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Same Structures, Different Settings: Exploring Computing Capital and Participation across Cultural Contexts

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Abstract

The number of people choosing to study computing in higher education remains low. Previous research has developed a research instrument to identify factors underlying student participation grounded in Bourdieu's sociocultural theory. This study replicates and extends the original study, which identified key social, cultural, and psychological factors linked to computing education participation in Sweden. Using the validated research instrument, we distributed a survey across 11 UK universities, gathering responses from 131 students. Through Confirmatory Factor Analysis, we assessed the robustness of the original study's constructs — career interest, subject-specific interest, influence from family and friends, confidence, and sense of belonging — and their relationship to subject choice in computing. After model refinements, the replication confirmed and validated the factor structure, supporting the stability of these constructs and their relationship to computing subject choice across cultural contexts. In addition, the current study adds additional open-ended questions to the research instrument to help explain the quantitative results. A thematic analysis further explains the correlation between previous experience, social influence, confidence, and gender, and how that relates to participation in the field. By replicating and extending the original study's methodology, this research evaluates the reliability and generalisability of its conclusions, contributing to the evidence base needed to design interventions that broaden participation in computing education.

CCS Concepts

• **Social and professional topics → Computing education**.

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Keywords

Computing education; broadening participation; capital; replication; psychometrics; factor analysis; gender; belonging

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1 Introduction

In 2014, the UK decided to remove GCSE[1] qualifications in Information and Communication Technology (ICT) from the National Curriculum, to be replaced by GCSE Computer Science (CS) to ensure that all young people had the opportunity to develop the digital skills necessary to be "active participants in the digital world" [13]. However, research by Copsey-Blake et al. [7] highlights a troubling shift in participation in the years since: while girls constituted 43% of GCSE ICT entries prior to its discontinuation in 2014, they represented merely 22% of CS students by 2020, dropping further to just 14% at A-Level[2]. Kemp et al. attribute this decline to fundamental changes in subject focus, noting that this new approach does "not appear to be equitable for girls" [19, p.4]. This new CS Curriculum, with its heavier emphasis on programming and reduced focus on creativity, appears to create barriers to participation, particularly for young people from underrepresented backgrounds [23]. This viewpoint is supported by the parent of a female student in a related study who suggested "an identity mismatch between herself (as someone interested in CS as a form of creative endeavour) and

[1] General Certificate of Secondary Education (GCSEs) qualifications are public exams taken in various subjects from the age of about 16 in England, Wales, and Northern Ireland. Equivalent exams in Scotland are National 5s, followed by Highers.
[2] Advanced Levels are academic qualifications in the UK, typically taken by students aged 16-19 after GCSEs.

a 'coder' identity" [16, p.19]. This pattern is similarly evident in Scotland, where despite maintaining ICT as an option, the revised CS curricula prioritises programming over the (potentially creative) applications of computing, coinciding with an overall decline in subject uptake following these curriculum changes [33]. In light of these developments, it is important to study why students choose computing in higher education, in order to design interventions to broaden participation in the field. In the 1970s French sociologist Pierre Bourdieu observed how educational participation and subject choice are intrinsically linked to the *capital* one possesses [4]. Moving beyond economic forms of capital, Bourdieu introduced social and cultural capital, for example being part of an academic family or having knowledge and skills that one can tap into to demonstrate competence and status [3]. More recently, research has used these theoretical constructs to explain participation in computing education from a Bourdieusian perspective [18]. Through extensive literature review, Kallia & Cutts identified an additional form of capital important for studying computing, namely psychological capital as it relates to self-efficacy and sense of belonging to the field. Based on this theoretical framework, a survey instrument was developed and validated in the Swedish higher education context, to capture these forms of capital among higher education students, and to relate it to their participation [24]. The study found differences between computing (n = 241) and non-computing students (n = 191) for 11 out of 14 survey items, whereas for male (n = 189) and female (n = 46) computing students, differences were observed for 6 items. These results suggest that there is a relationship between the proposed forms of capital and participation in computing education, and that this relationship is stronger for male computing students. At the same time, the study acknowledged the unique cultural and educational context of Sweden, and called for replication in other cultural contexts to see if the findings are generalisable beyond the study's context. That is, the current study provides the first empirical validation of these theoretical constructs specifically within the UK higher education context. Motivated by the need of research replication in the face of a replication crisis [34], the current project sets out to understand if the factor structure of the original study is reliable, by using the same research instrument across context and time. By surveying students from higher education institutions across the UK, the following research questions are to be answered:

- **RQ1** To what extent does the factor structure underlying participation in computing education hold across contexts and time?
- **RQ2** What additional insights do qualitative responses provide about the relationship between capital and participation in computing higher education?

The current study finds that the factors identified in the original article holds across samples and after merging the samples, supporting the robustness of the original model in capturing key dimensions of sociocultural and psychological capital influencing computing education participation. After model refinement (see [22]), the factors of career interest, subject-specific interest, influence from friends, confidence, and sense of belonging continue to be indicative of participation in the field. Less support is found for the factor influence from family in both studies in the quantitative results, but it is found to be important in the qualitative findings. When taking gender into account, differences are observed for 6 out of 14 survey items, in particular in confidence and sense of belonging, as was the case in the original study. A thematic analysis of open-ended questions further reveals a correlation between previous experience, social influence, confidence, and gender. Collectively, these findings highlight the robustness of the original survey instrument for measuring factors underlying participation in computing education, while the added open-ended questions provide deeper insights into the students' motivation of subject choice. The findings call for research, policy, and interventions that not only address structural barriers to participation, but also engage with the diverse motivational pathways that students follow when choosing to study computing.

2 Theoretical Background

In educational contexts, few concepts have had an impact as large as that of *capital*. The French sociologist Pierre Bourdieu identified the underlying mechanisms within education systems that contribute to persistent inequalities and significantly influence individuals' life trajectories [3, 9]. According to Bourdieu, formal education plays a crucial role in perpetuating social and economic inequality. This is because it masks the existing social structure as a system based on individual talent or merit [9]. He posited that, to understand the structure and functioning of the social world, one needs to reintroduce capital in all its forms.

In 1986, Pierre Bourdieu wrote: *"Capital is a vis insita, a force inscribed in objective or subjective structures, but is also a lex insita, the principle underlying the immanent regularities of the social world"* [3]. By that, Bourdieu suggested that capital is a deep-seated force that acts like an unspoken law or logic, embedded within both objective structures, such as institutions, and subjective structures, including dispositions and ways of thinking. Apart from economic capital, Bourdieu recognised that individuals' reactions to the world around them are influenced by their cultural upbringing, which shapes their thoughts and behaviors. To explain the often confusing variations in academic achievement among children from different cultural backgrounds, as well as differences in broader cultural and economic practices, he introduced the concept of cultural capital [15]. Cultural capital has allowed researchers to view culture as a resource that can lead to rewards and monopolisation and that can be transferred across generations [27]. In this regard, he identified three forms: the first is embodied, which indicates long-lasting dispositions of the mind and body, such as a particular accent; the second is objectified, which encompasses various cultural goods, including paintings and books; and the third is institutionalised, such as certificates [35]. Social capital is another form of capital recognised by Bourdieu; it refers to resources of networks of relationships that offer individuals a sense of belonging and mutual recognition [3]. A person's social capital is influenced by both the breadth of their network and the types and amounts of capital they hold.

Capital drives the dynamics in a field and determines its outcomes; it acts as the currency of a field [15]. It also shapes the ways individuals gain status or influence to navigate or dominate the field. Individuals in the field compete for resources and forms of capital that hold value within the field (ibid.). Therefore, fields act as sites of ongoing competition, and in these, individuals and groups compete for limited resources [11]. Thus, the nature of the field is also hierarchical [36]; an individual's position within the field is determined by the amount of valued capital they hold. Individuals with a good sense of the field can better judge when the status quo can be challenged and when existing practices can be defended [11]. For example, such strategic variations are particularly evident in education, where families with varying capital compositions adapt their approaches to best position their children within the system [26]. Bourdieu's social theory has provided a valuable conceptual pool for understanding the field of education, and his work has been applied in a variety of fields. For instance, in science education, Archer, DeWitt, Osborne, and their colleagues [2] introduced the idea of *science capital* as both a conceptual framework and a methodological approach. Their work aimed to shed light on how socioeconomic factors shape the participation, aspirations, engagement, and success of children and young people in science education [21].

Within computing education, recent studies have drawn on Bourdieu's theory of capital to understand inequities in the field better. An example is the work of Vrieler and Salminen-Karlsson [38] who combined Bourdieu's theory, science capital, and sociocultural learning theory to propose the concept of *CS capital*, linking it to the experiences of both students and teachers in computing education. In addition, Holmegaard et al. [16] conducted a longitudinal study and explored the impact of capital on the trajectory of nine young people within the CS domain through a series of interviews with students and their parents in England as they progressed through secondary education and into work. They reported that those with CS and maths capital found the path of studying or entering work in CS easier to navigate, and that capital was "unevenly distributed by class and/or gender".

Another work was conducted by Kallia & Cutts [18], which identified three factors that affect student participation and retention: cultural, social, and affective. The authors framed these factors as forms of capital that influence participation in the field and highlight how these capitals are unevenly distributed, contributing to persistent disparities. Building on this, Kunkeler & Nylén [24] used the theoretical framework to design and validate a survey instrument to measure the effects of capital in computing education on participation. Their findings revealed notable differences between groups, particularly between computing and non-computing students and between male and female computing students, suggesting that there is a relationship between the proposed forms of capital and participation in computing education, and that this relationship is stronger for male computing students. Finally, Kirdani-Ryan et al. [20] investigated the way institutional norms influence career pathways in a CS department. Through their work, they highlighted factors, such as industry recruitment practices, curriculum design, and career guidance, that influence students' decisions to pursue roles regarded as 'elite' while marginalising those who diverge from these expectations. Collectively, these studies demonstrate how capital operates within educational fields to shape opportunity, belonging, and exclusion.

3 Methodology

As a replication study, the research instrument for this study was previously developed and validated in the Swedish higher education context [24]. The original research instrument was inspired by Bourdieu's sociocultural theory aimed at measuring social, cultural, and psychological forms of capital that students have access to, allowing them to participate and succeed in the field. After the original study, less support was found for one of the factors in the model, which was subsequently removed [22]. The current study thus follows an established, refined model, which is validated in three samples: the original, the combined, and the current samples. In addition, open-ended questions were added to the research instrument to provide additional insights into the factor structure of the model from a qualitative perspective [31]. The open-ended questions were designed in such a way that, after an initial overarching question about motivations to engage in computing education, they captured each form of capital. For example, students were asked about the social influence on their choice of study (social capital), their sense of belonging (psychological capital), and their early experiences of computing (cultural capital). The full research instrument including design decisions can be found in a supplementing document [22].

3.1 Analysis

For quantitative methods, a Confirmatory Factor Analysis (CFA) was performed across samples and by merging them, where the survey structure identified in the original study was assessed in terms of model fit to the samples [6]. Here the goal was to validate whether the factor structure identified in the original study would also hold across the other samples, meeting the reliability criteria. In survey research, reliability refers to the consistency and stability of the measurement over time and under different conditions [8]. The CFA was performed using the statistical software library *lavaan* in *R* [32]. Using the validated survey structure, a Mann-Whitney *U* (MWU) test was used to analyse sample differences, to detect potential item-level differences that could signal measurement instability or context-specific bias. The MWU test was also used to analyse gender differences in the data, as was done in the original study.

To analyse the qualitative data, which included answers to the open-ended questions, a thematic analysis was conducted in an iterative manner [5]. Prior to the first round of analysis, demographic information from the respondents were hidden as to not influence the coding process. Then, a team of four researchers collaboratively developed and refined the coding framework based on an initial reading of the data. From here, a subset of 15 responses was independently coded, after which ambiguous responses were identified and collectively discussed, and refinements were made to the definitions of the themes to support clarity of interpretation. This resulted in a preliminary code book that each researcher used to analyse the entire dataset independently. After another round of discussion, the team agreed on a final codebook. A final round of coding was performed using the final code book by one of the four researchers. Furthermore, the frequency of each code was recorded per question to support comparative analysis in thematic categories.

Table 1: Survey participants by university

University	Count
Imperial College London	45
University of Strathclyde	21
University of Chester	21
University of Edinburgh	16
Aberystwyth University	8
Other	14

3.2 Sample

3.2.1 Sample size calculation. According to the Higher Education Statistics Agency [1], the total student enrolments to higher education in the UK for the year 2023/24 were 2,904,425 (N). Of these students, 6.6% were enrolled in Computing programmes, totalling 192,140 students. Thus, with a population proportion p of 6.6%, a Z-score of 1.96 for a confidence level of 95%, and a margin of error (e) of 5%, the following formulae were used for the sample size calculation [17] :

$$n = \frac{Z^2 p(1-p)}{e^2}$$

$$n_f = \frac{n}{1 + \frac{(n-1)}{N}}$$

Where $n_f = 95$ is the minimum sample size adjusted for a finite population.

3.2.2 Actual sample. The minimum sample size was exceeded, with the actual sample size including 131 students from 11 UK universities. The respondents were recruited through a contact person at their respective university, and participation was voluntary and not remunerated. The authors circulated the invitation at their own institution and through contacts at other universities in their networks. Students were sent an invitation to participate in the survey, including an information sheet regarding the data collected, processing and handling. The data collection was approved by the ethical review board at the University of Glasgow, which also included permissions to collect data at other universities in the UK. A GDPR-compliant survey tool, hosted by Uppsala University, was used for data collection. In addition, only researchers from the research team had access to the data collected.

3.2.3 Data cleaning. In order to prepare the collected data for analysis, the data was cleaned in the programming environment of *Jupyter Notebooks* using the programming language *Python* with the library *pandas* [29]. First, four respondents who incorrectly answered the Attention-Check question were removed from the dataset. Then, two duplicate survey responses were removed from the dataset. This resulted in the sample as can be found in Table 1. Finally, missing values were handled using a single-value imputation method based on the item-level median. While multiple imputation methods are generally preferred [28], the single imputation method was justified in the context of this study as the percentage of missing values was extremely low, namely 0.42%. Data inversion was applied to the three negative statements found in the survey.

3.2.4 External validity. External validity captures the extent to which inferences drawn from a given study's sample apply to a broader population or other target populations [12]. In other words, it refers to the representation of the research sample with regard to the population of computing students in the UK. As can be seen in Table 1, the sample included multiple large universities in the UK that span different geographical areas. From a gender perspective, the sample included 41 women (32.8%). This means that women in higher computing education in the UK were slightly overrepresented in the current study, since the population proportion is 25.3% for the academic year 2023/24 [1]. This difference falls within an acceptable range of deviation (<10%), especially since gender is not the key moderator of the study.

4 Quantitative results

The quantitative analyses consists of replication and group comparison across samples and between groups. After measurement adjustment, model fit indices were compared across independent samples, revealing consistent model adequacy and supporting the generalisability of the factor structure identified in the original study. Factor loadings demonstrated strong alignment across samples, indicating factor structure invariance. The CFA also suggests the dominant themes that relate to participation in computing higher education. Using MWU tests, the Swedish and UK samples are compared, as well as male and female students in the UK sample. Falling in line with the original study, gender differences are observed for 6 out of 14 survey items, and minimum item-level differences are observed between the samples, suggesting measurement stability and supporting the reliability of the research instrument.

4.1 Replication

The replication procedure in this study follows a three-sample design: the original sample, the current sample, and a combined sample. In the first instance, a CFA is performed on the combined sample to assess potential deviations in model fit compared to the original study. Next, model fit indices from the original study are compared with those from the combined sample to evaluate consistency. Finally, after confirming that the model holds across samples, the fit indices of the original and current samples are directly compared [3].

4.1.1 Comparison of model fit across samples. Since the model involved ordinal data, the Weighted Least Squares Mean and Variance (WLSMV) adjusted method was used for the CFA [30]. Then, using the Diagonally Weighted Least Squares (DWLS) estimator, the factor structure also converged combined sample, as can be seen in Table 2. Overall, the results indicate a highly consistent model fit across samples, suggesting strong replicability of the factor structure, especially after model refinements. The scaled chi-square statistic values were non-significant in both models, indicating acceptable fit; however, the combined sample approached significance (p = 0.072) more closely than the original (p = 0.218). While a non-significant chi-square is desirable, this test is known to be sensitive to sample size, and both values fall within a range

[3]For a full overview of the CFA standardised loadings, refer to the supplementing material of this publication

Table 2: CFA results

	Original sample	Combined sample
Scaled X^2 p	0.218	0.072
Robust CFI	0.969	0.97
Robust TLI	0.948	0.949
SRMR	0.038	0.033
Robust RMSEA	0.069	0.069

typically interpreted as reflecting adequate model fit. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) were virtually identical between the two models. These values are above the commonly accepted threshold of 0.95 (for CFI) and close to 0.95 (for TLI), indicating very good fit for both samples and near-perfect consistency in comparative model performance. The Standardised Root Mean Square Residual (SRMR) values — 0.038 (original) and 0.033 (combined) — were both well below the 0.08 threshold, suggesting excellent absolute fit in both models and a slight improvement in the combined sample. The Root Mean Square Error of Approximation (RMSEA) was identical across models at 0.069, which is just below the 0.07 threshold often considered indicative of a reasonable error of approximation in population. The consistency of RMSEA further supports the replicability of the factor structure of the model. In sum, the model fit indices from the combined sample closely mirror those from the original sample. The minimal differences observed across indices suggest a high degree of stability and generalisability of the factor structure proposed here across samples. These findings support the robustness of the factor structure in capturing key dimensions of sociocultural and psychological capital influencing computing education participation, and provide evidence for the model refinements made here.

4.1.2 Comparison of factor loadings across samples. In CFA, factor loadings indicate the strength and direction of the relationship between items and factors, with values ranging between -1 and 1. While there is no clear consensus on the acceptable value of a factor loading, a value $\geq$ 0.71 indicates a strong correlation between the item and factor [6]. Figure 1 visualises the factor structure of the survey and the factor loadings for each factor and item. As can be observed, most factor loadings exceeded the 0.71 treshold, indicating strong correlations between the items and factors. The pattern of factor loadings was highly similar in the original sample and the combined one, supporting structural equivalence. Most items demonstrated strong associations with their respective latent factors, with standardised loadings exceeding 0.71 across both samples. While minor item-level variation in loadings was observed, these differences were not substantial and did not undermine the overall integrity or interpretability of the factor structure. These results suggest that the construct was measured similarly across samples, reinforcing the robustness of the model.

4.2 Group comparison

The CFA suggests the dominant themes related to participation in computing higher education, as can be seen in Figure 1. To compare the distributions of the data between the gender groups, a MWU test was performed. Table 3 shows the median value for each survey

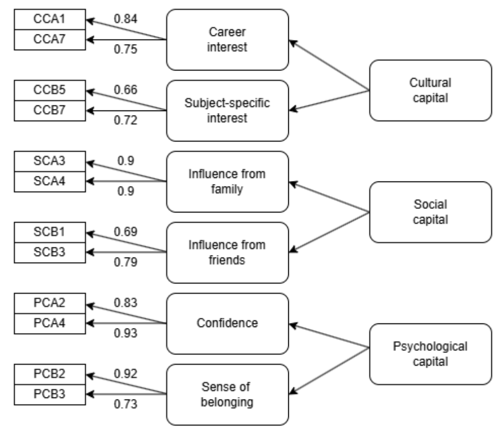

Figure 1: CFA factor structure on the combined sample

item per group, in addition to the associated test p-value and rank-biserial correlation effect size r_{rb}. Groups are said to be statistically significantly different for a survey item using a significance threshold of 0.05. No p-value adjustments (e.g. Benjamini-Hochberg) were applied in the context of this study or the original, since the MWU tests are not part of the main hypotheses or research questions, but rather serve as supplementary, item-level contextualisations of the CFA results [14].

4.2.1 General observations. Respondents scored high on the survey items, with Median values in the 3–5 range (min = 1, max = 5). Consistent with the original study, these higher median values were expected for computing students who are more likely to agree with the statements on the survey. This suggests that the factors which were identified in the CFA are indicative of participation in computing higher education. Notably, both groups scored 3 on one of the items (SCA4) on the *Influence from family* factor, but 4 on the other item (SCA3). This could suggest a problem with the question statement for SCA4, or that the respondents did not consider family an important factor for subject choice on the survey statements.

4.2.2 Gender differences. The obtained p-value is less than or equal to the predetermined significance level of 0.05 for 6 out of 14 survey items. These differences are mostly concentrated in the psychological capital elements of the survey. Most notably, women scored lower on factors *Confidence* and *Sense of belonging*. These findings were also reported in the original study, validating that this is a consistent barrier to computing participation for female students across cultural contexts.

4.2.3 Differences across samples. MWU tests were conducted to compare responses between the original sample and the current sample. The findings of this analysis can be found in Table 4. This analysis aimed to detect potential item-level differences that might signal measurement instability or context-specific bias. Of the 14 items analysed, only one item showed a statistically significant difference between the two samples (Z = 2.104, p = 0.04). The remaining 13 items did not yield significant group differences, indicating a high degree of consistency in responses across the two

Table 3: Gender differences by survey item

Factor	Item	Male median (n = 78)	Female median (n = 41)	MWU test p-value	Effect size r_{rb}
Career interest	CCA1	5	5	**<0.01***	0.24
	CCA7	4	4	0.56	0.06
Subject-specific interest	CCB5	5	4	0.07	0.18
	CCB7	5	4	**<0.01***	0.33
Influence from friends	SCA3	4	4	0.18	-0.14
	SCA4	3	3	0.36	-0.1
Influence from family	SCB1	4	4	0.18	0.14
	SCB3	4	4	0.03*	0.22
Confidence	PCA2	5	4	**0.01***	0.24
	PCA4	5	4	**<0.01***	0.44
Sense of belonging	PCB2	5	3	**<0.01***	0.42
	PCB3	4.5	4	0.19	0.14

Table 4: Sample differences by survey item

Factor	Item	Sweden median (n = 241)	UK median (n = 125)	MWU test p-value	Effect size r_{rb}
Career interest	CCA1	5	5	0.18	0.07
	CCA7	5	4	0.13	0.09
Subject-specific interest	CCB5	5	5	0.23	0.07
	CCB7	5	5	0.08	0.09
Influence from friends	SCA3	3	4	0.12	-0.1
	SCA4	3	3	0.17	-0.09
Influence from family	SCB1	4	4	0.91	0.01
	SCB3	4	4	0.99	0.01
Confidence	PCA2	5	5	0.72	0.02
	PCA4	5	5	0.35	0.05
Sense of belonging	PCB2	4	4	**0.04**	0.13
	PCB3	4	4	0.55	-0.04

national contexts. These results provide strong evidence of the instrument's reliability across time and context. The high degree of item-level stability suggests that the constructs measured retain their conceptual clarity and interpretability across cultural settings. Furthermore, the minimal variation across items supports the robustness of the factor structure confirmed in our CFA and reinforces the conclusion that the survey instrument retains its psychometric properties when applied to a new population. The pattern of results aligns with expectations for a reliable and generalisable instrument: only negligible item-level variation, with overall consistency across groups. This strengthens confidence in the replicability of the original study's findings and in the suitability of the instrument for future cross-contextual research in computing education. With that being said, an interesting observation for both samples is that students are neutral (median = 3) towards the factor *Influence from family*. As will become clear from the qualitative results, family is an important factor for studying computing at university, so this finding might indicate an issue with the measurement in the survey.

Table 5: Motivation for choice of study by category

Theme	Respondents	Prop female
Subject-specific interest	71 (68%)	24%
Career prospects	31 (30%)	42%
Nature of computing	29 (28%)	31%
Previous experience	22 (21%)	27%
Confidence	14 (13%)	29%
Social influence	10 (10%)	50%
Total number of responses	*105*	*30%*

5 Qualitative Results

The first open-ended question asked why the respondents participated in their study program and aimed to reveal overarching themes without prompting the respondents with the previously identified factors. The respondents' reflections revealed the themes career prospects, previous experiences, subject-specific interest, nature of computing, social influence, and confidence. Table 5 shows the number of respondents who mentioned each theme, as well as the proportion of females among these respondents. Female respondents are overrepresented among those who mention social influence and career prospects, while slightly underrepresented among those who mention subject-specific interest.

The theme Subject-specific interest describes topics within computing that influenced students' initial decision to study the subject, while Career prospects describes potential outcomes associated with studying computing that drew respondents to study the subject. The nature of computing describes the characteristics of the subject that attracted respondents to the field. The most frequently mentioned characteristics are that computing is creative, versatile, i.e., can be used in many different ways and contexts, and innovative. As for the theme social influence, students mentioned the impact of others on their decision to study computing, as can be seen in Table 6. For example, the respondents mentioned being influenced by family, friends and teachers, as well as people encountered through the media. In this sample, family is the most frequently mentioned (60%), followed by media (30%). Only female respondents mentioned being influenced by teachers. The theme of previous experience describes early computing experiences that were important for the choice of study program, and is detailed in Table 7. Of the responses that contributed to this theme, 59% referred to experiences in formal education. Other experiences mentioned were outreach activities (9%), computing-related work tasks (9%) and computing as a hobby (23%), where the latter two were only mentioned by male respondents. The theme of confidence concerns how respondents' belief in their ability to succeed in computing influenced their decision to study the subject. Of the respondents who mentioned confidence, 50% also mentioned previous experiences, and 21% also mentioned social influence. In many cases, these factors were not mentioned in isolation, but rather had a compounding effect on the participant's study choice. For example, the following response describes the social influence of family and teachers, as well as career prospects and confidence:

> I was encouraged to study computer science by my school and family due to doing well in maths and other

Table 6: Effect of social influence on choice of study

Theme	Respondents	Prop female
Inspiration	42 (41%)	36%
Support	36 (35%)	36%
None	20 (20%)	20%
Discouragement	4 (4%)	25%
Total number of responses	*102*	*31%*

> science subjects. I was encouraged to do something other than a maths degree due to computer science being a popular degree with job opportunities – Female respondent 111.

5.1 Social influence

The question of social influence revealed the themes of inspiration, support, none, and discouragement, as can be seen in Table 6. The theme inspiration describes being inspired to engage in computing or STEM by others, including role models, while the theme support refers to recommendations, support, or pressure from others to engage in computing. Hence, giving support is active and directed towards the respondent, while being an inspiration is more passive. Although the proportion of female respondents reporting support and inspiration is 36%, it is worth noting that the proportion of female respondents among those reporting inspiration from peers is as high as 50%, and for support from school and family, it is 67% and 53%. Though not explicitly asked, some respondents revealed the gender of those providing inspiration or support. For inspiration, 25% of the male respondents revealing gender reported a female role model, while the corresponding number for female respondents was 36%. No female respondent mentioned receiving support from a woman. The theme none describes responses where it is explicitly stated that no social influence affected the choice of study and discouragement describes that respondents have been actively influenced by others not to engage with computing.

5.2 Early experiences of computing

The responses to the question regarding early computing experiences were first coded to investigate the context and content of these experiences. Table 7 shows the themes that emerged, where school refers to formal education in primary and secondary school, outreach refers to informal and non-formal activities, and personal refers to participating in computing as a hobby, without any organised activity. The proportion of women who responded to the topics personal and outreach was lower than the total number of responses.

With respect to content, text- and block-based programming are the most frequently mentioned. General usage refers to using computers as a tool, e.g., for word processing, gaming, and more. Hardware includes all activities, not limited to working with software, such as building computers and working with robotics. Gamified activities include competitions, challenges, and so forth. Note that an activity can belong to several categories, e.g., a gamified activity can include programming. Of the respondents, 26% believed that early experiences affected their choice of study. At the same time, 24% did not perceive any effect, with the proportion

Table 7: Early experiences of computing and content type

Theme	Respondents	Prop female
Context		
School	74 (73%)	27%
Personal	24 (24%)	13%
Outreach	6 (6%)	17%
Content		
Text-based programming	38 (37%)	
Block-based programming	24 (24%)	
General usage	23 (23%)	
Hardware	14 (14%)	
Gamified activities	10 (10%)	
Total number of responses	*102*	30%

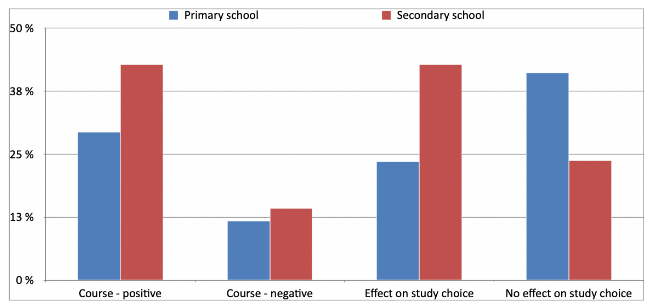

Figure 2: Perceptions of programming in school

of female respondents slightly higher among those who perceived an effect. A second round of analysis was conducted that focused on primary and secondary school. This analysis showed that block-based programming was included in 63% of the described primary school content. Similarly, text-based programming was included in 58% of the described secondary school content. Of those who did block-based programming in primary school, 29% were positive for the course curriculum while 12% were negative. Furthermore, 24% perceived that the experience may have affected their choice of study, while 41% did not perceive any effect. For text-based programming in secondary school, 43% were positive to the course curriculum, while 14% were negative, and 43% perceived an effect on their choice of study while 24% did not. These findings are summarised in Figure 2.

5.3 Sense of belonging

The question of whether respondents felt a sense of belonging to the computing community generated 93 responses which are summarised in Table 8. Of these respondents, 40 (43%) do feel a sense of belonging, while 33 (35%) do not. In addition, 7 (8%) respondents report that they "sometimes" feel a sense of belonging, often reporting that they feel belonging in one computing community, e.g. online, while not feeling that they belong in another, e.g., on campus. Another 7 (8%) respondents question the concept of a computing community since they perceive computing to be a solitary activity, as is exemplified by the following response:

Table 8: Feeling a sense of belonging in computing

Theme	Respondents	Prop female
Yes	40 (43%)	23%
No	34 (37%)	53%
Sometimes	7 (8%)	43%
No community activity	7 (8%)	0%
Total number of responses	*93*	*33%*

> No, I see it as a more solitary hobby. I never used GitHub, forums, or open-source projects. The barrier to entry feels high even now – Male respondent 102.

Female respondents are overrepresented among those who do not, or only sometimes, feel a sense of belonging. The identified factors that influence the sense of belonging in the computing community are summarised in Table 9. The most commonly mentioned factor is the skill level. Many mention the skill level as a barrier to community inclusion, which also allows participation once the level is achieved. In this context, mentions of how the discipline is competitive occur:

> I feel a constant sense of imposter syndrome thanks to so many of my peers having so many different skills I didn't even know existed, often making me feel like I'm faking my belonging. The understanding that this is a common feeling for many in this field helps! – Female respondent 16.

A closely related factor is language, referring to technical jargon used in the community:

> A lot of the time I feel like an outsider because a lot of random tech jargon gets thrown around a lot and I don't know what a lot of it means, a lot of the time it feels like I'm not smart enough to be in the community – Male respondent 8.

Having common interests is equally mentioned as an opportunity, within communities where interests are shared, and as a barrier, having slightly different interests excluding one from the community. An obstacle to feeling a sense of belonging is the lack of diversity and inclusion regarding cultures, religions, socioeconomic backgrounds, and more. The stereotypical computer scientist is mentioned in this context:

> No. The "computing community" is associated with a lot of stigma and stereotypes such as being nerdy, introverted, lacking social skills and even unhygienic – Male respondent 103.

Despite this sentiment, some students have found subcommunities that cater to diverse interests:

> However, I have met people in the same situation as me in a society for gender diversity in Informatics who are all very welcoming which is helping me find a sense of belonging in the community – Female respondent 114.

An additional factor is that of gender which was mentioned as a barrier for belonging with reports on how female students' skills are undervalued and sexist treatment still occurs:

Table 9: Factors influencing the sense of belonging in computing

Factor	Opportunity	Obstacle
Skill level	2 (2%)	25 (27%)
Language	1 (1%)	3 (3%)
Common interests	10 (11%)	10 (11%)
Diversity	3 (3%)	8 (9%)
Gender		13 (14%)
Online	13 (14%)	
Teaching	4 (4%)	
Total number of responses	*93*	

> Sometimes, it can be hard to be taken seriously as a woman and sadly this has been reflected in my brief experiences in industry – Female respondent 101.

> I have found that people including lecturers have been sexist towards me and believe that I cannot do things as I am a woman. I have also found people being more critical of myself than male counterparts which made me feel under a lot more pressure to achieve. A tutor I had used to single me out, would tell me to let other people talk when I answered a question, then would say I never talked and didn't know anything if I didn't answer the questions – Female respondent 65.

Opportunities for increasing the sense of belonging lie in including students in teaching and tutoring, as well as participation in online communities, where contributing to the communities seem to be of particular importance, as is exemplified by the following respondent:

> Yeah I do. I have contributed to some GitHub repos, but most of my feeling comes from following and interacting with people on tech Twitter – Male respondent 110.

6 Discussion

This study aimed to understand participation in computing education in the context of higher education in the UK by drawing on Bourdieu's sociocultural theory; by doing that, it helped us to elaborate how participation in computing education in the UK is shaped by individual aptitude or interest, and the distribution and interaction of various forms of computing capital – cultural, social, and psychological – during learning experiences and life trajectories of students. In doing so, the current research project validated existing research instruments in the UK higher education context and identified core factors for participation in computing education.

Comparison of the original study with the replication study here reveals a high degree of consistency in both the fit of the model and the structure of factors, supporting the robustness of the constructs between different samples. After recommended model adjustments, the replication confirmed the factorial validity of the constructs across three samples. Although minor variations were observed, particularly in relation to gender differences and sample-specific patterns, these did not significantly impact overall conclusions. From a quantitative perspective, the constructs of career interest, subject-specific interest, influence of friends, confidence, and the sense of belonging remain essential indicators of participation in computing higher education. Through the addition of open-ended questions, the current study further explains the correlation between these factors, providing in-depth explanations of the quantitative findings. In doing so, it was observed that family was indeed an influential factor in computing educational participation, something which was not observed from the survey results alone. Future research should consider the added value of open-ended questions on surveys for triangulation of the research data.

From a theoretical perspective, Bourdieu characterised education systems as reproduction mechanisms for social inequality; from this perspective, education systems legitimise existing hierarchies by rewarding those already granted the valued capital in these fields [3]. In the context of this study, many participants described how early experiences, particularly in formal schooling, outreach activities, personal computing experiences, as well as social capital formed through family and peers, were instrumental in shaping their confidence and interest. These experiences were funds of computing capital [18], giving them an advantage over peers who lacked such access, while also helping them to begin forming a computing identity before entering the field formally [40]. This early identification with computing plays a crucial role in shaping students' engagement with the subject at the university. As Lamoen et al. [37] suggest, a well-developed computing identity significantly influences students' sense of belonging and their capacity to further accumulate relevant capital.

However, only the possession of capital does not guarantee success or belonging. As Bourdieu notes, capital only becomes operational when it is socially recognised within the field [3]. For example, the current study revealed that the students' understanding of computing extended beyond programming or technical competence, encompassing broader notions of creativity, versatility, and interdisciplinarity. These conceptions inform the kinds of capital they attempt to mobilise. When such foci are recognised, they experience a sense of ease and inclusion, what Bourdieu describes as a "fish in water". In light of this, only 43% of the students reported feeling a sense of belonging, while 35% explicitly stated that they did not. Barriers to belonging included skill deficits that determine legitimacy, technical jargon that potentially indicates exclusion, a lack of diversity, and gender-related norms that delegitimise women's participation. For example, the quantitative data showed that several women reported lower confidence and a reduced sense of belonging. These findings risk revealing what Bourdieu refers to as *symbolic violence*: the imposition of dominant norms and values that make marginalisation of certain groups appear natural [39]. Everett [10] and Lane [25] explain that symbolic violence causes individuals to regard the existing social order as legitimate and appropriate. In our study, this suggests that women in computing may attribute their lack of confidence or may come to attribute their lack of confidence or alienation to personal inadequacy rather than the result of systemic misrecognition. This is further supported by the qualitative results, in which female participants were found to be more likely to experience these negative feelings, in particular due to the presence of peers with more computing-related experience or who experienced a stronger sense of belonging. Computing, being a male-dominated field, makes visible its expertise and tends to shape how others understand what it means to belong in the field. It can thus be observed that the field of computing in the UK, through its symbolic structures and norms, continues to privilege dominant narratives of competence and participation. This suggests that students who do not align with these narratives are on the verge of exclusion by interpreting structural inequity as personal failing; this misrecognition further perpetuates their marginalisation and also limits the transformative potential of computing education as a space for equity and social change.

7 Limitations

This study has several limitations that should be considered when interpreting the findings. First, our sampling approach relied on convenience sampling through institutional contacts, which may have introduced selection bias. Students who chose to participate may have been more engaged with computing than non-respondents, potentially overrepresenting those with higher levels of computing capital. Additionally, while we surveyed 11 UK universities, these institutions may not fully represent the diversity of UK higher education. While we acknowledged external validity in the context of this study, for example through sample size requirements and gender distribution, our findings may not be able to generalise to educational systems with substantially different structures or cultural contexts. Future research could address these limitations by employing more representative sampling strategies, and considering additional cultural contexts for replication. Doing so would build a more comprehensive understanding of participation in computing higher education across cultural contexts.

8 Conclusion

Participation and diversity in computing education remain low. This research project analysed this phenomenon at the higher education level in light of Bourdieu's sociocultural theory. Through CFA and MWU tests, this study confirmed important social, cultural, and psychological factors for higher education participation, which were then exemplified through the analysis of responses on open-ended questions. Having certain levels of capital, for example, through previous experience with computing, confidence, and experiencing a sense of belonging are all important indicators for participation in the field. Overall, our replication study aligns with original research and established narratives in the literature, but also extends this understanding by situating it more precisely within the context of the UK higher education system. The findings further highlight the need for institutions to move beyond inclusion at the level of access, and include curricula that focus on multiple legitimate ways of engaging with computing, and a re-examination of institutional culture and pedagogical practices that aim to recognise non-dominant forms of capital, and diverse identities. Policy could draw on the findings presented here and provide young people with more options for participation in computing, for example through non-formal education and provision of digital technology. Giving all young people, regardless of socioeconomic background and capital, the opportunity to participate in computing is fundamental to broadening participation in the field.

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