding attitudes in the children they surveyed, perhaps suggesting that the gender bias is less developed in younger students. Furthermore, they identified that confidence in mathematics was the variable that had the strongest association with coding confidence. More recently, Leonard et al. (2021) used the 'Student Computer Science Attitude Survey' in a study of 1316 young people aged 10–13 in schools in England. The authors found that girls generally had a less positive attitude to computer science compared to boys.

Social factors influencing attitudes

A young person's experience in the classroom appears to have an influence on their attitudes and outcome expectancies, including in STEM (Griggs et al., 2013; Jussim & Harber, 2005). Teachers can affect students' self-efficacy beliefs through social persuasion and positive feedback. Additionally, self-efficacy can be influenced in several ways: through the evaluation of the learner's own performance; through observing peers complete a task; or by becoming motivated by 'social persuasion' from a teacher, friend or family member. Furthermore, self-efficacy can be affected by an individual's emotional response to a task or event which can, in turn, amplify their self-efficacy beliefs (Bandura, 1977). However, previous research in this area is mixed. For example, Mason and Rich (2020) suggest that the perceptions students had of the value their teachers placed on coding did not consistently predict their attitudes to coding.

Previous research has shown that a mother's educational attainment can positively influence her child's self-efficacy, educational aspirations and academic achievement (Garg et al., 2007). Parental involvement and encouragement have also been found to be significant factors in developing attitudes and outcome expectancy in STEM (Lazarides et al., 2015; Turner & Lapan, 2002). Mason and Rich (2020) found that parent and peer influence had a substantial, significant mediating effect on young students' confidence with, interest in and perceptions of coding. A student's perception of coding was greater if they felt their parents valued coding. Self-efficacy in computing may be affected by earlier computing experience and performance, including at home. Existing studies have found that self-efficacy for programming decreased through a child's school years (Wei et al., 2021) but increases with computing experience (e.g. Gunbatar & Karalar, 2018). Females often have less programming experience (e.g. He & Freeman, 2010) and may show interest in computer science at an older age than males (Lang, 2010). Therefore, it is perhaps unsurprising that many studies, but by no means all, have demonstrated a gender difference in self-efficacy relating to computing, in particular those tasks involving more advanced computing skills such as programming (e.g. Cassidy & Eachus, 2002; Huang, 2013; Torkzadeh & Koufteros, 1994). Research by Cassidy and Eachus (2002) found that boys had higher self-efficacy scores than girls regardless of the amount of training the participants had received. However, when controlling for computing experience and familiarity with software packages, gender, training and age were not found to be significant predictors of computing self-efficacy. This suggests that computing experience is important when explaining variations in self-efficacy otherwise attributed to gender, training or age. Recently, previous experience and frequency of coding was found to influence coding confidence (Mason & Rich, 2020). Stereotypes and perceptions of people working in STEM can also affect a student's attitudes and expectancy beliefs (e.g. Cheryan et al., 2017). It has been recognised that gender stereotypes negatively influence the attitudes of girls in STEM, of which there are significant stereotypes surrounding computing (e.g. McGuire et al., 2020).

There is a well-established association between subject-specific academic attitudes and educational outcomes for young people (e.g. Bandura, 1977; Jansen et al., 2014; Valentine et al., 2004). For example, the concept of 'science capital' (Archer et al., 2015) is a useful tool for understanding the link between students' access to science-related knowledge, experiences and networks for their participation in science. Archer et al. (2015) found that young people with high self-efficacy in science generally had higher science capital and were thus more likely to pursue the sciences after the age of compulsory education. Recent work by Hamer et al. (2023) identified coding attitudes to be associated with aspiration to be a computer scientist amongst secondary-school aged young people in England.

Attitudes and expectancy beliefs are complex and interrelated and appear to be influenced by overarching themes including personal interest, perceived ability, parent and teacher encouragement and support, as well as the influence of peers. They are often poorly understood or ill-defined in the literature, which can be problematic when attempting to understand behaviours and their associated outcomes (Rüschenpöhler & Markic, 2019).

Methodology

This study advances our understanding of the factors that influence coding attitudes through the survey of a large sample of young people in schools in England. This has not previously been done with this age group and on this scale in the United Kingdom. The research questions (RQs) are as follows:

RQ1: How do coding attitudes vary in relation to background characteristics, especially gender?

RQ2: What are the social and background characteristics of a young person with 'high' coding attitudes?

The attitudes of learners towards coding were explored through an online survey. The survey was created based on the background literature described earlier and aimed to answer the specific research questions presented above. Survey items were developed using pre-validated scales where available, with the addition of new items covering theoretical aspects identified in the background literature. The next subsection describes the sample, development and operationalisation of the survey items. This is followed by details of the development of social composite factors which were used to decide which variables most strongly predict coding attitude.

Sample

A total of 4983 students from 15 state secondary schools in England took part in the survey. These were all co-educational. Single-sex, selective and independent schools were not invited as the focus of the project is to explore the relative attitudes and experiences of diverse groups of learners from state schools. The participating schools all offered GCSE Computer Science and had at least two classes of students in each GCSE year group choosing the subject. This sample is therefore not representative of schools across England, but rather represent a 'best case scenario', that is, schools that do particularly well at attracting students onto the GCSE Computer Science course. Furthermore, 5 of the 15 schools had over 30% of their GCSE Computer Science cohort as girls for the years 2020/2021 and 2021/2022, higher than the national average of 22% (Joint Council for Qualifications, 2020). Students in years 8, 9, 10 and 11 (age 12–16) were invited to complete the survey electronically and during school time. Institutional ethical approval was sought from and given by all participating students and their families. Data collection was undertaken between July 2021 and December 2021. A full description of the sample can be found in Hamer et al. (2023).

Development of survey items

There were 92 items within the survey relevant to this study.

The background data was followed by five-point Likert-type items covering multiple aspects of the learner's experience of computing education, including: participation in computing and coding-related activities; computing at the primary level; interest in different jobs; and attitudinal items relating to computing lessons and coding. Survey items used to create social composite factors were scored from 1 (Strongly Disagree) to 5 (Strongly Agree) to create a mean score for each student. Scores were adjusted for negatively worded items.

Many previously validated items from the available literature were used either verbatim or modified for the new context, such as 'I learn things quickly in science lessons' from DeWitt et al. (2011), modified to 'I learn things quickly in computing lessons'. To improve the content validity, new items have been added to match any themes identified in the literature that were not identified in existing surveys, and items were grouped according to theme. For example, items relating to computing activities outside of school were grouped together.

The items grouped as 'attitudes in relation to coding' were based on the study by Vandenberg et al. (2021). These authors validated 11 items around the constructs of self-efficacy and outcome expectancy in computer science, particularly in coding. This instrument was designed for young people aged 8 to 11 in the United States. The authors modified the previously validated Student Attitudes towards STEM (S-STEM) instrument by Unfried et al. (2015).

Computing classroom and teacher-centred items are new or modified from existing research. Items included 'I am better at computing than my classmates', which was adapted from an instrument by Blouin (2011) containing 15 Likert-type items predominantly based on self-efficacy beliefs. This instrument was used with 217 students of senior high-school age. Numerous items were also adapted from the ASPIRES and ASPIRES 2 research based in the United Kingdom (e.g. DeWitt et al., 2011). The first phase of this extensive research on attitudes and aspirations in science involved just under 300 young people aged 10–14 years in English schools (DeWitt et al., 2011). Expansion of this research over the following decade informed the items grouped around themes of family influence (DeWitt & Archer, 2015), stereotypes and careers (Dewitt et al., 2014). These authors used these items to survey the science aspirations and attitudes of over 9000 students, aged 10 to 14 years, in schools in England.

Given the digital changes that have occurred over recent years, we drew on the work of Heidegger (1977) and McGeeny and Hanson (2017) to create new items that focused on how students felt about computers and their impact on themselves and society. Items included five-point Likert-type questions on whether they felt computers make the world a better place. The survey ended with multiple-choice items to collect background data (e.g. gender, ethnicity, parent/carer working in computing or technology). As our study has been explored through a social survey, we focused our analysis of attitudes on gender identity, with students being asked whether they were a girl; a boy; their identity is not listed; or prefer not to say (Westbrook & Saperstein, 2015).

Survey analysis

Analysis of survey data was a two-step process and began by exploring the reliability and validity of the data. Exploratory factor analysis (EFA) with principal factor extraction and Cronbach's alpha were utilised to determine internal consistency and unidimensionality of survey items. EFA was undertaken, as many of the items used were either transformed to reflect the computing domain or wholly new items. The sampling adequacy was excellent (Kaiser-Meyer-Olkin test = 0.93), and Bartlett's test of sphericity demonstrated that correlations between items were large enough for factor analysis (Approx. Chi-square = 68136.45, d.f = 1431, $p < .001$) (Bartlett, 1950; Humble, 2020).

The EFA using Direct Oblimin rotation was carried out on 3007 surveys, after incomplete responses (on any of the items) were removed. This revealed 12 social composite factors. Other rotation methods, including Promax, were also used and showed comparable results, therefore increasing the validity of the findings. Items were retained and grouped as social composite factors if there was a minimum eigenvalue of 1.0 and pattern coefficients greater than 0.34 (Appendix A). Measures of internal reliability were calculated using Cronbach's alpha for each social composite factor (Appendix B–D). Various benchmarks for Cronbach's alpha have been cited, which typically range from 0.7 to above 0.9 (e.g. Tavakol & Dennick, 2011). The high Cronbach's alpha for each social composite factor provides evidence of homogeneity within items and demonstrates that, despite being composite factors, each item contributes to the measurement of a single construct. Each social composite factor was additionally tested using 'alpha if item deleted' to ensure only items that contributed to the social composite factor were included. The social composite factors were tested for gender invariance by repeating the EFA separately for girls and boys and produced comparable results indicating gender invariance. There are significant and consistent Pearson correlations between social composite factors, a minority of which were more than 0.5 (Appendix A).

In this study the dependent/outcome variable was the social composite factor 'coding attitude'. The background independent/predictor variables used in this study were as follows:

- Gender (girl; boy; not listed; prefer not to say)
- Ethnicity (Asian; Black; Chinese; Mixed; Other; prefer not to say; White)
- Qualification: GCSE Computer Science (yes; no; not yet chosen)

- Socio-economic background: Recipient of Free School Meals (FSM) in the last six years (yes; no; don't know)
- Parent(s)/carers went to university (yes; no; don't know)
- Recall doing computing at primary school (yes; no; not sure)
- Parent(s)/carers work in technology or a job that uses advanced computing skills (yes; no; don't know)
- Cultural capital: Number of books in the home (five-point scale turned in a dichotomous item of: many-none-few, adapted from Sieben & Lechner, 2019)
- Which school the student attended (dichotomous item: coded yes or no depending on whether the school has over 30% girls in the GCSE Computer Science cohort).

This was followed by exploration of the coding attitudes variable in relation to background characteristics. Finally, multivariable logistic regression analysis, using the background variables and social composite factors that emerged from the EFA, was undertaken to identify which variables are associated with a student having positive attitudes towards coding.

Data analysis

Composite factors that were identified through the EFA were considered continuous variables (Joshi et al., 2015). Because the distribution of scores on the composite factors were not sufficiently close to the normal curve, univariate analyses using Kruskal-Wallis tests were used to identify whether students' responses on the various social composite factors differed by gender to answer RQ1. Post-hoc Dunn tests were used to identify differences between specific genders, ethnicities and by whether the student had received free school meals (as a proxy for socio-economic background).

To answer RQ2 on which background characteristics and social factors are associated with a high coding attitude score, multivariable logistic regression analysis was used. The aim of the regression analysis was to investigate which variables had a statistically significant relationship with high coding attitude and to investigate the strength of any relationships. A high mean coding attitude score was identified as those 25% of students with the highest coding attitude scores (i.e. the top quartile), therefore turning the coding attitude variable into a dichotomous variable with a high-low outcome (see DeWitt & Archer, 2015). The cut-off was chosen to capture the highest scoring learners whilst retaining an adequate sample size for the model. Several methods were used to construct the model described above, including manually building models, 'forwards selection', 'stepwise selection' and 'backwards deletion method' (Chowdhury & Turin, 2020). All methods indicated the same key variables as being significant and stepwise results are presented here. Data analyses were undertaken using the psych package in RStudio (Revelle, 2021).

Results

How do coding attitudes vary in relation to background characteristics, especially gender?

The student scores on the 12 social composite factors were calculated and Kruskal-Wallis tests and post-hoc Dunn tests were used to look more closely at the variables according to gender (Table 1). Ethnicity and socio-economic background were also explored in relation to the coding attitude composite factor only. All the social composite factors, except for stereotypes and aspiration to professional jobs, indicated a statically significant difference according to gender. Coding attitude was found to be significantly associated with gender ($H(4) = 238.63$, 3 d.f, $p < .001$). Furthermore, pairwise comparisons using Dunn's test indicated that girls' coding attitude scores were observed to be significantly lower than those of boys ($p < .001$), not listed ($p < .001$) and 'prefer not to say' ($p = .011$). Boys' coding attitude scores were also found to be significantly higher than those who 'prefer not to say' ($p = .014$). Ethnicity was found to be significantly associated with coding attitudes ($H(6) = 40.50$, 6 d.f, $p <$ 0.001). In particular, those students of Asian ethnicity had higher scores than those of Black ethnicity ($p = .03$) and White ethnicity ($p < .01$). Lower scores were found between students of White compared to those of Mixed ethnicity ($p = .04$) and those that preferred not to state their ethnicity ($p = .03$). No statistically significant differences were found by socio-economic background.

There was a statistically significant difference in coding attitude scores between boys and girls regardless of whether they are studying GCSE Computer Science or had not yet chosen (Figure 1). For those studying GCSE Computer Science, ($H(4) = 8.55$, 3 d.f, $p = .04$), with girls having a lower coding attitude score compared to boys ($p < .001$). For those that did not choose the subject, it is also significant – ($H(4) = 24.60$, 3 d.f, $p < .001$) – with the difference between girls and boys also being significant ($p < .001$). The same pattern also extends to those students who had not yet chosen their GCSE subject options ($H(4) = 118.14$, 3 d.f, $p < .001$) and is again significant between girls and boys ($p < .001$).

Table 1. Student scores for composite factors by gender.

			Gender							
	Full sample		Boy		Girl		Not listed		Prefer not to say	
Social composite factor	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1. Teacher support***	3.7	1.0	3.8	1.0	3.6	1.0	3.7	0.9	3.4	1.1
2. Coding attitudes**	2.8	1.2	3.1	1.1	2.4	1.1	3.0	1.2	2.8	1.1
3. Computing lesson***	2.9	1.1	3.1	1.1	2.5	1.0	2.9	1.1	2.0	1.1
4. Perceptions of computer scientists***	3.7	0.7	3.7	0.8	3.6	0.7	3.8	0.7	2.8	0.8
5. Computing and society ***	3.0	0.8	3.2	0.8	2.9	0.8	3.3	0.9	2.9	0.9
6.Parent support***	3.5	0.9	3.6	0.9	3.4	0.9	3.5	1.0	3.3	0.9
7. Stereotypes	2.8	0.8	2.8	0.8	2.8	0.8	2.8	0.9	2.8	0.8
8. Digital making***	1.4	0.5	1.5	0.6	1.3	0.4	1.7	0.7	1.4	0.6
9. Computing literacy***	2.1	1.1	2.3	1.2	1.8	1.0	2.5	1.1	2.1	1.1
10. Technical jobs***	2.4	1.1	2.8	1.0	1.9	0.9	2.4	1.2	2.3	1.0
11. Creative jobs***	2.7	1.1	2.5	1.1	3.0	1.1	3.5	1.1	3.1	1.3
12. Professional jobs	2.8	1.1	2.7	1.1	2.8	1.1	2.6	1.1	2.6	1.1

*** Difference according to gender $p < .001$.

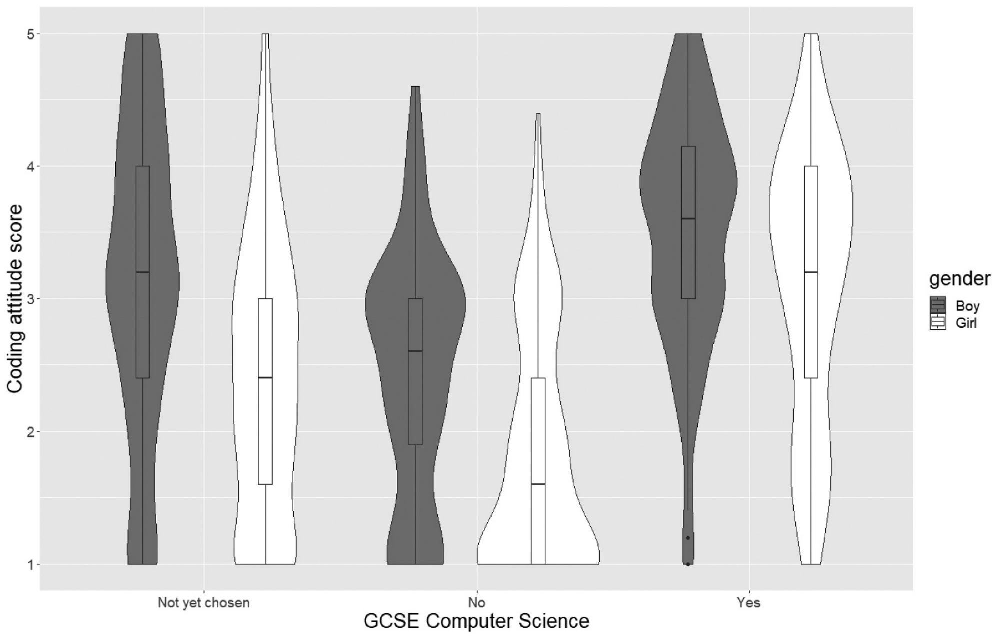

Figure 1. Coding attitude score by gender and whether they are taking GCSE Computer Science, $n = 2810$. Note: all differences by gender are statistically significant ($p < .05$).

What are the social and background characteristics of a young person with a 'high' coding attitude?

A multivariable logistic regression model was used to explore which of the social composite factors and background variables described previously were associated with a high coding attitude. This model identified nine significant predictor variables associated with a high coding attitude: computing lessons; teacher support; perceptions of computer scientists; family support; computing literacy; digital making; aspiration to technical jobs; choosing to take GCSE Computer Science; and being a boy (Table 2). Specifically, this model indicates that for every one-point increase in the 'digital making' composite score there is a 113% (95% CI [1.65, 2.77]) increase in the odds of having a high coding attitude. For the 'perceptions of computer scientists' composite factor, the increase in odds is 99% (95% CI [1.54, 2.58]), 'family support' (87% (95% CI [1.53, 2.30])), 'computing lesson' (82% (95% CI [1.53, 2.18])), 'teacher support' (46%, (95% CI [1.19, 1.81])), 'aspirations to technical jobs' (39% (95% CI [1.20, 1.62])) and 'digital literacy' (21%, (95% CI [1.05, 1.39])).

Discussion

This analysis was drawn from a sample of 15 schools who do particularly well in terms of numbers of students choosing GCSE Computer Science. Therefore, the generalisability of these findings must be treated with caution as they represent some of the best scenarios for secondary schools offering the subject. However, given the sample size and the spread of participating schools across England, there are some broad themes that are worthy of discussion.

Table 2. Association between high coding attitude with background variables and social composite factors, $n = 1949$.

Independent variable	Odds ratio	95% Confidence interval	*p*-value
Computing lesson	1.82	1.53, 2.18	**<.001**
Teacher support	1.46	1.19, 2.81	**<.001**
Perceptions of computer scientists	2.99	1.54, 2.58	**<.001**
Parent support	1.87	1.53, 2.30	**<.001**
Computing literacy	1.21	1.05, 1.39	**.016**
Digital making	2.13	1.65, 2.77	**<.001**
Technical jobs	1.39	1.20, 1.62	**<.001**
Qualification: Not yet chosen	—	—	—
Qualification: Taking CS	1.45	1.06, 1.99	**.020**
Qualification: Not taking CS	0.65	0.35, 1.12	.133
Gender: Boy	—	—	—
Gender: Girl	0.60	0.42, 2.03	**.003**
Gender: Not listed	0.44	0.42, 2.03	.127
Gender: Prefer not to say	0.96	0.42, 2.03	.908

Coding attitude and gender

The link between coding attitudes and gender in this study is clear. Girls generally have a lower coding attitude when compared to boys, regardless of whether they have chosen GCSE Computer Science. However, the gender differences between scores for those students that have chosen the subject are more similar than those that have not chosen or opted not to choose the subject, perhaps indicating the influence of inclusive teaching practices by their GCSE Computer Science teachers. Or, alternatively, that these girls have particularly high coding attitudes compared to their contemporaries, therefore leading them to choose the subject at GCSE. Furthermore, this narrowed gap in coding attitudes for those girls taking the subject at GCSE may be a consequence of them spontaneously adjusting and calibrating their working self-concept to fit with their social context (e.g. Markus & Kunda, 1986). The especially low scores for girls who do not choose GCSE Computer Science should be of particular concern when compared to boys in the same group, especially when attitudes are also linked with the career aspirations of young people (e.g. Hamer et al., 2023; Kutnick et al., 2018). The association between gender and computing, particularly coding attitude, is one that has been documented elsewhere in the literature, and so it is unsurprising that it has been found here (e.g. Leonard et al., 2021; Vandenberg et al., 2021). It is important to note that despite girls being associated with having lower coding attitude scores, this does not necessarily indicate that they are less able at computer science (OECD, 2015), but it may influence future participation in the subject (Hamer et al., 2023; Lips & Temple, 1990).

Classroom experience

Variables linked to the classroom experience appear to play a vital role in how competent a young person believes they are in relation to coding. Positive teacher–student relationship building, encouragement and constructive feedback from the computing teacher are likely to have an important part to play. Indeed, how a student feels in their computing lesson, whether they consider themselves to be ‘good’ or ‘bad’ at computing, and their self-identified position of academic ability in relation to their peers appears to be one of the biggest predictors of coding attitude. Previous authors have also indicated that it is the ‘quality’ of the teaching rather than the duration which is associated with computing self-efficacy (e.g. Torkzadeh & Koufteros, 1994; Cassidy & Eachus, 2002). This indicates that classroom practices that focus on building attitudes are likely to have a positive impact on coding attitudes. Classroom practices which improve attitudes have been proposed by Margolis and McCabe (2006), and include incorporating tasks that provide frequent, small, clear and achievable goals that show students evidence of their own success. These authors suggest that communication by teachers that frequently reminds and persuades students of their successes in the subject can also help. Furthermore, Burgess et al. (2022) found additional feedback on performance in STEM by external parties appears to have a greater impact on girls when it comes to later subject choice. The mechanism for this is likely to be through the feedback increasing attitudes and subject and career decisions (Hamer et al., 2023).

Digital making and computing literacy

Practical computing activities out of school, such as building mobile apps or reading about computing online, are associated with coding attitudes, with those young people indicating high coding attitudes being more likely to be spending extracurricular time doing computing-related activities. Previous studies have found that hands-on ‘doing’ activities in the sciences is pivotal for the development of self-efficacy (e.g. Jansen et al., 2015), which seem to apply in computing as well. However, it may be that those that choose to do computing at home do so *because* they have higher coding attitudes (e.g. Compeau & Higgins, 1995; Hill et al., 1987). Conversely, it may be that young people who do more computing activities benefit from these activities, and, consequently, increase their coding attitude. However, until causality is shown, this is still very much ‘chicken and egg’ speculation.

The role of the parents and carers

Parent/carer support for the young person to study computer science and the value that is placed on computing appears to be a significant predictor of coding attitudes. It is also likely that a link exists between parental support and extracurricular computing activities, as described by Archer et al. (2012) in relation to science. These authors found that the families of students with the most positive attitudes towards science were also more likely to work in science themselves, be middle class and have a child that participates in extra-curricular science activities. This is similar to findings from this study, where when considering the background variables only, having parents who work in computing or tech, and whether they had been to university, were found to predict having higher coding attitudes.

Job aspirations

Students who have a greater aspiration to work in technical jobs (e.g. network engineer or tech entrepreneur) appear more likely to have higher coding attitudes than those who do not. These types of jobs are likely to use more coding and skills that require greater computing-related technical knowledge than those within the creative jobs (e.g. dancer or designer) or a job in the professions (e.g. doctor or scientist). The association of aspiration to work in technical jobs with coding attitudes is likely to be intricately linked to outcome expectancies in this subject area. Those young people who consider themselves good at coding, and who therefore have high coding attitudes, are more likely to see themselves as having future success in this area and consider it as thinkable for them (Hamer et al., 2023; Wong, 2016).

Perceptions of computer scientists

Interestingly, positive perceptions of the importance of computer scientists appears to be one of the biggest predictors of whether a young person has high coding attitude. This phenomenon is likely to be linked to personal identity, where individuals tend to choose subjects and career paths that feel more aligned with their own self-concept and their perceptions of those studying and working in that field (e.g. Dasgupta, 2013). Therefore, it is likely that those who identify to some degree with those positive perceptions of computer scientists are also likely to have a higher coding attitude.

Conclusion and implications

Despite evidence existing of the importance of attitudes when it comes to attainment and subject choice (e.g. Zeldin & Pajares, 2000), a tricky question remains around whether attitudes determine academic outcomes and choices, or whether academic outcomes and choices determine a learner's attitude (Pajares, 2001). For students making subject choices, coding attitudes are intricately associated with all the factors described above. Those young people who identify as boys, have parents that support their aspirations in computing, have the opportunity and resources to do computing activities in their own time and have a supportive teacher and classroom environment appear more likely to believe they are good at coding and see it as a skill in their future career (Hamer et al., 2023). The findings from this study should make us question whether a computing curriculum, that has considerable coding at its core to the detriment of other areas of computing, is really a subject that will contribute to a diverse digital workforce. Perhaps until there is significant curriculum change in relation to coding content, certain groups of young people, including girls, will continue to be less well represented in this subject.

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Ethics statement

Approval for this research was given by the King's College London Research Ethics Committee.

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Appendix

Appendix A: Eigen values, variance explained, and factor correlations for rotated factor solution

Factor	1	2	3	4	5	6	7	8	9	10	11	12
Eigan values	3.94	3.69	2.93	2.38	2.25	2.26	1.80	1.63	1.78	1.64	1.37	1.19
Proportion Var	0.07	0.07	0.05	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.02
Cumulative Var	0.07	0.14	0.20	0.24	0.28	0.32	0.36	0.39	0.42	0.45	0.48	0.50
Proportion Explained	0.15	0.14	0.11	0.09	0.08	0.08	0.07	0.06	0.07	0.06	0.05	0.04
Cumulative Proportion	0.15	0.28	0.39	0.48	0.57	0.65	0.72	0.78	0.84	0.91	0.96	1.00
Factor 1	1.00	0.38	0.38	0.41	0.34	0.30	−0.24	0.08	0.25	0.08	0.09	0.07
Factor 2	0.38	1.00	0.62	0.32	0.44	0.45	−0.21	0.33	0.53	0.39	0.17	0.12
Factor 3	0.38	0.62	1.00	0.27	0.41	0.39	−0.16	0.28	0.43	0.28	0.05	0.11
Factor 4	0.41	0.32	0.27	1.00	0.43	0.31	0.02	0.05	0.19	0.09	0.10	0.11
Factor 5	0.34	0.44	0.41	0.43	1.00	0.35	−0.11	0.13	0.32	0.20	−0.01	0.08
Factor 6	0.30	0.45	0.39	0.31	0.35	1.00	−0.16	0.10	0.28	0.22	0.16	0.20
Factor 7	−0.24	−0.21	−0.16	0.02	−0.11	−0.16	1.00	−0.05	−0.16	0.02	−0.06	−0.01
Factor 8	0.08	0.33	0.28	0.05	0.13	0.10	−0.05	1.00	0.45	0.13	0.09	0.00
Factor 9	0.25	0.53	0.43	0.19	0.32	0.28	−0.16	0.45	1.00	0.30	0.05	0.08
Factor 10	0.08	0.39	0.28	0.09	0.20	0.22	0.02	0.13	0.30	1.00	0.10	0.29
Factor 11	0.09	0.17	0.05	0.10	−0.01	0.16	−0.06	0.09	0.05	0.10	1.00	0.20
Factor 12	0.07	0.12	0.11	0.11	0.08	0.20	−0.01	0.00	0.08	0.29	0.20	1.00

Appendix B: Social composite factors, items with factor loadings and Cronbach α

Social Composite factor	Item	Factor number 1	2	3	4	Cronbach α
1) Teacher support	My computing teacher listens to what students think	**0.88**	−0.02	−0.01	−0.01	0.91
	My computing teacher believes that mistakes are OK as long as we are learning	**0.83**	−0.01	0.01	0.01	
	My computing teacher treats all students the same regardless of their computing ability	**0.80**	−0.03	0.00	0.02	
	I like my computing teacher	**0.79**	0.06	0.02	0.01	
	My computing teacher is enthusiastic about computing	**0.74**	0.03	−0.03	0.04	
	My computing teacher is interested in me as a person	**0.60**	0.05	0.11	−0.05	
2) Coding attitudes	I want to use coding to be more creative in my future jobs	−0.01	**0.86**	0.01	0.01	0.91
	I would like to use coding to make something new	0.00	**0.81**	0.06	−0.01	
	Using code will be important in my future jobs	0.02	**0.75**	−0.03	0.03	
	If I learn coding, then I can improve things that people use every day	0.05	**0.67**	0.02	0.08	
	I am interested in what makes computer programs work	0.08	**0.64**	0.06	0.01	
3) Computing lesson	I am good at computing	0.03	0.02	**0.82**	0.02	0.89
	I learn things quickly in computing lessons	0.06	−0.01	**0.82**	0.01	
	I am better at computing than my classmates	−0.11	0.00	**0.79**	−0.01	
	I understand everything in computer lessons	0.04	0.02	**0.77**	0.01	
4) Perceptions of computer scientists	People who work in computer science. . ..do valuable work	0.02	0.06	0.04	**0.71**	0.78
	. . .make a difference	0.00	0.05	0.00	**0.59**	
	. . .are brainy	0.04	−0.11	0.04	**0.57**	
	. . .make a lot of money	0.03	0.09	−0.03	**0.56**	
	. . .have to be creative in their work	0.08	0.03	0.05	**0.55**	
	. . .are respected by people in this country	0.08	0.08	−0.03	**0.44**	

Appendix C: Social composite factors, items with factor loadings and Cronbach α

Social composite factor	Item	Factor number 5	6	7	8	Cronbach α
5) Computing and society	Computers make the world a better place	**0.75**	0.00	−0.02	0.00	
	Computers are a force for good	**0.71**	0.02	0.02	0.01	
	Computers make the world a safer place	**0.68**	0.02	0.04	−0.01	0.77
	Computers help to strengthen my relationships with others	**0.49**	0.00	0.00	0.02	
	Computer companies or firms can be trusted	**0.44**	−0.03	−0.05	−0.01	
6) Parent support	My parents/carers would be happy if I became an IT professional in the future	0.00	**0.90**	0.00	−0.01	
	My parents/carers would be happy if I became a computer scientist in the future	0.02	**0.85**	−0.01	0.03	0.83
	My parents/carers think computing or IT is interesting	0.00	**0.47**	−0.04	−0.06	
	My parents/carers think it is important for me to learn computing or IT	−0.01	**0.45**	0.01	−0.04	
7) Stereotypes	People who work in computer science . . . are odd	0.01	−0.02	**0.75**	−0.03	
	. . .are geeks	−0.01	0.00	**0.69**	0.01	
	. . .don't have many other interests	−0.05	−0.04	**0.52**	0.02	0.70
	. . .spend most of their time working by themselves	0.00	−0.02	**0.42**	0.04	
	. . .are usually men	0.08	0.02	**0.39**	−0.01	
8) Digital making	In my spare time I. . . make websites	0.00	−0.01	0.01	**0.61**	
	. . .make phone Apps	0.00	−0.03	−0.03	**0.59**	
	. . .make computer games	0.03	0.03	0.01	**0.57**	0.66
	. . .3D printing	0.01	0.00	−0.02	**0.40**	
	. . . digital music creation	−0.04	0.06	0.00	**0.35**	
	. . . Programming/Coding	0.01	0.04	−0.02	**0.34**	

Appendix D: Social composite factors, items with factor loadings and Cronbach α

Social composite factor	Item	Factor number 9	10	11	12	Cronbach α
	In my spare time I. . .. read about computing or IT online	**0.79**	0.02	−0.02	0.00	
9) Computing literacy	. . . read about computing or IT on social media	**0.67**	0.02	0.02	−0.01	0.71
	. . .read a book, magazine or newspaper about computing or IT	**0.49**	−0.04	0.03	0.09	
	I would like to be an. . . engineer	−0.02	**0.70**	0.00	0.05	
10) Technical jobs	. . . electrician, plumber, builder, or in a trade	0.01	**0.66**	0.02	−0.03	0.72
	. . . network engineer	0.11	**0.52**	0.02	0.04	
	. . . tech entrepreneur	0.10	**0.38**	0.00	0.04	
	I would like to be an. . . artist, musician, actor or dancer, or in the arts	−0.04	−0.15	**0.66**	0.07	
11) Creative jobs	. . . digital artist	0.02	0.09	**0.66**	−0.06	0.67
	. . . designer	0.03	0.11	**0.60**	0.04	
	I would like to be a . . . doctor	0.03	−0.02	0.00	**0.82**	
12) Professional jobs	. . . lawyer	−0.03	0.11	0.08	**0.44**	0.63
	. . . other scientist	−0.04	0.17	0.02	**0.43**	