Mears, Matthew, Dash, Louise, Galloway, Ross, Karpenko, Calvin, Labrosse, Nicolas, Mason, Victoria and Quinn, Mark (2025) *Mixed-Methods Study of First-Year Physics Students: Soft Barriers to Coding.* Journal of Science Education and Technology, 34 (2). pp. 420-435. ISSN 1573-1839.

Journal of Science Education and Technology (2025) 34:420–435
https://doi.org/10.1007/s10956-025-10198-0

Mixed-Methods Study of First-Year Physics Students: Soft Barriers to Coding

Matthew Mears[1] · Louise Dash[2] · Ross Galloway[3] · Calvin Karpenko[1] · Nicolas Labrosse[4] · Victoria Mason[5] · Mark Quinn[1]

Accepted: 17 January 2025 / Published online: 1 February 2025

Abstract

Digital proficiency, including coding, is increasingly essential in physics education. However, disparities in coding skills among students are influenced by demographic factors and prior educational exposure. This study examines barriers to pre-university coding exposure for first-year physics students across five UK institutions, proposing a fourth level of the digital divide that emphasizes technical and production knowledge in coding. A survey of 199 first-year physics students reveals significant gender and ethnicity differences in coding experience. Males were more than twice as likely to have prior coding experience than females. Students with no prior coding experience viewed it as more challenging, requiring advanced math and powerful computing resources. Despite these challenges, both groups strongly disagreed that gender affects coding ability. Qualitative data pointed to technical difficulties, a lack of role models, and insufficient pre-university exposure as major obstacles. Black, Asian, and Minority Ethnicity (BAME) students reported less teacher encouragement and faced structural barriers similar to those found in literature. The study identifies a fourth level of the digital divide in coding knowledge, stressing the need for targeted interventions to enhance diversity and inclusivity in physics coding education. Recommendations include improving pre-university coding exposure, using gender-sensitive teaching methods, providing consistent encouragement to students, and deeply integrating coding into physics curricula. These steps are vital for preparing students for the digital demands of their academic and professional futures, ensuring equitable access to essential digital competencies.

Keywords Digital divide · Socioeconomic barriers · Coding barriers · Physics

Louise Dash, Ross Galloway, Calvin Karpenko, Nicolas Labrosse, Victoria Mason, and Mark Quinn contributed equally to this work.

✉ Matthew Mears
m.mears@sheffield.ac.uk

Louise Dash
louise.dash@ucl.ac.uk

Ross Galloway
ross.galloway@ed.ac.uk

Calvin Karpenko
c.karpenko@sheffield.ac.uk

Nicolas Labrosse
Nicolas.Labrosse@glasgow.ac.uk

Mark Quinn
m.quinn@sheffield.ac.uk

[1] Department of Physics & Astronomy, University of Sheffield, Hounsfield Road, Sheffield S3 7RH, UK

[2] Department of Physics & Astronomy, University College London, Gower Street, London WC1E 6BT, UK

[3] School of Physics & Astronomy, University of Edinburgh, Peter Guthrie Tait Road, Edinburgh EH9 3FD, UK

[4] School of Physics and Astronomy, University of Glasgow, University Place, Glasgow G12 8QQ, UK

[5] Formerly of School of Physics and Astronomy, University of Kent, Park Wood Road, Canterbury CT2 7NH, UK

Introduction

Digital Age and Digital Divide

Recent decades have witnessed a growth in digital technologies and systems that are increasingly more integrated into society and many aspects of our everyday lives. In the USA, the digital economy is predicted to reach 8.3% by 2025 (Manyika et al., 2017) and is estimated to have contributed £149 billion to the economy in the UK in 2018 (Department for Digital, Culture, Media & Sport, 2020). Access to the internet allows individuals to improve their knowledge about healthcare issues and to seek information about disease prevention, treatment, and other medical information (Lin et al., 2016) and enables social connectivity and participation for older persons who might otherwise face isolation (Fang et al., 2019). Devices such as iPads are shown to have benefits for school students learning in mathematics (Perry & Steck, 2015), science (Ward et al., 2013), and art (Wang, 2018), and the higher education sector has embraced digital approaches such as blended learning (Bernard et al., 2014) and flipped classrooms (O'Flaherty & Phillips, 2015). Subramony (2014) describes how access to technology can result in skills that lead to improved professional development and, in turn, socioeconomic status which then provides even greater access to technology, a cycle Subramony terms the "virtuous cycle" (Rogers, 2016).

This virtuous cycle is only of benefit to those who have access to it, and a lack of engagement or access opportunities results in the "vicious circle" in which a lack of consideration in creating inclusive technology alienates those who do not see learning about or using technology as part of their self-identity (Rogers, 2016; Subramony, 2014). This gap between those who do or do not have access to technology is more commonly known as the digital divide (Ganesh & Barber, 2009; Lythreatis et al., 2022; van Dijk, 2005, 2006, 2020); though more recently, as technology and internet access has improved, some have identified the second level digital divide that focuses on digital skills and digital usage (Mossberger et al., 2003; Riggins & Dewan, 2005; van Deursen & van Dijk, 2011; van Deursen et al., 2016) and a third level where internet skills and usage lead to beneficial outcomes for the individual (Shakina et al., 2021; van Deursen et al., 2016).

The existence of this digital divide is not consistent across society and is more prevalent between marginalized and non-marginalized groups (Schradie, 2011). Wang and Hejazi Moghadam (2017) found that despite showing a higher interest in computer science, Black and Hispanic students in the United States experienced greater structural barriers to accessing computer science classes and to computers more generally. They also found that girls reported a lower awareness of computer science opportunities outside of the classroom compared to boys, despite having similar levels of access to these resources. Enoch and Soker (2006) found similar gender and ethnicity barriers for university students in Israel attempting to access web-based learning resources. The type of occupation a person has can introduce or widen the digital divide if their jobs do not involve using and developing their skills on computers or the internet (Holcombe-James, 2022; Manyika et al., 2017). For children in education, access to technology and the internet at home, in schools, and in outside locations (for example, churches, libraries, and community centers) all play an important role in the presence of the digital divide alongside socioeconomic status (Dolan, 2016) and the support or encouragement from teachers (Ritzhaupt et al., 2012; Soomro et al., 2020). Finally, low-income families and individuals are impacted by the digital divide at all three levels (i.e., lack of direct access to computers through to internet skills that lead to beneficial outcomes) (Gonzales, 2016; Wamuyu, 2017; Watts, 2020; Wong et al., 2015) though some work suggests low-income groups in some countries are catching up with middle-income groups for mobile cellular, Internet, and fixed broadband access (Chang et al., 2020).

Barriers in Coding

This three-level model describing the digital divide (access to technology; digital skills and usage; internet skills and usage) provides a structural framework for understanding the gap for more general and everyday digital usage. We propose there is an additional level currently missing in the literature that describes more technical or production knowledge and skills—the three existing levels consider the digital divide relating to *digital use* but do not describe knowledge and skills of *digital creation*. An extension into a fourth level could encapsulate both the skills and benefits of building desktop computers (DiSalvo et al., 2013) or physical computers such as Arduinos (DesPortes & DiSalvo, 2019) as well as learning coding or programming languages (Department for Education, 2018; Guzdial, 2016; Israel et al., 2015). It is this second case that this work seeks to explore, investigating whether this fourth level exists amongst the cohort studied and how prevalent it is. The terms coding and programming are often used interchangeably and within this work, we will use "coding" to encapsulate both two terms.

There is a substantial body of literature that has considered the technical difficulties that novice programmers face when learning to code. Kelleher and Pausch (2005) considered various teaching methods including attempts to make syntax easier to use for novices and different ways of learning to program as well as providing motivating contexts for

Table 1 Number of participants, cohort size, and response rate at each of the 5 UK institutions involved

Institution	Responses/total	Response rate
University College London (UCL)	43/230	18.7%
University of Edinburgh	67/314	21.3%
University of Glasgow	42/239	17.6%
University of Kent	19/121	15.7%
University of Sheffield (Lead)	28/86	32.6%
Total	199/900	20.1%

novice programmers such as building robots. Lahtinen and colleagues (2005) studied the difficulties that novice programmers faced when learning to program and collected student views towards particular aspects of learning a coding language to help inform the development of coding courses, something that Cartile (2020) notes as a significant barrier due to the lack of consensus in approaches to teaching and learning coding that may be addressed by the development of a taxonomy of computational thinking (Selby, 2015). Preformed misconceptions in coding can also provide additional barriers when learning a new language (Qian & Lehman, 2018) which can be further exacerbated by different and inconsistent methods of teaching coding (Piteira & Costa, 2013).

This paper brings a unique perspective by exploring the barriers typically associated with the digital divide (non-coding specific) within a cohort of undergraduate physics students in the United Kingdom (UK). The physics focus is of particular interest due to its niche, if not unique, position whereby coding competence and knowledge is now a crucial component *within* the curriculum but is not a stand-alone component *of* the curriculum as it is in, for example, a computer science degree comprising of dedicated coding modules. This is particularly noteworthy for the institutions that contributed to this study. All physics degree programs accredited by the Institute of Physics[1] are *required* to teach and assess coding during the course. The students surveyed as part of this work are therefore *knowingly* undertaking a course that requires knowledge and competence in coding, but this is not the core focus of their course and is better described as part of the hidden curriculum of a physics degree.

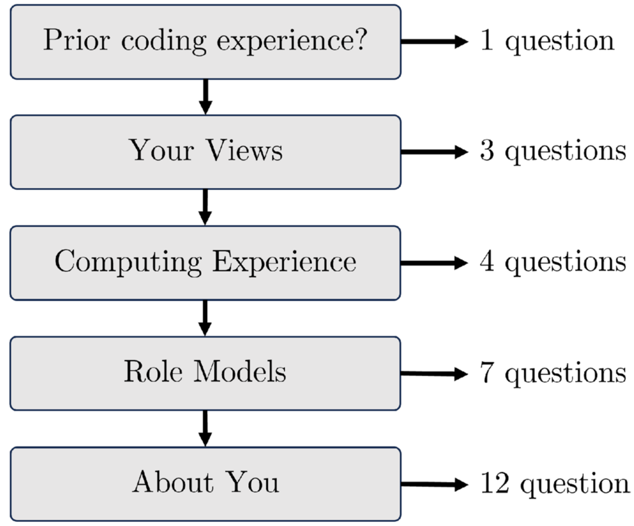

Fig. 1 The survey structure by headings with associated questions within each group. The full survey can be found in the Appendix

The question this paper seeks to address is "does the proposed fourth level of the digital divide model exist amongst physics students, and if so to what extent does it impact on the experiences and preconceptions of coding for undergraduate physics of different backgrounds and identities?".

Methods

Sample Demographics

An online survey was sent to the five university physics departments in the United Kingdom (UK) (see Table 1) where the authors were located at the time of the study. The survey was disseminated by email, and students chose to opt into the study by completing the survey after confirming their understanding of the project and providing their consent. Students were in the first year of their studies and were recruited during the first month of their first semester in 2019. For degree programs in the UK, students will have enrolled in their subject course (or courses for dual degree programs) at the beginning of their first year and will spend their time only studying this course until graduation. This context is important compared to degree programs in other countries where first-year students may only be studying physics as a minor or optional component of their studies. For this study, all participants at English universities were enrolled in and intended to complete a physics degree that includes one or more taught courses in coding. A small number of students enrolled at Scottish universities (Edinburgh and Glasgow in our cohort) elect to take a physics module as part of a different program; however, our recruitment was

[1] The Institute of Physics monitors the standard and content of accredited physics degree programmes in the UK and in the Republic of Ireland.

Table 2 Demographic data of all respondents who included their gender and ethnicity information

	Total	Gender			Ethnicity		
		Female	Male	Total	BAME	White	Total
No Prior (NPE)	82	40	39	79	24	52	76
Prior (PE)	117	35	74	109	31	80	111
Total	199	75	113	188	55	132	187

targeted to students enrolled in a physics degree program and screened via question 17 of the survey (see Appendix).

Data Collection and Analysis

Participants were invited to take part by email distributed by staff in each institution using a common template, and participation was through an anonymous Google Form. Data were collated and analyzed by the lead institution (University of Sheffield) before summary data were shared between all authors for discussion and interpretation.

Participants were presented with 27 questions under 5 categories as shown in Fig. 1 (the full survey is included in the Appendix). Some of the questions in this survey (Q5–7, 9–11, 13, and 14) were taken or adapted from Wang and Hejazi Moghadam (2017) (our adaptations changed the wording from "Computer Science" to "coding") and all other questions created for this survey following an extensive literature search and in collaboration with all authors to decide on the final questions.

Question 1 was used to split respondents into one of two groups, those who have experience with coding prior to attending university ("Prior Experience" group, PE) and those without ("No Prior Experience" group, NPE). All questions were identical for both groups except for question 3 that was different in asking for motivators for (PE) or barriers preventing (NPE) learning to code prior to attending university. Free text questions (Q3 and Q4) were presented before the Likert scale questions to avoid priming of written responses. Similarly, demographic questions were asked at the end of the survey to minimize the impact of implicit bias.

This research has approval from a formally constituted university ethics committee at the lead institution (reference number 030865). Participants were provided with an information sheet with the recruitment email detailing the study, how their information will be used and how they can opt out of the study at any point by closing the survey. Consent was reaffirmed at the point of completion of the survey before their anonymous responses were added to the dataset.

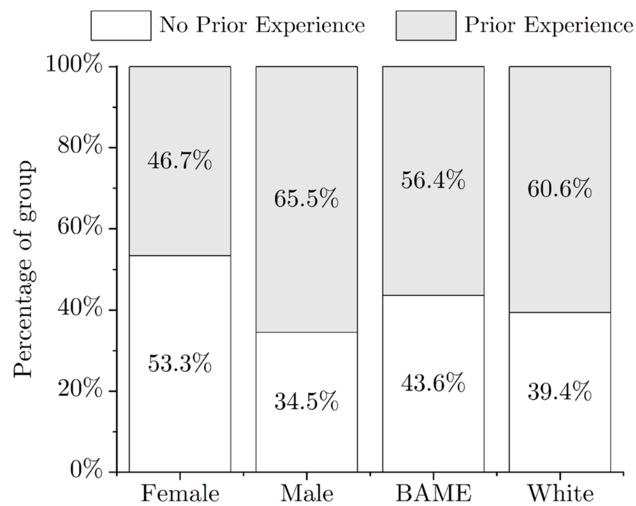

Fig. 2 Percentage of No Prior and Prior Experience respondents within each demographic group. Raw count values are shown in Table 2

Results

Quantitative Results

Demographic Profile and Prior Experience

The demographic profile of NPE and PE groups is summarized in Table 2, excluding those who chose not to disclose their gender identity or ethnicity, and Fig. 2 shows the fraction of NPE and PE within each demographic group.

Of the 199 respondents, 188 reported identifying as Female or Male, with 11 students either identifying as non-binary or choosing not to disclose their gender identity. As the response rate for non-binary students was small, they are not included in quantitative analyses relating to gender but are included in other quantitative analyses and in all qualitative analyses described in the "Free-Text Responses" section. Ethnicity was disclosed by 187 respondents under 16 categories (see question 22 in the Appendix) and subsequently collated under Black, Asian, and Minority Ethnicity (BAME) or White groups. Due to the small numbers of respondents for some of the ethnicity categories included in the survey all ethnicities other than "White," "Not Known" and "Prefer Not To Say" are combined under the BAME group, though we recognize that the experience of different ethnicities are not homogenous and care must be taken to avoid assuming any findings between White and BAME groups are identical for all ethnic minority groups. There was a significant association between gender and prior coding experience ($\chi^2(1) = 6.554$, $p < 0.05$, $\Phi = 0.187$), and all expected frequencies met the assumption for a χ^2 test of being greater than 5 (Field, 2009, pp. 691–692). Based on the odds ratio (a measure of association between a grouping variable (in this case, gender) and an outcome (having prior coding experience)), the odds of male students having prior experience was 2.17 times higher than female students. There was no significant difference between BAME and White students ($p = 0.626$, $N = 187$).

Prior Experience vs No Prior Experience

ANOVA analysis of the ordinal data collected for question 2 was performed using IBM SPSS (v29.0.0.0), comparing PE and NPE groups as shown in Table 3. Effect sizes (Cohen's *d*) were calculated using G*Power (v3.1.9.6).

For questions 2a, 2b, and 2c the No Prior group holds the view that coding is difficult and requires good mathematical skills and a powerful computer, respectively. Similarly, they are less likely to hold the counter view that coding is simple (question 2e), with both difficulty-related questions showing moderate effect sizes. It is also worth noting that while there is no difference between the two groups for question 2f ("Gender plays a part in coding ability") both groups on average Strongly Disagree with this statement.

The nominal data responses for questions 5 through 27 (excluding 16, 17, and 19) were analyzed using chi-squared tests using SPSS, with Cramer's V used as a measure of power for questions where a statistically significant difference was observed between Prior and No Prior groups. Question 19 ("How old are you?") provides continuous data and was analyzed using a Mann–Whitney test, and questions 16 and 17 relating to the institution and course of study were not included in the analyses. Table 4 shows the results of these chi-squared and Mann–Whitney tests.

Under "Computing Experience," there was a statistically significant difference for all four questions (Q5–Q8). The lack of specific coding classes and embedding coding into other courses was noted as one reason behind the lack of experience in the No Prior group, but perhaps most noteworthy is the largest effect size corresponds to question 7 where respondents were asked about their *awareness* of websites that allow them to learn to code online. As these resources are widely available and do not require a school to provide support this is one area of awareness raising that could benefit students who are considering taking a degree program in physics (or any other coding-intensive subjects); it should be noted that there was no statistically significant difference between the groups regarding access to a computer at home (Q26) or at school (Q27) suggesting that physical-digital poverty may not be the reason why the No Prior group were not aware of the online resources and instead may be due to a lack of signposting from parents, caretakers/carers, or teachers.

Within the "Role Models" section, respondents in the Prior group were more likely to have access to clubs at school (Q10) or communities outside of school (Q11) where they could learn to code. Respondents from the Prior group were more likely to have friends who code (Q12) or have been told by a teacher that they would be good at coding (Q13) highlighting the importance of peer and authority figure support, but there was no difference in the presence of an adult who works with computers or technology in their lives (Q9). Finally, those in the Prior group were more likely to have seen or heard of someone like them who codes (Q15).

Gender Differences

The dataset was split into two groups based on the response to question 21 ("What is your gender identity?"). There were a small number (< 10) of respondents who identified outside of the gender binary who are excluded from the following analysis due to small sample sizes, and we recognize that this will lose important information about the experiences and views of non-binary students. These two separate

Table 3 Results from comparisons between NPE and PE groups for question 2 (ordinal responses) that are found under the Your Views section of the survey. The "Summary" column provides a condensed statement of the question asked for ease of reference, with the exact question wording provided in the Appendix

Q	Summary	Avg ± σ		p	F	Effect size
		NPE, $N=82$	PE, $N=117$			d
2a	Coding is difficult	3.6 ± 1.0	2.8 ± 1.0	0.000	26.685	0.3938
2b	Coders must be good at math	3.3 ± 1.0	2.9 ± 1.1	0.007	7.307	0.1875
2c	Powerful computer needed	2.5 ± 1.0	2.0 ± 0.9	0.000	14.608	0.2590
2d	Coding is abstract	3.0 ± 0.9	2.9 ± 1.1	0.200	1.654	-
2e	Coding is simple	2.2 ± 0.8	2.8 ± 1.0	0.000	24.488	0.3281
2f	Gender plays a role	1.3 ± 0.7	1.3 ± 0.7	0.846	0.038	-

Table 4 Results from comparisons between NPE and PE groups for each quantitative question in the survey (see Appendix). Cramer's V values are only quoted when there is a statistically significant difference between the groups. The "Summary" column provides a condensed statement of the question asked for ease of reference, with the exact question wording provided in the Appendix

Section	Q	Summary	χ^2	p	Cramer's V	N
	5	Coding specific classes at school?	16.816	<0.001	0.291	199
Computing Experience	6	Coding in other classes at school?	8.877	0.004	0.211	199
	7	Awareness of online resources	51.251	<0.001	0.524	187
	8	ICT or computing qualifications	19.621	<0.001	0.314	199
	9	Adult in life who works with computers?	0.853	0.389	-	199
	10	Coding clubs at school?	17.830	<0.001	0.316	179
	11	Community opportunities to code?	8.958	0.010	0.253	140
Role Models	12	Friends who code?	4.537	0.027	0.151	199
	13	Teacher encouragement at school?	11.516	<0.001	0.241	199
	14a	Seen coding on TV?	0.437	0.813	-	199
	14b	Seen coding in movies?	2.599	0.274	-	199
	14c	Seen coding on social media?	5.145	0.079	-	199
	15	Do you see people like you coding?	11.655	0.003	0.242	199
	18	Computer use per day (hours)	6.396	0.095	-	199
	19	Age	$p=0.958$, Mann–Whitney $U=4815.5$			
	20	Disability	1.350	0.365	-	188
	21	Gender identity	6.554	0.015	0.187	188
	22	Ethnicity	0.290	0.626	-	187
	23	Looked after young person	0.119	0.553	-	190
About You	24	Young Carer (see Appendix note)	0.769	0.573	-	191
	25	Free school meals or Pupil Premium	0.261	0.631	-	191
	26	Access to computer at home?	0.061	1.000	-	193
	27	Access to computer at school?	0.455	0.643	-	193

sub-datasets (Female and Male) were analyzed using the same appropriate tests as described in the previous section and are presented in Table 5 for question 2 and Table 6 for questions 5–15. Questions 18–27 were not included in the analysis for gender (nor for ethnicity in the "Ethnicity Differences" section) as multiple layers of demographic filtering reduced sample sizes and meant some participants with intersectional marginalized identities could be identifiable.

The difference between Prior and No Prior responses for questions 2a, 2c, and 2e for the Male group aligns with those seen in Table 3 but is not observed among Females. Males with no prior experience are more likely to believe that coding is difficult and that powerful computers are a requirement, and less likely to believe coding is simple. Similarly, the difference seen in question 2b for Table 3 only persists among Females and is not seen in the Male group suggesting

Table 5 Results from comparisons between NPE and PE groups for question 2 after splitting responses by gender identity

Q	Female					Male				
	Avg ± σ		p	F	Effect size, d	Avg ± σ		p	F	Effect size, d
	NPE	PE				NPE	PE			
2a	3.6 ± 1.1	3.1 ± 1.1	0.056	3.776	-	3.6 ± 0.9	2.8 ± 1.0	< 0.001	17.151	0.4231
2b	3.3 ± 1.0	2.7 ± 1.1	0.016	6.059	0.2856	3.3 ± 1.0	3.0 ± 1.1	0.125	2.384	-
2c	2.6 ± 0.8	2.2 ± 1.0	0.062	3.596	-	2.5 ± 1.1	2.0 ± 0.9	0.008	7.405	0.2584
2d	3.0 ± 0.8	2.8 ± 1.3	0.352	0.878	-	3.2 ± 0.9	2.9 ± 1.0	0.179	1.832	-
2e	2.2 ± 0.9	2.6 ± 1.1	0.096	2.844	-	2.1 ± 0.8	2.9 ± 0.9	< 0.001	20.655	0.4286
2f	1.3 ± 0.7	1.4 ± 0.8	0.509	0.440	-	1.3 ± 0.7	1.3 ± 0.6	0.981	0.001	-
	N = 40	N = 35				N = 39	N = 74			

Table 6 Comparing NPE and PE groups within subsets of the data split by gender identity. The *p*-values quoted are two-sided exact values. Cramer's *V* values are only quoted when there is a statistically significant difference between the NPE and PE groups and the exact significance of the symmetric measures are $p < 0.05$

Q	Female				Male			
	χ^2	p	Cramer's V	N_{NPE}, N_{PE}	χ^2	p	Cramer's V	N_{NPE}, N_{PE}
5	9.211	0.003	0.350	40, 35	8.516	0.006	0.275	39, 74
6	3.693	0.066	-	40, 35	5.609	0.029	0.223	39, 74
7	26.325	< 0.001	0.613	35, 35	29.360	< 0.001	0.521	37, 71
8	3.555	0.083	-	40, 35	14.665	< 0.001	0.360	39, 74
9	2.513	0.162	-	40, 35	0.141	0.843	-	39, 74
10	13.463	< 0.001	0.459	33, 31	5.562	0.066	-	35, 70
11	10.376	0.004	0.451	25, 26	1.276	0.515	-	39, 74
12	3.013	0.147	-	40, 35	1.670	0.289	-	39, 74
13	5.672	0.025	0.275	40, 35	5.919	0.020	0.229	39, 74
14a	0.103	0.950	-	40, 35	1.338	0.527	-	39, 74
14b	2.710	0.263	-	40, 35	0.230	0.901	-	39, 74
14c	1.489	0.477	-	40, 35	3.759	0.148	-	39, 74
15	3.834	0.159	-	40, 35	11.677	0.003	-	39, 74

that females with no prior experience are more likely to believe that good mathematical ability is required for coding.

The largest effect observed (based on Cramer's *V*) within this subset of questions shown in Table 4 was for Q7 where both gender groups reported a difference in awareness of websites dedicated to learning code online. Both gender groups report that coding classes being available at school were more likely for students within the Prior group, though only the Male group reported a difference between Prior and No Prior in terms of coding being taught as part of other classes. The cause of this is uncertain but may be due to gender bias when choosing A-level courses[2] in school or college.

In terms of other differences between gender groups, Female respondents differed in the opportunities available with school clubs and external groups where attendees could learn to code, though it is unclear from this dataset whether the opportunities were less available to the Female No Prior subgroup or whether they were available, but respondents chose not to or could not attend. Males with Prior experience were more likely to have seen or heard of other people like them coding (average score 1.41 ± 0.60), whereas Females overall and Males with No Prior on average reported "Sometimes" on question 15 (1.08 ± 0.56 and 0.97 ± 0.67, respectively). It is impossible to state whether this relationship seen for the Male Prior group is causal; however, it is important to note the link between seeing or hearing of "people like me" and engaging with coding prior to attending university.

Finally, it is important to note that both gender groups noted a difference in receiving positive encouragement from teachers in starting their coding experience (Q13). While this difference is something that should be addressed by teachers providing encouragement to all students, it is positive to note that no gender bias was observed in this study.

Ethnicity Differences

The full dataset was split into two groups based on the response to question 22 ("Please choose the category which you feel most closely describes your ethnicity."). These categories were then collated into two groups, White and Black, Asian, and Minority Ethnicities (BAME). While we acknowledge the limitations inherent in the use of the term "BAME," particularly its potential to homogenize diverse ethnic experiences and overlook nuanced disparities, it was deemed necessary for the purpose of this study to employ a broad categorization due to constraints related to respondent anonymity and the small sample sizes of specific ethnic groups. This decision was made with careful consideration of the trade-off between granularity and confidentiality, recognizing the complexities involved in capturing the full spectrum of ethnic identities and experiences within the constraints of our research methodology. These two separate sub-datasets (BAME and White) were analyzed using the same appropriate tests as described in the previous section and are presented in Table 7 for question 2 and Table 8 for questions 5–15.

The difference between Prior and No Prior responses for questions 2a, 2c, and 2e for both BAME and White group aligns with those seen in Table 3 for questions 2a, 2c, and 2e but not for question 2b. This suggests that any differences seen between the NPE and PE groups are not related to ethnicity for this question.

[2] A levels are advanced academic qualifications in the UK, typically pursued by students aged 16 to 18, which serve as a standard for university entrance requirements.

Table 7 Results from comparisons between NPE and PE groups for question 2 after splitting responses by ethnicity

Q	BAME					White				
	Avg ± σ		p	F	Effect size, d	Avg ± σ		p	F	Effect size, d
	NPE	PE				NPE	PE			
2a	3.6 ± 1.0	2.9 ± 1.0	0.022	5.603	0.3153	3.6 ± 1.0	2.8 ± 1.0	< 0.001	19.776	0.3893
2b	3.5 ± 1.0	3.1 ± 1.2	0.227	1.496	-	3.2 ± 1.0	2.8 ± 1.1	0.060	3.608	-
2c	2.9 ± 1.1	2.2 ± 0.8	0.015	6.289	0.3408	2.4 ± 0.8	2.0 ± 0.9	0.010	6.807	0.2299
2d	3.4 ± 0.9	3.1 ± 1.1	0.252	1.342	-	2.9 ± 0.8	2.8 ± 1.1	0.399	0.715	-
2e	2.2 ± 0.8	2.8 ± 0.9	0.006	8.192	0.3854	2.2 ± 0.9	2.8 ± 1.0	< 0.001	13.091	0.3198
2f	1.6 ± 1.1	1.6 ± 0.7	0.888	0.020	-	1.1 ± 0.4	1.2 ± 0.7	0.277	1.193	-
	$N = 24$	$N = 31$				$N = 52$	$N = 80$			

With Q13, a statistically significant difference is found within the White group, with those with prior experience more likely to get positive praise from teachers (43.8% for PE compared to 21.1% for No Prior). The BAME group shows no difference between NPE and PE groups for the same question, and only 25.5% of all BAME students received positive encouragement from teachers. A similar observation is made to that for gender in Table 5 with regard to whether respondents had seen or heard of someone like them coding (question 15). BAME respondents showed no statistically significant difference between PE and NPE, with an average response of (1.16 ± 0.66) whereas White Prior respondents had a higher average score (1.34 ± 0.62).

Free-Text Responses

Free text responses were collected in Q3 and Q4 ("What benefits do you think there are in being able to code?"), where the wording for Q3 differed depending on their response in Q1 (Prior: "What factors motivated you in learning to code?" and No Prior: "What factors have prevented you from learning to code"). Thematic analysis was performed on the responses following the well-established 6-step framework developed by Braun and Clarke (2006). Given its extensive validation and widespread acceptance in qualitative research, we do not provide a detailed description of the methodology here. Readers are directed to Braun and Clarke's original paper and subsequent works (Braun et al., 2019; Xu & Zammit, 2020) for comprehensive guidance on the approach and its validity. Codes were generated at the question level for NPE and PE groups separately. The codes were then condensed into themes for Q3 and Q4 by combining the prior and no prior datasets, but the dataset information was retained for quantitative comparison after the thematic analysis was completed.

Q3: Motivators and Barriers

There were 36 codes identified for Q3 which condensed into six overarching themes as summarized in Table 9, and the frequencies of codes within each theme split by NPE and PE groups as well as by positive or negative meaning are shown in Fig. 3.

Respondents with prior coding experience expressed motivators under the Purpose/Tool theme related to coding having a purpose or being a tool such as problem-solving and the development of websites, games, and apps. Despite this, the most frequent code in this theme (and indeed in all themes) is that coding was a requirement for their studies. Similarly, the group with no prior experience stated the lack of requirements as part of their other courses as a barrier to learning to code.

For the prior experience group, those codes grouped under the Personal theme mentioned personal development and challenge as well as several references to enjoyment and social aspects of coding. The group with no prior experience discussed a lack of interest and motivation alongside the view that learning to code would be difficult and complicated under the Personal theme.

Thirty of the 109 codes from the PE group clustered under the Own Future theme. These respondents highlighted the benefit to their own career and degree aspirations, with a small number mentioning the long-term financial benefit of higher salaries. The three codes from the NPE group under this theme were all positive and indicated that while they themselves did not engage with learning to code previously they can see the future career and financial benefit of having some coding ability.

Influence was cited as a motivating factor for the Prior group, with influence ranging from teachers and parents to TV and games. Two respondents from the No Prior group stated that coding was "not encouraged at a girl's school," though it is unclear whether this is a lack of encouragement or active discouragement. Nevertheless, the gender stereotype has had some influence on their opportunity to learn to code.

Table 8 Comparing NPE and PE groups within subsets of the data split by ethnicity. The *p*-values quoted are two-sided exact values. Cramer's *V* values are only quoted when there is a statistically significant difference between the NPE and PE groups and the exact significance of the symmetric measures are $p < 0.05$

Q	BAME				White			
	χ^2	p	Cramer's V	N_{NPE}, N_{PE}	χ^2	p	Cramer's V	N_{NPE}, N_{PE}
5	12.823	< 0.001	0.483	24, 31	5.648	0.019	0.207	52, 80
6	3.625	0.099	-	24, 31	6.941	0.012	0.229	52, 80
7	17.363	< 0.001	0.583	21, 30	31.099	< 0.001	0.499	48, 77
8	7.700	0.005	0.374	24, 31	10.956	< 0.001	0.288	52, 80
9	0.127	0.466	-	24, 31	1.823	0.121	-	52, 80
10	6.154	0.048	0.362	18, 29	10.300	0.006	0.288	49, 75
11	5.164	0.061	-	14, 23	3.881	0.148	-	36, 60
12	2.957	0.156	-	24, 31	3.875	0.056	-	52, 80
13	1.733	0.226	-	24, 31	7.078	0.008	0.232	52, 80
14a	0.364	0.885	-	24, 31	0.866	0.681	-	52, 80
14b	1.807	0.628	-	24, 31	4.285	0.104	-	52, 80
14c	0.041	1.000	-	24, 31	7.602	0.020	0.240	52, 80
15	2.668	0.309	-	24, 31	8.936	0.011	0.260	52, 80

The factors preventing the No Prior group were predominantly in the Logistics theme, with a lack of opportunity at school being highlighted as one factor (in line with the differences found for question 5 in Table 4). Other logistical barriers faced are a lack of time, either in school due to clashes between subjects or other commitments outside of school preventing independent learning or joining community classes, and in some cases the lack or limited access to suitable computers either at school or in their home life. There were no codes from the PE group under the Logistics theme, either positive or negative.

Q4: Benefits

There were 25 codes identified for Q4 which condensed into 4 overarching themes as summarized in Table 10, and the frequencies of codes within each theme split by NPE and PE groups are shown in Fig. 4.

Employability and developing transferable skills, primarily "problem solving" and "logical thinking," were the most frequent responses by the prior experience group. The No Prior group also recognized that employability is a benefit of learning to code but did not comment as often on the transferable skills. It is particularly noteworthy that the most common code from the No Prior group is under "data handling and automation" which suggests that these respondents have some general appreciation of what coding is used for but only recognize the end tool.

Question 4 asked both Prior and No Prior groups to identify any benefits that result from being able to code. Both groups identified a better understanding of how computers and technology works. Under the Personal theme, both groups similarly noted that coding helps provide new insights, different ways of thinking, and access to higher levels of science, but only the Prior group coded against "Patience and Creativity" and "Enjoyable."

Within the theme of Purpose, both groups noted that coding can provide benefits as a tool for problem-solving, saving time and automation, and for simulations and modeling. More respondents in the No Prior group specified using coding for data handling specifically whereas the Prior group focused more on broader task automation and efficiency, something that may indicate a misconception about the breadth of application that coding has beyond specific data handling and analysis tasks.

The transferable skills theme is where a significant difference was seen between the Prior and No Prior groups. The Prior group made frequent references to developing a wide range of skills (72 across all skill codes) whereas the No Prior group made far fewer references (11 in total) with no references against reasoning or abstract thinking skills. Both groups referred to employability as a benefit, slightly more common in the Prior group with 29 codes representing 24.7% of this group compared to 16 in the No Prior group representing 19.5%.

Discussion and Conclusion

The digital age has brought forth unprecedented opportunities and advancements, contributing significantly to economic growth, education, and social connectivity. However, the benefits of the digital age are not uniformly distributed, leading to the emergence of the digital divide. This divide is multifaceted, extending beyond mere access to encompass digital skills and usage patterns. As the digital landscape evolves, it becomes imperative to explore and understand additional dimensions of this divide. This paper contributes to the ongoing discourse by examining barriers within a specific cohort of undergraduate physics students in the UK, shedding light on a potential fourth

Table 9 Themes identified from the free text responses for question 3 using the Thematic Analysis protocol developed by Braun and Clarke (2006). The PE group was asked about motivators only and NPE about barriers only

Theme	Code
Gender	Gender split. No role models
	Show that girls can do it
	From parents
Influence	From teachers
	From TV and games
	Not encouraged at a girl's school
	No computing access
	No opportunity
Logistics	No teaching at school
	No time
	Prioritized/clashed with other courses
	Career aspirations
Own Future	Degree aspirations
	Leads to money
	A personal challenge
	Better use of my time
	Cool thing to do
	Develop logical thinking
	Difficult and complicated
Personal	Lacking in motivation
	No interest
	No patience
	Not fun, only practical
	Skills development
	Social, fun, enjoyment
	Better use of electronics
	Create video games
	Lots of work with no clear benefit
	Mandatory for course/school work
Purpose/Tool	No reason to. Not necessary for other courses
	No purpose
	Skill of debugging
	Systems control, automation, and AI
	Tools for other outcomes (e.g., websites and apps)
	Understand how computers work
	Useful tool for solving problems

Table 10 Themes identified from the free text responses for question 4 using the Thematic Analysis protocol developed by Braun and Clarke (2006)

Theme	Code
Computers & Technology	Understand how computers work
	Access to higher level science
	Different way of thinking
	Enjoyable. Good use of free time
Personal	Money
	New insights
	Patience and creativity
	Personal resilience and health
	Satisfaction
	Cost and/or time saving
	Data handling and automation
Purpose	Modeling
	Simulations
	Task automation/task efficiency
	Tool for problem solving
	Broader computer literacy
	Creative in the digital age
	Employability
Transferable Skills	Improves skills: i. Abstract thinking ii. Analytical thinking iii. Logical thinking iv. Mathematics v. Problem solving vi. Reasoning
	Teaches goal-oriented project management
	Useful for niche areas/jobs

level of the digital divide related to technical and production knowledge, particularly in coding.

The three-level model of the digital divide has been instrumental in capturing disparities in general digital usage. However, our study suggests the existence of a fourth level that delves into technical and production knowledge. This level encompasses skills related to building desktop computers, physical computing devices such as Arduinos, and proficiency in coding languages. Recognizing this fourth level is crucial as science and technology increasingly demand computational skills. These findings align with the broader focus on integrating technical expertise into science education, ensuring students are equipped with the competencies required in both academic and professional contexts.

Our research reveals the challenges faced by undergraduate physics students in the UK when it comes to learning coding. Novice programmers encounter technical difficulties, ranging from syntax complexities to misconceptions inherited from previous coding experiences. These barriers are consistent with existing literature but take on a new dimension when examined within the specific context of physics education. The lack of consensus in teaching methodologies, as noted by Cartile (2020), poses a significant obstacle that warrants attention and a potential shift toward developing a taxonomy of computational thinking. Our study further highlights demographic disparities in coding education. Gender differences are evident, with male students exhibiting higher odds of prior coding experience. Additionally, the perceived requirement for significant mathematical ability and advanced computing resources

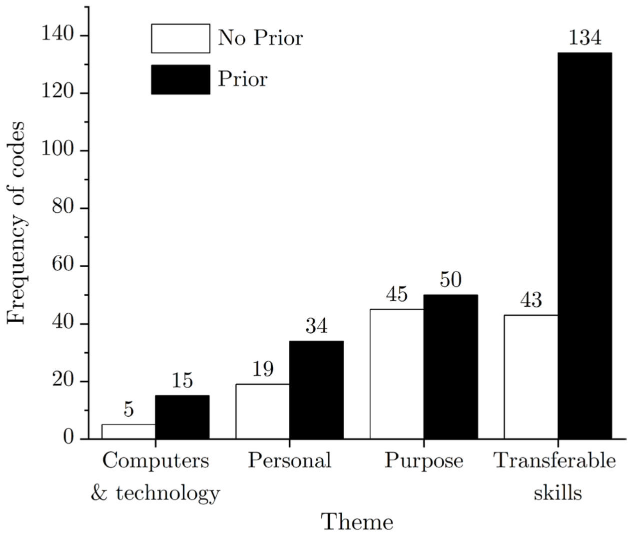

Fig. 4 Frequency of codes present in free text responses to question 4, grouped by themes identified using the thematic analysis protocol (Braun & Clarke, 2006)

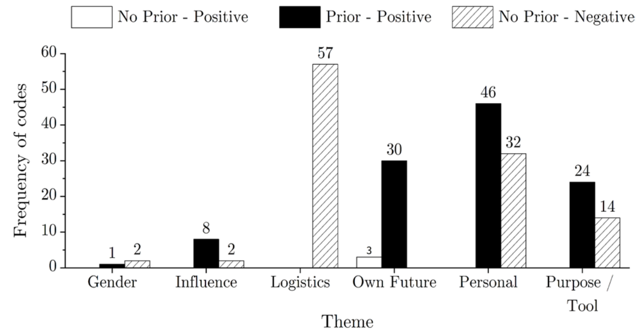

Fig. 3 Frequency of positive and negative codes present in free text responses to question 3, grouped by themes identified using the thematic analysis protocol (Braun & Clarke, 2006). There were no instances of negative codes in the Prior group

among students without prior experience highlights the need for better communication about coding's accessibility and relevance.

Our findings also highlight significant demographic disparities. Gender differences are evident, with male students exhibiting higher odds of prior coding experience, a trend aligning with the broader narrative of gender imbalances in certain STEM fields. Ethnicity also plays a role, with varying levels of access to coding-related resources and positive encouragement from teachers across different ethnic groups. Addressing these disparities is essential for fostering diversity and inclusivity in coding education. The lack of role models and encouragement, particularly among female and BAME students, underscores the importance of representation in both the classroom and broader educational initiatives. Beyond demographic disparities, this study highlights a concerning gap in the recognition of transferable skills associated with coding. Students with prior coding experience were more aware of the broad applicability of these skills, including problem-solving, logical thinking, and employability benefits, compared to their peers without such experience. These findings underscore the need to reshape perceptions of coding from a niche technical skill to a critical component of modern education, with significant applications across scientific, technological, and social domains.

The educational differences observed in this study emphasize the critical role institutions and educators play in shaping coding exposure. Variations in access to coding classes, embedding coding into other courses, and the promotion of coding resources directly influence student experiences. These disparities highlight the need for cohesive strategies that integrate coding into physics curricula, leveraging contextualized exercises and accessible platforms to address both logistical and perceptual barriers.

Additionally, this study points to broader implications for science education and the integration of technology. Coding, as both a technical and transferable skill, serves as a gateway to interdisciplinary innovation. Embedding coding into physics education provides opportunities for students to engage with cutting-edge research, develop innovative solutions to real-world problems, and build a foundation for lifelong learning in a rapidly evolving technological landscape. These efforts not only prepare students for the demands of their academic and professional futures but also contribute to addressing global challenges where computational thinking and problem-solving are essential.

In summary, this study contributes to understanding how barriers to coding align with a new dimension of the digital divide, and the findings highlight critical opportunities for intervention. By addressing these barriers through inclusive pedagogical approaches and systemic changes, educators and institutions can ensure that coding education is accessible, equitable, and impactful for all students.

Future Directions and Recommendations

While this research provides valuable insights, it opens avenues for future exploration. Understanding the root causes of the digital divide within technical domains, such as building computers and coding, requires further investigation. Additionally, exploring the effectiveness of different pedagogical approaches in addressing coding barriers can contribute to the development of comprehensive and inclusive coding education programs.

The extension of the fourth level to the digital divide model should be explored further with the construction and validation of a more comprehensive opinion-based survey that educators could use to identify potential perceptual barriers amongst their students and use this to guide their support and strategies for both the teaching of coding and the use of coding in their physics curriculum.

Future work should focus on linking the opinions (Q2 of survey), experiences (Q3–16, Q18), and identity (Q19–Q27) of respondents with both confidence in their coding ability and their coding proficiency at the start and end of their physics programs. Such a longitudinal study will help refine this survey into a semi-diagnostic tool that could shape the pedagogical approaches taken to support students with less confidence or experiences prior to joining university.

This study contributes a nuanced perspective to the discourse on the digital divide by identifying a potential fourth level related to technical and production knowledge. The disparities uncovered within the cohort of undergraduate physics students underscore the importance of addressing coding barriers to ensure a more inclusive and equitable digital future. This fourth level adds to the existing model by emphasizing the need for targeted interventions that go beyond access and usage, focusing on the skills required for digital creation.

While this research provides valuable insights, it also highlights avenues for further exploration. A deeper understanding of the root causes of this fourth-level digital divide, particularly in technical domains such as coding, is necessary. Longitudinal studies linking students' opinions, experiences, and identities with their confidence and proficiency in coding would provide critical data to refine teaching practices and interventions.

We propose the following recommendations grounded in the findings of this study:

1. Provide early and equitable access to coding resources: The study highlights that students without prior coding experience often lacked awareness of accessible online resources for learning coding. Universities, schools, and educators should proactively signpost and promote platforms such as free coding websites, tutorials, or apps to both current students and prospective students during outreach activities. Examples of free resources include freeCodeCamp (https://www.freecodecamp.org/), Codecademy (https://www.codecademy.com/) and Khan Academy (https://www.khanacademy.org/).
2. Embed contextualized coding projects into the curriculum: Students without prior experience frequently viewed coding as niche or specific to particular tasks. Incorporating projects that connect coding with diverse problems, such as modeling physical systems, analyzing experimental data, or simulating real-world phenomena, can expand student perceptions of coding's utility (Wolz et al., 2020).
3. Enhance teacher training and support: A significant finding of this study was the lack of teacher encouragement reported by underrepresented groups. Professional development programs for educators should focus on inclusive teaching practices, enabling teachers to provide positive reinforcement and avoid perpetuating stereotypes about who "belongs" in coding (Artze-Vega et al., 2014).
4. Develop scaffolded learning pathways: Many students without prior experience identified coding as intimidating or overly complex. Introducing scaffolded exercises that gradually increase in difficulty, supported by peer mentoring or tutoring programs, can help students build confidence and proficiency incrementally (Kaldaras et al., 2024; Lee et al., 2024).
5. Promote awareness of transferable skills: Students with prior coding experience were more likely to recognize transferable skills such as logical thinking and problem-solving. Educators should explicitly highlight these broader applications of coding, linking them to employability and the development of key skills relevant to physics and other disciplines (Scherer et al., 2019).
6. Address institutional barriers to equity in coding education: Institutional differences in access to coding classes and resources were evident in this study. Universities should ensure that coding is a mandatory and integrated part of the physics curriculum, with equitable access to the necessary equipment, such as loaner laptops or high-performance computing facilities, for all students (Rea, 2022; Chikwe et al., 2024).
7. Increase representation and visibility of role models: The findings indicated that students without prior experience were less likely to have seen role models who reflected their identities. Institutions should work to increase the visibility of diverse role models in coding through guest lectures, mentoring schemes, and student showcases that celebrate diverse projects and achievements (Cheryan et al., 2013; Gladstone & Cimpian, 2021).
8. Enhance outreach and engagement programs: A lack of pre-university exposure to coding was a recurring theme. Outreach efforts should include partnerships with schools to deliver workshops that focus on coding fundamentals, particularly targeting underrepresented groups, including female and ethnic minority students (Chen et al., 2023).
9. Conduct longitudinal studies to measure impact: The differences observed in students' initial perceptions of coding suggest that longitudinal studies could provide valuable insights. Tracking students' confidence and coding proficiency over time would enable educators to better understand how interventions shape outcomes and refine teaching strategies accordingly.

These recommendations align closely with the findings of this study, offering practical steps to address the barriers faced by students from diverse backgrounds. By implementing these targeted interventions, educators and institutions can help bridge the fourth level of the digital divide, fostering a more inclusive and equitable environment for coding education.

Appendix. Survey questions

Table 11

Table 11 Survey questions sent to participants. Numbers in brackets under Responses indicate codes assigned for analysis using SPSS

Q	Question Text	Responses
1	Do you have any prior coding experience?	Yes (1) No (0)
2	Please indicated whether you agree or disagree with the following statements:	Strongly Disagree (1) Disagree (2) Neither Disagree nor Agree (3) Agree (4) Strongly Agree (5)
2a	Coding is difficult	
2b	Coders need to be good at maths	
2c	A powerful computer is needed for coding	
2d	Coding is abstract	
2e	Coding is simple	
2f	Gender plays a part in coding ability	
3	What factors have prevented you from learning to code [if No in Q1] What factors motivated you in learning to code? [if Yes in Q1]	Free text response
4	What benefits do you think there are in being able to code?	Free text response
5	At school were there any classes where ONLY coding was taught?	Yes (1) No (0)
6	Was coding taught as part of any other classes in your school?	Yes (1) No (0)
7	Are you aware of websites where you can learn to code online?	Yes and I use them (2) Yes but I don't use them (1) No, I'm not aware of any (0) Not sure
8	Do you have any ICT or Computing qualifications?	Yes (1) No (0)
9	Is there an adult in your life who works with computers or other types of technology?	Yes (1) No (0)
10	Were there any clubs or groups that meet at your school where students learn to code?	Yes and I attended them (2) Yes but I didn't attend them (1) No, there were no clubs or groups (0) Not sure
11	Were there opportunities in your community for students like you to learn to code outside of your school?	Yes and I attended them (2) Yes but I didn't attend them (1) No, there were no opportunities (0) Not sure
12	Do you have any friends who code?	Yes (1) No (0)
13	Has a teacher ever told you that you would be good at coding?	Yes (1) No (0)
14	How often do you see or read about people coding in the following places:	Often (2) Sometimes (1) Never (0)
14a	- in TV shows	
14b	- in movies?	
14c	- online through social media / articles / videos?	
15	How often do you see or hear of people like you coding?	Often (2) Sometimes (1) Never (0)
16	Which institution are you studying at?	University College London University of Edinburgh University of Glasgow University of Kent University of Sheffield
17	What is your degree course title?	Free text response

Table 11 (continued)

Q	Question Text	Responses
18	How many hours a day do you use a computer?	0 h (0) 1 – 3 h (1) 4 – 6 h (2) 7 – 9 h (3) 10 + hours (4)
19	How old are you?	Free text response
20	Do you consider yourself to have a disability?	Yes (1) No (0) Prefer not to say
21	What is your gender identity?	Free text response
22	Please choose the category which you feel most closely describes your ethnicity	White Gypsy or Traveller Black or Black British—Caribbean Black or Black British—African Other Black background Asian or Asian British—Indian Asian or Asian British—Pakistani Asian or Asian British—Bangladeshi Chinese Other Asian background Mixed White and Black background—Caribbean Mixed White and Black background—African Mixed White and Asian Other mixed background Arab Other Ethnic background Not known Prefer not to say
23	Are you (or have you been) a Looked After Young Person?	Yes (1) No (0)
24	Are you a Young Carer?[a]	Yes (1) No (0)
25	At school, were you entitled to free school meals or the Pupil Premium?[b]	Yes (1) No (0)
26	Do you have access to a computer at home?	Yes (1) No (0)
27	Did you have access to a computer at school?	Yes (1) No (0)

[a]A “Young Carer” in the UK refers to a young person who has caring or caretaking responsibilities for someone, such as a disabled or elderly parent or relative

[b]In the UK, free school meals are provided to students from low-income families as a form of financial assistance to ensure access to adequate nutrition during the school day. Eligibility is typically based on household income and receipt of certain welfare benefits. The Pupil Premium is additional funding allocated to schools by the government to support students from disadvantaged backgrounds, including those eligible for free school meals, children in care, and those with parents in the armed forces

Acknowledgements The authors would like to thank Drs. Jenny Burnham, Ross Mathieson, Alex Ramadan, and Bianca Sala (all at the University of Sheffield) and Dr. Drew Tarmey (University of Manchester) for their helpful contributions in refining the manuscript, and to Dr. Drew Tarmey for helpful discussions on appropriate statistical methods.

Author Contribution MM, CP, and MQ designed the initial study. All authors were responsible for recruiting participants. MM analyzed and interpreted the quantitative and qualitative results. All authors read and approved the final manuscript.

Data Availability The datasets analyzed during the current study are available in the ORDA repository at https://doi.org/10.15131/shef.data.26053501.

Declarations

Ethics Approval and Consent to Participate This research has approval from a formally constituted University ethics committee at the lead institution (University of Sheffield, reference number 030865). Informed consent was obtained from all individual participants included in the study.

Consent for Publication The authors affirm that human research participants provided informed consent for the publication of their anonymized data.

Competing Interests The authors declare no competing interests.

References

Artze-Vega, I., Richardson, L. and Traxler, A. (2014). Stereotype threat–based diversity programming: Helping students while empowering and respecting faculty. *To Improve the Academy*, 33(1). https://doi.org/10.3998/tia.17063888.0033.102

Bernard, R. M., Borokhovski, E., Schmid, R. F., Tamim, R. M., & Abrami, P. C. (2014). A meta-analysis of blended learning and technology use in higher education: From the general to the applied. *Journal of Computing in Higher Education, 26*(1), 87–122. https://doi.org/10.1007/s12528-013-9077-3

Braun, V., Clarke, V., Hayfield, N., & Terry, G. (2019). Thematic analysis. In P. Liamputtong (Ed.), *Handbook of research methods in health social sciences*, 843–860. Springer. https://doi.org/10.1007/978-981-10-5251-4103

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Cartile, A. (2020). Barriers to digital literacy: Learning to program. *Proceedings of the Canadian Engineering Education Association (CEEA)*. https://doi.org/10.24908/pceea.vi0.14177

Chang, Y. S., Jeon, S., & Shamba, K. (2020). Speed of catch-up and digital divide: Convergence analysis of mobile cellular, internet, and fixed broadband for 44 African countries. *Journal of Global Information Technology Management, 23*(3), 217–234. https://doi.org/10.1080/1097198X.2020.1792231

Chen, C., Rothwell, J., & Maynard-Zhang, P. (2023). In-school and/or out-of-school computer science learning influence on CS career interests, mediated by having role-models. *Computer Science Education, 34*(4), 753–777. https://doi.org/10.1080/08993408.2023.2290435

Cheryan, S., Drury, B. J., & Vichayapai, M. (2013). Enduring influence of stereotypical computer science role models on women's academic aspirations. *Psychology of Women Quarterly, 37*(1), 72–79. https://doi.org/10.1177/0361684312459328

Chikwe, C. F., Dagunduro, A. O., Ajuwon, O. A., & Ediae, A. A. (2024). Sociological barriers to equitable digital learning: A data-driven approach. *Comprehensive Research and Reviews in Multidisciplinary Studies, 2*(1), 027–034. https://doi.org/10.57219/crrms.2024.2.1.0038

Department for Education. (2018). Prime Minister announces £20 million institute of coding. Retrieved February 2, 2024, from https://www.gov.uk/government/news/prime-minister-announces-20-million-institute-of-coding

Department for Digital, Culture, Media & Sport. (2020). DCMS annual report and accounts 2019–20, Technical report, Department for Digital, Culture, Media & Sport. Retrieved February 23, 2024, from https://www.gov.uk/government/publications/dcms-annual-report-and-accounts-2019-20

DesPortes, K., DiSalvo, B. (2019). Trials and tribulations of novices working with the Arduino. In *Proceedings of the 2019 ACM Conference on International Computing Education Research*, 219–227. https://doi.org/10.1145/3291279.3339427

DiSalvo, B., Guzdial, M., Meadows, C., Perry, K., McKlin, T., & Bruckman, A. (2013). Workifying games: Successfully engaging African American gamers with computer science. In *Proceeding of the 44th ACM Technical Symposium on Computer Science Education*, 317–322. https://doi.org/10.1145/2445196.2445292

Dolan, J. E. (2016). Splicing the divide: A review of research on the evolving digital divide among k–12 students. *Journal of Research on Technology in Education, 48*(1), 16–37. https://doi.org/10.1080/15391523.2015.1103147

Enoch, Y., & Soker, Z. (2006). Age, gender, ethnicity and the digital divide: University students' use of web-based instruction. *Open Learning: The Journal of Open, Distance and e-Learning, 21*(2), 99–110. https://doi.org/10.1080/02680510600713045

Fang, M. L., Canham, S. L., Battersby, L., Sixsmith, J., Wada, M., & Sixsmith, A. (2019). Exploring privilege in the digital divide: Implications for theory, policy, and practice. *The Gerontologist, 59*(1), e1–e15. https://doi.org/10.1093/geront/gny037

Field, A. (2009). *Discovering statistics using SPSS*. Sage Publications.

Ganesh, S., & Barber, K. F. (2009). The silent community: Organizing zones in the digital divide. *Human Relations, 62*(6), 851–874. https://doi.org/10.1177/0018726709104545

Gladstone, J. R., & Cimpian, A. (2021). Which role models are effective for which students? A systematic review and four recommendations for maximizing the effectiveness of role models in STEM. *International Journal of STEM Education, 8*, 59. https://doi.org/10.1186/s40594-021-00315-x

Gonzales, A. (2016). The contemporary us digital divide: From initial access to technology maintenance. *Information, Communication & Society, 19*(2), 234–248. https://doi.org/10.1080/1369118X.2015.1050438

Guzdial, M. (2016). *Learner-centered design of computing education: Research on computing for everyone*. Springer. https://doi.org/10.1007/978-3-031-02216-6

Holcombe-James, I. (2022). Digital access, skills, and dollars: Applying a framework to digital exclusion in cultural institutions. *Cultural Trends, 31*(3), 240–256. https://doi.org/10.1080/09548963.2021.1972282

Israel, M., Wherfel, Q. M., Pearson, J., Shehab, S., & Tapia, T. (2015). Empowering k–12 students with disabilities to learn computational thinking and computer programming. *TEACHING Exceptional Children, 48*(1), 45–53. https://doi.org/10.1177/0040059915594790

Kaldaras, L., Wang, K. D., Nardo, J. E., Price, A., Perkins, K., Wieman, C., & Salehi, S. (2024). Employing technology-enhanced feedback and scaffolding to support the development of deep science understanding using computer simulations. *International Journal of STEM Education, 11*, 30. https://doi.org/10.1186/s40594-024-00490-7

Kelleher, C., & Pausch, R. (2005). Lowering the barriers to programming: A taxonomy of programming environments and languages for novice programmers. *ACM Computing Surveys, 37*(2), 83–137. https://doi.org/10.1145/1089733.1089734

Lahtinen, E., Ala-Mutka, K., J¨arvinen, H.-M. (2005). A study of the difficulties of novice programmers. In *Proceedings of the 10th Annual SIGCSE Conference on Innovation and Technology in Computer Science Education*, 14–18. ACM. https://doi.org/10.1145/1067445.1067453

Lee, H.-Y., Wu, T.-T., Lin, C.-J., Wang, W.-S., & Huang, Y.-M. (2024). Integrating computational thinking into scaffolding learning: An innovative approach to enhance science, technology, engineering, and mathematics hands-on learning. *Journal of Educational Computing Research, 62*(2), 431–467. https://doi.org/10.1177/07356331231211916

Lin, W.-Y., Zhang, X., Song, H., & Omori, K. (2016). Health information seeking in the web 2.0 age: Trust in social media, uncertainty reduction, and self-disclosure. *Computers in Human Behavior, 56*, 289–294. https://doi.org/10.1016/j.chb.2015.11.055

Lythreatis, S., Singh, S. K., & El-Kassar, A.-N. (2022). The digital divide: A review and future research agenda. *Technological Forecasting and Social Change, 175*, 121359. https://doi.org/10.1016/j.techfore.2021.121359

Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, L., Batra, P., Ko, R., Sanghvi, S. (2017). Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages. Technical report, McKinsey Global Institute. Retrieved February 23, 2024, from https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages

Mossberger, K., Tolbert, C. J., & Stansbury, M. (2003). *Virtual inequality: Beyond the digital divide*. American governance and public policy series.

O'Flaherty, J., & Phillips, C. (2015). The use of flipped classrooms in higher education: A scoping review. *The Internet and Higher Education, 25*, 85–95. https://doi.org/10.1016/j.iheduc.2015.02.002

Perry, D. R., & Steck, A. K. (2015). Increasing student engagement, self-efficacy, and meta-cognitive self-regulation in the high school geometry classroom: Do iPads help? *Computers in the Schools, 32*(2), 122–143. https://doi.org/10.1080/07380569.2015.1036650

Piteira, M., & Costa, C. (2013). Learning computer programming: Study of difficulties in learning programming. *In: Proceedings of the 2013 International Conference on Information Systems and Design of Communication*, 75–80. ACM. https://doi.org/10.1145/2503859.2503871

Qian, Y., & Lehman, J. (2018). Students' misconceptions and other difficulties in introductory programming: A literature review. *ACM Transactions on Computing Education, 18*(1), 1–24. https://doi.org/10.1145/3077618

Rea, A. (2022). Coding equity: Social justice and computer programming literacy education. *IEEE Transactions on Professional Communication, 65*(1), 87–103. https://doi.org/10.1109/tpc.2022.3143965

Riggins, F., & Dewan, S. (2005). The digital divide: Current and future research directions. *Journal of the Association for Information Systems, 6*(12), 298–337. https://doi.org/10.17705/1jais.00074

Ritzhaupt, A. D., Dawson, K., & Cavanaugh, C. (2012). An investigation of factors influencing student use of technology in k-12 classrooms using path analysis. *Journal of Educational Computing Research, 46*(3), 229–254. https://doi.org/10.2190/EC.46.3.b

Rogers, S. E. (2016). Bridging the 21st century digital divide. *TechTrends, 60*(3), 197–199. https://doi.org/10.1007/s11528-016-0057-0

Scherer, R., Siddiq, F., & Sánchez Viveros, B. (2019). The cognitive benefits of learning computer programming: A meta-analysis of transfer effects. *Journal of Educational Psychology, 111*(5), 764–792. https://doi.org/10.1037/edu0000314

Schradie, J. (2011). The digital production gap: The digital divide and web 2.0 collide. *Poetics, 39*(2), 145–168. https://doi.org/10.1016/j.poetic.2011.02.003

Selby, C. C. (2015). Relationships: computational thinking, pedagogy of programming, and Bloom's taxonomy. *In: Proceedings of the Workshop in Primary and Secondary Computing Education*, 80–87. ACM. https://doi.org/10.1145/2818314.2818315

Shakina, E., Parshakov, P., & Alsufiev, A. (2021). Rethinking the corporate digital divide: The complementarity of technologies and the demand for digital skills. *Technological Forecasting and Social Change, 162*, 120405. https://doi.org/10.1016/j.techfore.2020.120405

Soomro, K. A., Kale, U., Curtis, R., Akcaoglu, M., & Bernstein, M. (2020). Digital divide among higher education faculty. *International Journal of Educational Technology in Higher Education, 17*(1), 21. https://doi.org/10.1186/s41239-020-00191-5

Subramony, D. P. (2014). Revisiting the digital divide in the context of a 'flattening' World. *Educational Technology, 54*(2), 3–9.

Van Deursen, A. J. A. M., Helsper, E. J., & Eynon, R. (2016). Development and validation of the Internet Skills Scale (ISS). *Information, Communication & Society, 19*(6), 804–823. https://doi.org/10.1080/1369118X.2015.1078834

Van Deursen, A. J. A. M., & Van Dijk, J. A. G. M. (2011). Internet skills and the digital divide. *New Media & Society, 13*(6), 893–911. https://doi.org/10.1177/1461444810386774

Van Dijk, J. A. G. M. (2005). *The deepening divide: Inequality in the information society*. Sage Publications.

Van Dijk, J. A. G. M. (2006). Digital divide research, achievements and shortcomings. *Poetics, 34*(4–5), 221–235. https://doi.org/10.1016/j.poetic.2006.05.004

Van Dijk, J. A. G. M. (2020). *The digital divide*. Polity.

Wamuyu, P. K. (2017). Bridging the digital divide among low income urban communities. Leveraging use of community technology centers. *Telematics and Informatics, 34*(8), 1709–1720. https://doi.org/10.1016/j.tele.2017.08.004

Wang, J., & Hejazi Moghadam, S. (2017). Diversity barriers in k-12 computer science education: Structural and social. *Proceedings of the 2017 ACM SIGCSE Technical Symposium on Computer Science Education*, 615–620. https://doi.org/10.1145/3017680.3017734

Wang, T. W. (2018). Empowering art teaching and learning with iPads. *Art Education, 71*(3), 51–55. https://doi.org/10.1080/00043125.2018.1436353

Ward, N. D., Finley, R. J., Keil, R. G., & Clay, T. G. (2013). Benefits and limitations of iPads in the high school science classroom and a trophic cascade lesson plan. *Journal of Geoscience Education, 61*(4), 378–384. https://doi.org/10.5408/13-008.1

Watts, G. (2020). Covid-19 and the digital divide in the UK. *The Lancet Digital Health, 2*(8), 395–396. https://doi.org/10.1016/S2589-7500(20)30169-2

Wolz, U., Carmichael, G. and Webber, A. M. (2020). A framework for designing contextualized computing curriculum, In: *2020 Research on Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT)*, 1–4, https://https://doi.org/10.1109/RESPECT49803.2020.9272497

Wong, Y. C., Ho, K. M., Chen, H., Gu, D., & Zeng, Q. (2015). Digital divide challenges of children in low-income families: The case of Shanghai. *Journal of Technology in Human Services, 33*(1), 53–71. https://doi.org/10.1080/15228835.2014.998576

Xu, W., & Zammit, K. (2020). Applying thematic analysis to education: A hybrid approach to interpreting data in practitioner research. *International Journal of Qualitative Methods, 19*, 1609406920918810. https://doi.org/10.1177/1609406920918810