Capital and the Social Reproduction of Inequality in Computing Education

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Abstract

Computing education in Western countries has traditionally been characterised by low levels of participation and diversity among its student population. In order to broaden participation in the field, it is fundamental to understand the various mechanisms through which power structures and inequality are reproduced. From a Bourdieusian perspective, this licentiate thesis sets out to understand the interaction between capital, class, and habitus which allows a dominant class to thrive at the expense of other classes.

Paper I shows that capital serves as a barrier for non-computing students entering the computing field, whereas in Paper II a dominant class is identified as possessing higher levels of capital, which is then related to their higher levels of participation in the field. In addition, Paper I provides insight into the ways the non-dominant class internalises and acts upon their lower levels of capital.

This licentiate thesis lays out the groundwork for studying capital in computing education by developing and validating research instruments which can be used for further study. In addition, relevant theories to educational participation are discussed, with a particular focus on capital theory. More work is needed to understand the reproductive mechanism through which the dominant class legitimises their capital within the field of computing education, thereby establishing their class position. Future work is recommended in the domain of habitus and capital-inclusive pedagogy. Ultimately, the goal is to reduce the reproduction of inequality in computing education by assessing the various mechanisms involved, and designing pedagogy which can be used for successful engagement of students with varying levels of capital.
At the time of writing this licentiate thesis, my mother passed away. It goes without saying that this thesis would not have been possible without you, Els Flach, for you gave me the gift of life, and raised me to be the man I am today. I dedicate this thesis to you, hoping that I will continue to make you proud. I would also like to thank my father and brother, Henny and Paul Kunkeler, for their continued support.

My research journey in computing education started at the Raspberry Pi Foundation, where I was mentored by brilliant people like Oliver Quinlan, Hayley Leonard, Katharine Childs, Sue Sentance, and Jane Waite. You sparked my interest in the field which has now become the cornerstone of my life, and I want to thank you for that. This journey continued at Uppsala University where I am guided by the wonderful Aletta Nylén. I was lucky enough to find a supervisor who values my academic freedom, personal growth, and wellbeing, while providing feedback and direction where needed. Aletta has helped me make sense of Sweden as I moved here, and provided the best support I could have wished for when it comes to teaching. In a similar vein, I would like to thank my second supervisor, Mats Daniels, for providing me with the freedom and support to conduct this research. Listening to other Ph.D students makes me realise how lucky I am with my supervision team, as I feel valued for who I am, and for the work that I do. Thank you both so much.

Of course, my gratitude extends to the entire Uppsala Computing Education Research Group (UpCERG), where I have been received with open arms as I embarked on this Ph.D journey in a foreign country. The intellectual discussions from our seminars have formed the backbone of this thesis, and I would like to thank, in no particular order: Virginia Grande, Bedour Alshaigy, Karl Marklund, Anna Eckerdal, Anders Berglund, Lars-Åke Nordén, Arnold Pears, Caroline Uppsäll, Tina Vrieler, and Johan Snider. I also welcome Calkin Suero Montero and Niklas Humble who recently joined our research group.

Finally, I would like to express my sincerest gratitude to my significant other, Sara Kreiiger, whom I was fortunate enough to meet during my Ph.D studies. Living in a foreign country can be daunting, so having someone who can help me make sense of the complexities of the local culture is truly wonderful. Where I am chaotic and disorganised, Sara is calm and collected. Everyone deserves a Sara in their life.
List of Papers

This licentiate thesis is based on the following papers:


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Chapter 1

Introduction

At the core of any society is an unequal distribution of resources, or capital, which can be understood as a resource which is legitimate, valuable, and exchangeable. Bourdieu identified four key types of capital, determining an individual’s class position by volume and structure [10]. Economic capital refers to money and financial resources. Social capital relates to social networks and relationships. Cultural capital are credentials, dispositions, and cultural goods, while symbolic capital refers to the resources that are based on recognition, prestige, and social status. These forms of capital do not exist in isolation, but interact together within a given field to determine an individual’s class position [11]. The field serves as a social space where individuals are positioned in terms of capital and power relationships, and can be grouped by a dominant class and subordinate classes. Through these power relationships, the dominant class imposes their capital as legitimate, allowing others to enter and compete in the field depending on their capital [12]. Different fields are relatively autonomous but structurally homologous: all fields are subsumed by the social space and reproduce inequality at large. In this licentiate thesis, I demonstrate that computing education is a field where:

I Capital relates to participation in computing education, and

II Capital serves as a motivation and a barrier for participation in computing education
The findings from the studies presented here are framed within Bourdieu’s theory of reproduction, which is understood as the maintenance and continuation of existing power and class relationships [12]. The education system is reproductive through various mechanisms. Foremost, education is capital exclusive, i.e. a predetermined level of capital is required for participation. Paper I shows that capital serves as a barrier for non-computing students entering the computing field, whereas Paper II shows how capital relates to participation in computing education of various classes\(^1\). In addition, Paper I provides insight into the ways the non-dominant class internalises and acts upon their lower levels of capital. In Paper II, a dominant class is identified as possessing higher levels of capital, which is then related to their higher levels of participation in the field. Through these papers, this licentiate thesis shows that computing education is an exclusionary field, where capital not only serves as a prerequisite for participation, but also becomes a barrier for those within the field.

Through the work presented here, this licentiate thesis lays out the groundwork for studying capital in computing education by developing and validating research instruments which can be used for further study [13]. In addition, relevant theories to educational participation are discussed, with a particular focus on capital theory. More work is needed to understand the reproductive mechanism through which the dominant class legitimises their capital within the field of computing education, thereby establishing their class position. A useful conceptual tool in this domain is habitus, described by Bourdieu as a “subjective but not individual system of internalised structures, schemes of perception, conception, and action common to all members of the same group or class” [14, p.86]. A follow-up study will be conducted to assess the habitus of various classes in computing education, aiming to understand how capital is embodied and acted upon to create exclusionary practices within the field. Once this study has concluded, a capital-inclusive pedagogy for computing can be designed, addressing the interaction between capital, habitus, and field in order to engage students from a wider variety of backgrounds. Ultimately, the goal is to reduce the reproduction of inequality in computing education by assessing the various mechanisms involved, and designing pedagogy which can be used for successful engagement of students with varying levels of capital.

\(^1\)It should be noted that Paper I and II do not explicitly mention classes. The concept of class can be applied in this context by looking at the groups and their respective volume of capital.
1.1 Thesis outline

This licentiate thesis is structured as follows. Chapter 2 forms the theoretical foundation of this thesis, covering some of the most significant theories on educational participation. Through carefully assessing the strengths of each theory, an argument is made for capital theory for studying educational participation and inequality. In Chapter 3, Bourdieusian approaches to capital are showcased in the context of two different yet related fields, namely science and computing education. In doing so, this chapter highlights the role of capital in educational participation for both fields, while acknowledging field-specific differences. The contributions of Paper I and II are also described in this chapter. Paper I draws inspiration from science capital research, whereas Paper II assesses the validity of a theoretical framework on capital in computing education. Findings from both research papers are reported and discussed in this chapter. Finally, Chapter 4 discusses some of the limitations of this licentiate thesis, and directions for future research. It is acknowledged that while this thesis addresses capital in computing education, more work is needed on the Bourdieusian concept of habitus and capital-inclusive pedagogy.
Chapter 2

Theories on Educational Participation

This chapter covers four of the most significant theories on educational participation, namely Capital Theory, Social Cognitive Career Theory, Expectancy-Value Theory, and Intersectionality Theory. For each theory, relevant empirical work is selected showing how the theories can be used for educational research. In the concluding section, an argument is made for Capital Theory for the study of educational participation and inequality.

2.1 Capital Theory

Pierre Bourdieu’s Capital Theory [10] focuses on the concept of capital and how it relates to an individual’s position in society, as well as their patterns of behaviours. Broadly put, capital can be understood as a type of resource that holds value and can be exchanged to generate social advantage. Moving beyond its economic understanding, Bourdieu identified social, cultural, and symbolic capital which influences an individual’s access to education, and shapes their educational experience.

Economic capital refers to an individual’s wealth, which can be measured directly through money, or by institutionalised forms such as property rights and investments. Economic capital influences the educational choices available to individuals. For example, Lynch and Moran show how the availability of economic capital allows middle-class parents to choose fee-paying schooling or to opt out of the formal school sector entirely [15]. They show that in the context of Ireland, private businesses emerged in the form of “grind schools”, with enrolment costing on average 5100 euro per annum. Paralleling the grind schools is another private market for individual tutors, with an average rate of 30 euro per hour. Economic capital therefore
Chapter 2. Theories on Educational Participation

influences the range of educational options a person can consider, including participation in enrichment programs or accessing additional learning resources.

Social capital refers to the social networks that individuals have, including family, friends, and other types of social relationships. Social networks can provide valuable information about educational opportunities and resources. Family social capital, for example, has shown to relate to school choice [16] and educational achievement [17]. Individuals with strong family social capital may therefore be more aware of various educational paths and have access to advice and guidance from knowledgeable contacts. Moreover, the academic decisions made by both parents and siblings can impact an individual’s own choice of study, commonly referred to as the family spillover effect [18]. Social capital therefore influences the educational choices individuals make in terms of which schools to attend and what subjects to study.

Cultural Capital can be distinguished in three forms: embodied, objectified, and institutionalised. Embodied cultural capital includes skills, habits, and tastes acquired through personal experiences and upbringing. Objectified cultural capital consists of cultural goods like books, art, and educational materials. Institutionalised cultural capital refers to recognised credentials and qualifications. From the perspective of embodied cultural capital, students may believe that they do not belong in a field of education, or that the problems they must overcome make it too risky to participate [19]. In terms of objectified cultural capital, there is an unequal distribution in learning materials and ways to access them, even in countries where wealth distribution is more equal [20]. Especially with the digitalisation of education, students are often required to access their educational materials using computers and the Internet, leading to a digital divide between those who have access to technology, and those who have not. Finally, institutionalised cultural capital takes on the form of educational credentials and qualifications, and in turn, contributes to occupational success [21]. It can therefore be said that cultural capital influences not only the level of access that individuals have when it comes to education, but also the decisions made within the system.

Symbolic capital refers to the resources individuals possess that are based on recognition, prestige, and social status. It includes symbolic elements such as titles, credentials, reputation, and other forms of recognition that can be valuable in social interactions. In the context of education, it has been shown that elite institutions recruit students from elite schools, despite ongoing efforts of democratisation [22]. And, at the top universities in the United States, a legacy system is in place which favours students from alumni family [23]. In practice, this means that the educational system can
be divided into two, one for the children of common people, and one for the privileged children who possess high levels of symbolic capital. While levels of symbolic capital can be detrimental to an individual’s educational access, its influence on educational participation goes even further. Attending a prestigious school or university can enhance an individual’s symbolic capital, potentially opening doors to opportunities and shaping social perceptions. This, in turn, makes prestigious institutions desirable choices for education, influencing an individual’s choice of schooling and field of study.

Figure 2.1: Bourdieu’s Forms of Capital

In summary, Bourdieu suggests that economic, social, cultural, and symbolic capital significantly influences educational participation. Capital theory provides a lens through which to understand how social and cultural factors contribute to the unequal distribution of educational opportunities and outcomes in society. Individuals with more capital are often better positioned to engage with and succeed in the educational system, while those with less face additional challenges and barriers.

2.2 Social Cognitive Career Theory

Social Cognitive Career Theory (SCCT), as developed by Robert Lent and Steven Brown [24], focuses on the interplay among a variety of personal, environmental, and behavioural variables that are hypothesised to influence the processes through which people develop basic academic and career interests, make and revise their educational and vocational plans, and achieve performances of varying quality in their academic and career pursuits. SCCT includes variables such as self-efficacy, outcome expectations, and interests, which have shown to influence educational participation.
Self-Efficacy refers to an individual’s belief in their ability to successfully perform a specific task or achieve a particular goal [25]. Self-efficacy affects students’ motivation and learning, and in turn, the educational choices that they make [26]. Self-efficacy is subject specific, and a higher self-efficacy in a subject relates to increased motivation to participate and pursue challenging academic goals.

Outcome Expectations are the beliefs individuals hold about the consequences or outcomes of performing particular behaviours [24]. Positive outcome expectations, such as the belief that education leads to desirable career outcomes, can motivate individuals to actively participate in educational activities [27]. Conversely, negative outcome expectations may deter individuals from engaging in education.

Interests are an individual’s liking for something or someone. In the context of education, students tend to develop interests in subjects for which they possess strong self-efficacy and positive outcome expectations [28]. Individuals are more likely to participate in education when it aligns with their interests and when they perceive a connection between their educational pursuits and future career possibilities.

Social support and barriers form the social context in which individuals make educational decisions. Supportive social environments not only encourage students to pursue education, but it also increases student retention [29]. Conversely, social barriers, such as discrimination based on gender and ethnicity, discourage students to pursue a particular education [30].

According to SCCT, self-efficacy promotes favourable outcome expecta-
tions, and students tend to develop interests in academic subjects at which they possess strong self-efficacy and positive outcome expectations. Educational participation, including choice of study, is seen as a result of self-efficacy, outcome expectations, and interests, and is affected by the presence of social support and the relative absence of barriers [28]

2.3 Expectancy-Value Theory

Expectancy-Value Theory (EVT), as developed by John Eccles [31] and Allan Wigfield [32], posits that individuals’ expectancy for success, and the value they have for succeeding, are important determinants of their motivation to perform tasks.

Expectancy for success can be defined as an individual’s belief about how well they will perform on an upcoming task. While related to the concept of self-efficacy, one important distinction is that expectancy for success primarily focuses on the expectation of a positive outcome, whereas self-efficacy encompasses a broader sense of personal belief in one’s ability. Thus, individuals are more likely to participate in educational activities when they believe they have an expectancy for success, that is, the skills, competence, and capacity to succeed [33].

Value can be broadly construed as an individual’s belief about a desired end state [34]. Attainment value, for example, is defined as as the importance of doing well on a given task, while intrinsic value is the enjoyment one gains from doing the task [31]. Utility value, on the other hand, refers to how a task fits into an individual’s future plans, such as career success or social approval. Individuals are more likely to participate in education when they perceive a task as valuable and relevant to their personal or future goals [35].

Expectancy-value calculus is a mental activity by individuals weighing the expectancy of success against the perceived value of the outcomes. If individuals believe they can succeed in education and find value in the outcomes, they are more likely to be motivated to participate [33]. Conversely, if either the expectancy or the perceived value is low, motivation may be diminished.

In summary, Expectancy-Value Theory highlights the importance of individuals’ beliefs about their ability to succeed (expectancy) and the perceived value of educational tasks (value) in shaping their motivation and participation in education.
2.4 Intersectionality Theory

Intersectionality theory, developed by Kimberlé Crenshaw [36], provides a framework for understanding how various social identities, such as race, gender, class, and others, intersect and interact to shape individuals’ experiences and opportunities.

Complex identity is the culmination of an individual’s intersecting identities that cannot be understood in isolation. While gender is often recognised as the primary identity in higher education research, other identity dimensions such as race, ethnicity, and sexuality shape an individual’s experience in education [37]. This intersectionality of identities influences how individuals navigate educational spaces and systems [38]. For example, a person who belongs to a marginalised racial group with a different gender identity and socioeconomic status faces multiple forms of oppression [36]. Having these intersecting identities causes unique challenges that differ from those experienced by individuals with a single-axis identity.

Structural inequity is embedded in educational systems determining who has access to what. Policies, practices, and institutional norms perpetuate inequalities based on intersecting identities [39]. To put this into context, the intersectional perspective highlights how systemic racism, sexism, or classism can impact an individual’s access to quality education and participation in academic and extracurricular activities [40].

Identity-based bias is a differential treatment based on an individual’s single-axis or intersecting identities. Intersectionality sheds light on how identity-based biases can influence educational experiences. Stereotypes,
prejudices, and discriminatory practices may affect individuals differently depending on the intersections of their identities [41].

Figure 2.4: Intersectionality and educational participation

In summary, Intersectionality Theory informs our understanding of the complexity of individuals’ experiences in education by acknowledging the interplay of multiple identities, which in turn affects participation in education.

2.5 Conclusion

All theories described in this chapter explain educational participation in various yet related ways. Capital theory highlights the forms of capital that individuals possess, and how that can be used for educational advantage. SCCT takes into consideration self-efficacy, outcome expectations, and interests which influence an individual’s decision making in education. EVT stresses the calculus of expectancy and value, whereas intersectionality theory focuses on the complexity of identity and how that affects educational experience and outcome.

Each of the theories listed here would be an excellent choice for studying educational participation. With that being said, the appeal of capital theory lies within its versatility. That is, capital theory acknowledges the concept of field, a social arena or a structured space where individuals or groups compete for various forms of capital [11]. The education system is a prime example of a field, but it is too broad as an object of study. Instead, researchers focus on fields within a field, and this has allowed capital to be operationalised in various ways for distinct purposes. That is, the capital
that is required to participate in a fine arts degree differs from a computing degree, and Bourdieu acknowledges that through the concept of field.

The wider appeal of capital theory lies within the study of inequality. Society is characterised by an uneven distribution of capital, where each individual has capital – through birth, upbringing, or individual success – which is then used to generate more capital and social advantage. This allows researchers to quantify capital and to study educational participation and inequality through capital distributions. From a qualitative perspective, capital theory allows researchers to focus on the individual and how they use their capital to navigate fields and generate advantage. In the context of this thesis, it means that capital can be measured quantitatively and related to participation in computing education (Paper II). On an individual level, capital can be viewed as a motivation and a barrier to participate in education, and studied qualitatively to provide insight into students’ views and dispositions, confidence and knowledge, and other factors which are important for understanding student engagement (Paper I). In the following chapters, capital theory is first applied broadly to the field of science education, before delving in to the field of computing education.
Chapter 3

Capital in Science and Computing Education

The strength of one’s capital and the ability to generate social advantage is dependent on the field in which it is utilised in. In this chapter, I acknowledge two important fields for this thesis, namely the wider field of science education, and the more specific field of computing education. In doing so, I show that capital plays a significant role in educational participation for both fields, while acknowledging field-specific differences.

3.1 Capital in Science Education

Science Capital Theory, as developed by Louise Archer and colleagues [42], applies the Bourdieusian concept of capital to science education in order to explain science aspirations and engagement, with a particular focus on young people. Science capital is understood as all the “science-related knowledge, attitudes, experiences, and resources that you acquire through life” [43].

Scientific literacy is an individual’s scientific knowledge, skills, and ability to understand how science “works” [42].

Scientific-related attitudes, values and dispositions refers to the extent to which an individual sees science as relevant to everyday life, for instance through valuing the role of science in society, or holding the view that science is “everywhere” [42], [43].

Knowledge about the transferability of science is about understanding the utility and broad application of science qualifications, knowledge, and skills used in science to other fields [43].

Science media consumption relates to the volume of consumption of science through various forms of media, such as science-related television programmes, books or magazine, and the Internet [42].
Participation in out of school science learning contexts is about the frequency of participation in informal science learning contexts, such as science museums, science clubs, and science fairs [43]. It also includes everyday contexts, such as doing experiments at home, or programming computers [42].

Family science skills, knowledge and qualifications relates to the science-related skills, qualifications, jobs, and interests an individual’s family possesses [43].

Knowing people in science-related roles is about the people an individual is connected with (in a meaningful way), such as family friends, peer and community circles who work in science-related roles [42].

Talking about science in everyday life is the frequency with which an individual talks about science with “key people” in their lives, for example friends, siblings, or parents, and the extent to which an individual is encouraged to continue with science by key people in their lives [42].

These dimensions are said to relate to educational participation in science in various ways, with particular dimensions of science capital – science literacy, transferability of science, family influences – being more closely related to anticipated future participation and identity in science than others [44]. With regards to science consumption, research shows that watching TV programs about science, reading books on scientific discovery and watching, reading, or listening to science fiction were found to be highly effective activities for promoting children’s science achievement and self-efficacy [45]. In terms of familial influences, students in science tend to have more supportive parents or family members with favourable views towards science education [46]. In addition, parents using scientific discourse and talking about science at home are shown to advantage students at school. Other work shows that children who have close family members who work in a science-related job are far more likely to aspire to science-related careers than those whose parents do not work in these fields [47]. Relatedly, other researchers found that being motivated and encouraged to study maths or physics by a key adult was an important predictor of a student’s decision to study science [48]. In terms of knowledge about the transferability of science, an appreciation of science qualifications in relation to the labour market has been shown to be a predictive factor of science education participation [48]. Similarly, the extrinsic value of science qualifications can be considered a culturally valued form of knowledge which can be strategically used for advantage by those who possess it [49].

In short, science capital research explains differential patterns of science aspirations and engagement by operationalising the different forms of science capital that individuals possess, and how this is used for participation in the field of science education.
3.2 Contributions: Paper I

Drawing inspiration from the concept of science capital, Paper I aimed to understand why students engage with a programme involving computing, and what they aspire to get out of their education. The idea behind the research design was to carefully study the research instruments which were developed for science capital, and then adjust these for the field of computing education. This research design was justified as the concept of science capital is broad, and misses out on discipline-specific interest. This point was also made by the science capital researchers themselves, as they suggest that science capital, while “strongly related to engineering and physical science future study aspirations, was not strongly related to the pursuit of either
maths or technology postsecondary study” [50, p.1228].

To make the science capital survey relevant to computing education, the decision was made to adapt the original survey, changing instances of “science” with “computing” for the most part. In addition, some of the survey statements had to be adapted to match the demographic of the research population. While science capital research generally focuses on young people, Paper II involved university students.

Once the survey instrument was finished, the decision was made to study bioinformatics students. These students were selected since they recently switched from biology to a programme involving computing, allowing them to reflect on their motivation, aspirations, and outcome expectations when it comes to their study programme. The sample size included 29 students from a course in Information Management Systems. Once the data had been collected, the survey results were analysed using descriptive statistics and three themes were identified, namely, seeing the value of computing, positive beliefs about computing, and low levels of computing confidence. An additional round of data analysis was used to score students based on their survey responses, revealing gender differences ($p = 0.002$), in particular as it relates to computing knowledge and skills ($p = 0.03$), and computing media consumption ($p < 0.001$).

Acknowledging low sample size, the decision was made to continue the research from a sequential mixed methods design, in order to further explore the survey findings from a qualitative perspective. An interview instrument was designed inspired by the findings from the survey, which allowed for further exploration of the themes identified. Out of the 29 students who participated in the survey, 10 agreed to a follow-up interview. Through analysis of the survey results and interview transcripts, it became clear that the motivation to study a computing-related discipline was related to career aspirations and positive beliefs and values when it comes to computing. At the same time, students reported mixed levels of computing knowledge and confidence, and a perceived gap between skills and future careers.

While the study showed that existing science capital instruments can be adapted to other educational fields to study factors underlying participation, some concerns were raised about the validity of the research instruments with regards to the field being studied. In the following sections, I will discuss capital research in the field of computing education, before going into the contributions of paper I, which covers a validated research instrument for studying capital in computing education.
3.3 Capital in Computing Education

As mentioned before, science capital is broad, and misses out on discipline-specific capital. In a similar vein, the strength and volume of capital is valued in the field that it is used in. With this in mind, researchers have set out to understand the forms of capital that are specific to the field of computing education, investigating the factors which are important for student engagement and success.

To this end, a literature review of 147 research papers identified various forms of capital affecting student participation in computing [51]. From the perspective of cultural capital, 65% of the papers covered culturally-related factors for participation in the field, such as knowledge and skills and views and dispositions towards computer science/scientists. In terms of social capital, 60% of the papers mention social-related factors for participation, including having a supportive environment and access to CS people and role models. Finally, 32% of the papers covered psychological factors, such as self-efficacy and confidence and identity and sense of belonging. While different papers also acknowledged the role of economic capital in computing education participation, alone it did not provide any further information other than that economic factors may prohibit access to computing resources which is also what is reflected under cultural capital. The forms of capital in computing education are summarised in Table 3.1

<table>
<thead>
<tr>
<th>Cultural Capital</th>
<th>Social Capital</th>
<th>Psychological Capital</th>
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<tbody>
<tr>
<td>Knowledge and skills</td>
<td>Views and dispositions</td>
<td>Supportive environments</td>
</tr>
<tr>
<td>Access to CS courses</td>
<td>Views about CS as school subject</td>
<td>Access to CS people and role models</td>
</tr>
<tr>
<td>Previous experience and skills</td>
<td>Views and concerns about CS as a career</td>
<td></td>
</tr>
<tr>
<td>Stereotypes</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Using the framework, Kallia & Cutts investigate how inequalities in computing education can be understood from a Bourdieusian perspective. In doing so, they identify the dominant class as consisting of students with a good background of knowledge and/or skills related to computer science, and thus, the course content appears familiar to them; these students share a common language and discourse re-
lated to computer science, a specific style of communication and interaction with their peers of the same position and with their teachers, a code of interaction relevant to computer science and accessible to those with high computer science capital and positive views and dispositions towards the discipline (habitus) that aligns with their future goals.

Through these higher levels of capital, the dominant class is able to leverage their capital within the field, and therefore, have the advantage over the other classes, by possessing the necessary capital to succeed and position themselves higher in the hierarchy. From the perspective of the non-dominant classes, a certain group of people will experience the field of computing as an “hostile, alien field, a social-cultural world different from the world they are coming from” [51, p.388]. Because of that, many students internalise that computing is not for them, for instance by not possessing the capital recognised in the field, or by not having the means to acquire it.

### 3.4 Contributions: Paper II

The goal of paper II was to validate the theoretical framework as developed by Kallia & Cutts using empirical evidence, which is fundamental to theory development. To this end, a survey was designed based on existing survey research and expert review, which was then cross-validated by one of the authors of the original theoretical framework. Validity and reliability of the survey instrument was carefully addressed, and the survey was distributed among a total of 432 students from all over Sweden. In terms of validation of the survey structure, Confirmatory Factor Analysis (CFA) was used. In the context of survey research, factor analysis can be used to confirm that the survey items align with the intended constructs or dimensions, ensuring that the survey is measuring what it is designed to measure. Paper II answers two research questions:

**RQ1** What is the factor structure of the survey, and how well does it represent the underlying latent constructs?

**RQ2** What group differences can be observed for the forms of capital in computing education and how does this relate to participation in the field?

In terms of RQ1, the hypothesised survey structure was assessed in terms of model fit to the observed data, and adjusted to achieve a survey with high internal consistency among the items and factors (robust: $X^2_p = 0.119$;
CFI/TLI = 0.97/0.95; RMSEA = 0.06, SRMR = 0.041). The pre- and post-validated survey structure can be found in a supplementing report [13].

Then, the validated survey structure was used to answer RQ2. Using the proposed model, group differences were observed using the Mann-Whitney $U$ test. Using a significance threshold of 0.05, differences between computing ($n = 241$) and non-computing ($n = 191$) students were observed 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.

3.5 Discussion

Through these research papers, this licentiate thesis covered a fundamental component of Bourdieu’s sociocultural theory, namely capital, and applied it to the field of computing education. In doing so, research instruments were developed and validated which can be used to further study capital in computing education. The research findings of the studies conducted here can be framed within Bourdieu’s theory of reproduction, which is understood as the maintenance and continuation of existing power and class relationships [12]. Paper I showed that capital serves as a barrier for non-computing students entering the computing field, whereas Paper II showed how capital relates to participation in computing education of various classes. In addition, Paper I provided insight into the ways the non-dominant class internalises and acts upon their lower levels of capital. In Paper II, a dominant class was identified as possessing higher levels of capital, which is then related to their higher levels of participation in the field. Through these papers, this licentiate thesis showed that computing education is an exclusionary field, where capital not only serves as a prerequisite for participation, but also becomes a barrier for those within the field.
Chapter 4

Limitations and future work

This licentiate thesis has laid the groundwork for studying capital in computing education, with a particular emphasis on how that relates to participation in the field. What is less clear, however, is how the dominant class establishes their class position and imposes their capital as legitimate. A useful conceptual tool in this domain is habitus, described by Bourdieu as a “subjective but not individual system of internalised structures, schemes of perception, conception, and action common to all members of the same group or class” [14, p.86]. In Paper I, some observations were made with regards to the habitus of students entering the field, for example, their beliefs and values, and how they act on this. What is missing from the research thus far, however, is a comparative study of the habitus of various classes in computing education. Such research is fundamental for understanding the ways in which capital is embodied and how exclusionary practices come to be in the field in computing. Once this study has concluded, a capital-inclusive pedagogy for computing can be designed, addressing the interaction between capital, habitus, and field in order to engage students from a wider variety of backgrounds. Ultimately, the goal is to reduce the reproduction of inequality in computing education by assessing the mechanisms involved, and designing pedagogy which can be used for students with varying degrees of capital.


From Science to Computing: a Study of Capital among Bioinformatics Students
Thom Kunkeler and Aletta Nylén

Abstract—Contribution: This article applies science capital research to computing education in order to understand why students engage with a programme involving computing, and what they aspire to get out of their education.

Background: Capital is a concept which has been used in educational research to study inequality, aspiration and achievement. Previous work has looked at capital in science education, but misses out on discipline-specific capital. This article applies science capital research to the field of computing education, providing insight into students’ views and dispositions of computing, their confidence and knowledge, and other factors which are important for understanding student engagement with the subject.

Research Questions: How can science capital research be adapted to computing education? Further to this, what insights can be generated from such a methodology?

Methodology: Inspired by the concept of science capital, a survey has been developed and tested among 29 bioinformatics students with a biology background. These students were selected since they recently switched to a programme involving computing, allowing them to reflect on their motivation, aspirations, and outcome expectations. Informed by the initial results, a follow-up interview was designed, and 10 students participated.

Findings: Science capital research proves useful for studying factors underlying participation in computing. Students in this study are driven by career opportunities, as well as positive beliefs and values when it comes to computing, while perceiving barriers such as low levels of computing confidence, and a gap between their skills and future careers. In addition, gender differences among survey results were observed ($p = 0.002$).

Index Terms—computing education, capital, broadening participation

I. INTRODUCTION

Given low levels of diversity in computing, and an increasing demand for people with computing-related qualifications [1], it is important to understand factors underlying student participation in the subject. Previous research has highlighted a number of structural, social, and psychological explanations for why students engage with computing education, including students’ social support [2] and perceptions of role models [3], self-efficacy [4], and beliefs and values [5], [6]. Other educational research emphasises the role of capital [7]–[10] a social, cultural, and economic resource associated with aspiration and achievement. In science education, for example, the concept of science capital has been developed to understand “why some young people participate in post-16 science and others do not” [11, p. 2]. Research based on this concept has found relations between science capital and science aspirations among young people, in particular for dimensions such as science literacy and family influences [12]. Drawing on this work, this research paper aims to develop a methodology for studying capital in computing education, by adapting research instruments from science capital. Using a sequential mixed methods research design [13], the goal is to explore factors underlying participation in computing education. Our current findings suggest that science capital research can be adapted to computing for varying purposes, but we recommend a mixed methods research design to validate the survey findings and to improve instrument quality. Future research can draw on the methodology proposed here, and consider additional items to be added to the research instruments. Ultimately, the goal is to broaden participation in computing, by developing an understanding of students’ engagement with computing education, and what they aspire to get out of it.

II. RELATED WORK

One way of studying inequality, aspiration and achievement in education is through the notion of capital. Capital can be understood as a resource that is considered legitimate, valuable, and exchangeable [15]. While capital is often interpreted in its economic sense, for instance referring to monetary exchange, it can also be seen from a cultural or social perspective. Cultural capital, for instance, is associated with cultural tastes, educational qualifications, knowledge, and skills, while social capital is linked to membership in a group, like family or school. Building onto these forms of capital, researchers in science education have defined science capital as all the “science-related knowledge, attitudes, experiences, and resources that you acquire through life” [11, p. 2].

<table>
<thead>
<tr>
<th>Scientific Literacy</th>
<th>Science-related attitudes, values and dispositions</th>
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</thead>
<tbody>
<tr>
<td>Knowledge about the</td>
<td>Science media consumption</td>
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<td>transferability of</td>
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<td>science</td>
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<td>Participation in out-of-school</td>
<td>Family science skills, knowledge and qualifications</td>
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<td>science learning contexts</td>
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<td>Knowing people in</td>
<td>Talking about science in everyday life</td>
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<td>science-related roles</td>
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Table I
FORMS OF SCIENCE CAPITAL, © 2024 IEEE

Research has shown a correlation between score on the science capital dimensions illustrated in Table I and science aspirations among young people [12]. It should be noted, however, that science education is broad, and science capital misses out on discipline-specific interest. As the researchers...
suggest, science capital, while “strongly related to engineering and physical science future study aspirations, was not strongly related to the pursuit of either maths or technology postsecondary study” [14, p.1228]. A similar point is made by Kallia and Cutts [8], who emphasise that the value of capital is determined by the field that it is used in. They propose an operationalisation of capital in computing education more specifically, looking at cultural, social, and psychological capital as important factors for student engagement. Considered dimensions are, for example, having access to a supportive environment, possessing knowledge and skills in computing, and experiencing a sense of belonging to the field of computing. Other research in this field aims to measure capital in computing education. Vrieler [16], for example, adapted the original science capital survey to study children in a computing summer camp, and found that while boys and girls had access to similar parental support, girls were less likely to appreciate computer science, and to aspire to a computing career. Based on this study and other research, Vrieler developed the Computer Science Capital Framework [9], including forms of capital, as well as behaviours and practices which are considered valuable in computing education. While the current study also draws on the original science capital survey, the difference is that students are scored based on their responses, essentially calculating a “computing capital index”. Such efforts have also been made in the original research conducted by Archer et al. [7], which has shown to be effective for explaining differences in educational aspiration and participation among young people. Based on this, and the literature exploring capital in computing education, the constructs in Table II are chosen for further analysis.

### Table II

<table>
<thead>
<tr>
<th>Computing knowledge and skills</th>
<th>Computing support from family and friends</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computing goals and career aspirations</td>
<td>Participation in computing activities</td>
</tr>
<tr>
<td>Computing media consumption</td>
<td>Computing attitudes and values</td>
</tr>
</tbody>
</table>

### III. METHODS

#### A. Context

This study was conducted as part of a first-year international master’s course in Information Management Systems at a Swedish university. The students, both Swedish and international, were part of a bioinformatics programme and studied biology prior to starting their master’s degree. These students were selected for the study since they had recently switched to a programme involving computing, allowing them to reflect on their motivation, aspirations, and outcome expectations.

#### B. Survey instrument adaptation

To make the science capital survey relevant to computing, the decision was made to adapt the original survey [7]. This meant that the word ‘science’ was changed to ‘computing’ in many cases. In addition, since the science capital survey was intended for young people before their university studies, some of the statements had to be replaced or removed altogether. The goal of the survey design was to keep the core of the original survey, while changing the subject from science to computing.

The survey was sent out, along with a project information sheet, to the students prior to the start of the course. It was also made clear to the students that participation in the survey was voluntary and that data provided in no way affected their course performance. Some personal identifying information was collected (e.g. gender), but results were anonymised during data analysis. A total of 29 students participated in the survey, of which 17 were women. The survey instrument can be found in [17].

#### C. Interview instrument development

To further explore aspects of science capital in computing, the decision was made to continue the research in a sequential mixed methods design [13, p. 65]. From a methodological perspective, this allowed the researchers to evaluate both research instruments for future studies, and how they can complement one another. The interview design was informed by the initial results of the survey. Additional semi-structured questions were added, relating to background and motivation of the students, and challenges that they faced in their studies and career progression. The interview guide can be found in [17].

Out of the 29 students who filled in the survey, 10 agreed to participate in the follow-up interview. They were sent out an information sheet with more details on the research project, data collection and handling, and right to withdrawal. At the start of the interview, this information was repeated and participants were asked to sign a consent form. Interviews lasted around 30 minutes and took place in-person or via video call.

#### D. Reliability and validity

As an exploratory study of research instruments, the results of this research aim to inform further research design, and by doing so, increase reliability and validity of the methods developed. It should be noted that the original science capital survey by Archer et al. [7] reported high levels of internal consistency among the survey items, and the survey used for this study follows a close resemblance. The researchers paid particular attention to making sure the survey was as clear as possible, for instance by providing definitions of ‘computing’ and ‘computer science’. However, since the original survey was developed for pre-school children, a pretest of the survey was needed to make sure the survey was appropriate for university students. A variety of people were invited to participate in a first iteration of the survey, and their feedback was used to further develop the research instrument. As for the interview, the goal was to provide additional depth to the initial survey findings, and to ensure that the survey was measuring what it was supposed to measure. In order to do so, the interview questions had to reflect the most important
themes from the survey. Once the initial draft of the interview guide was complete, it was tested with two students before continuing with the remainder of the sample in this study. While some questions were removed for redundancy, the core of the interview guide remained.

IV. MIXED METHOD DATA ANALYSIS

A. Phase I: Descriptive statistics and interviews

Initially, the survey results were analyzed using descriptive statistics and divided into three subthemes, namely, seeing the value of computing, positive beliefs about computing, and low levels of computing confidence. These results informed the interview design, and an additional subtheme, perceived gap between ability and future career, was discovered during qualitative data analysis. The themes and subthemes are visualized in Figure 1.

Figure 1. Subthemes and themes identified, © 2024 IEEE

B. Phase II: Inferential statistics

After phase I, preliminary findings and curriculum recommendations were reported in [18]. The decision was made to revisit the results to perform additional analyses and to further develop the research instruments for future studies. During this second round of data analysis, the students were scored based on their survey responses. For example, in likert-scale questions that ranged from strongly disagree to strongly agree, students scored anywhere between -2 and 2 based on their answer. The survey items and full scoring system can be found in [17]. It should be noted that the goal of the scoring system was not to identify an outcome measure as in Archer et al. [7], or to generalise the survey results beyond the sample. Instead, the goal of this data analysis phase was to develop a first iteration of an index which could be used for further science capital research in computing. The statistical analyses chosen for this study were the independent samples t-test and Mann-Whitney U test to explore gender differences among the students. These tests compare unrelated groups, namely male and female students, to show that there are different scores for each group. However, one of the assumptions for the independent samples t-test is that the data is normally distributed [19], a criteria which was not satisfied for two of the constructs in the analysis. For these constructs, the Mann-Whitney U test was used, a nonparametric alternative to the t-test [20].

V. FINDINGS

Through analysis of the survey results and interview transcripts, it became clear that the motivation to study a computing-related discipline was related to career aspirations and positive beliefs and values when it comes to computing. At the same time, students reported mixed levels of computing knowledge and confidence, and a perceived gap between skills and future careers. An additional round of data analysis was used to score students based on their survey responses, revealing gender differences (p = 0.002), in particular as it relates to computing knowledge and skills (p = 0.03), and computing media consumption (p < 0.001). These themes and findings are covered in more detail below.

A. Motivation to study a computing-related discipline

1) Career opportunities and general interest: At the start of the interviews, the biology students were asked when they decided to study bioinformatics, and what triggered the decision. The reasons provided were varied: a majority indicated an interest in bioinformatics and computing, and about half of the students based their decision on career-related reasons. For instance, three students specifically indicated not wanting to pursue a traditional biology profession: “I have some research experience before, only focusing on a wet lab. And it was extremely boring. And I kind of felt that I don’t want to be working in wet labs in my future [...] but I also think bioinformatics is really interesting” (int. 8). Similarly, two interviewees mentioned that job prospects after the master’s degree were an incentive to study bioinformatics: “In evolutionary biology, you kind of have to continue to research, there’s not so much actual industrial work you can do. While in bioinformatics, you have more of an option. You can both do the research or go to industry” (int. 6).

Figure 2. Survey statements related to computing, goals, and jobs, © 2024 IEEE

To relate this back to the survey statements as can be seen in Figure 2, students agreed that computer science and computing creates new jobs, and also that it is useful to achieve goals in life. When asked to elaborate on this during the interviews, a majority of the students mentioned their careers as a goal, and how computing supports that: “I think that computing will be more and more present [...] I guess I’ll apply that for my
work whenever I get a job as well. Because it will hopefully be bioinformatics” (int. 1).

The students were also asked why they thought that students with a traditional biology background would go into a computing-related discipline or profession, such as bioinformatics or computer science. Again, most of the reasons provided were career related, such as the job market being more appealing, there being more opportunities, a higher salary, and finally, high levels of competition for traditional biology roles: “Because the job market is huge for anything computing related [...] You get more opportunities, and the pay is very high. It’s not only that, I feel like it’s exciting, because every day, there is new technology emerging” (int. 7).

What these findings seem to suggest is that while biology students are motivated by an interest in bioinformatics and computing, they also perceive the value of it in terms of their future. Some want to move away from traditional biology roles involving a laboratory, whereas others are encouraged by a higher salary and better opportunities.

![Computing beliefs and values](image1)

**Figure 3. Survey statements related to computing beliefs and values, © 2024 IEEE**

2) Positive beliefs and values when it comes to computing:

The students were also motivated to study a computing-related discipline because of the positive beliefs and values they held when it comes to computing, as can be seen in Figure 3.

During the interviews, when asked if everyone should learn computing, all of the students indicated that they would support this: “I think I would support that. Yeah. But again, I think it’s mostly just good to learn that type of thinking and learning, creative problem solving. So it’s more so the skills you pick up when you learn programming, rather than the programming itself actually being useful” (int. 3). Another student reflected on the way computing teaches her to think in different ways: “It kind of feels that it makes you think in different ways, or thinking about a problem and how to solve it, for example. And it feels really useful to me” (int. 4). And another student mentioned the impact computing has on our lives: “I think that everyone should have a feeling for it. And with the increased impact that computers have on our lives, the increased amount of computers everywhere, the more important it becomes to know how they work” (int. 5). Additionally, most of the students supported the idea that computing courses should be introduced at the bachelor’s level of education of biology.

As can be seen in Figure 3, most of the students strongly agreed or agreed to the statement “it is useful to know about computers in my everyday life”. During the interview, the students were asked to provide an example of this. Two of the students indicated that they use programming for side projects in their free time, two indicated that they play a tech support role for friends and family, and another student mentioned that they were becoming better at finding solutions through Google. The remaining students talked about cybersecurity and awareness, and having better knowledge than others, for instance older generations.

**B. Challenges faced in computing**

![Confidence and knowledge](image2)

**Figure 4. Survey statements related to computing confidence and knowledge, © 2024 IEEE**

1) Low levels of computing confidence: Despite being motivated by career opportunities and positive beliefs and values, the students involved in this study reported barriers when it comes to computing. The most evident one is the mixed levels of confidence and perceived knowledge when it comes to computing, as can be seen in Figure 4. During the interviews, the participants were asked to further elaborate on their strengths and weaknesses when it comes to computing, and also their perceived difficulty of computer science courses in their master’s programme. All but one student indicated that their weaknesses were related to computing, mathematics, and technical skills: “My weaknesses are definitely the programming, the maths, so the understanding of what is going on behind the scenes” (int. 5). For two students, this meant that they had to spend a disproportionate amount of time on their coursework: “the computing, and [its] challenges also lead to spending a lot of time on solving it” (int. 1).

2) Perceived gap between ability and future career: Students were also asked what their biggest challenges would be when it comes to pursuing bioinformatics or computing-related professions. Three of the students identified high levels of competition for jobs: “most biology labs, they want people with a computer science background [...] So it is quite hard for me to outcompete those people” (int. 8). Another of the students mentioned that jobs in bioinformatics and computing require a high level of skill, something which she thought not to be trained for.
Despite the students being appealed to the bioinformatics and computing job market, they perceived themselves not to be good enough to compete: “we can write our own little mini script to do some bioinformatics stuff. But I don’t think that we’ll be able to be a competitive developer” (int. 5). However, at the same time, some of the students were unable to indicate how much computing they needed for their future profession: “I think maybe all the courses we did here kind of scare me off with MATLAB, Python, HTML, and PHP. Maybe I don’t need any of that at all” (int. 1). Although the student indicated to have technical ability in four programming languages, she feels that this is not sufficient enough for her future profession. Like other students, there seems to be uncertainty about their own ability, and what they think is required of them after their master’s degree.

C. Exploring gender differences through survey scores

An additional round of data analysis was used to score students based on their survey responses, revealing gender differences ($p = 0.002$), in particular as it relates to computing knowledge and skills ($p = 0.03$), and computing media consumption ($p < 0.001$). The full list of score by construct and $p$-values can be found in Table III. If the $p$-value reported for a construct is $\leq 0.05$, this means that there is sufficient evidence to say that statistical significant differences for the groups for that construct exist.

Table III

<table>
<thead>
<tr>
<th>Computing knowledge and skills</th>
<th>Female student $\mu$</th>
<th>Male student $\mu$</th>
<th>T-test $p$</th>
<th>Mann-Whitney U test $p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computing goals and career aspirations</td>
<td>12.3</td>
<td>13.1</td>
<td>0.54</td>
<td></td>
</tr>
<tr>
<td>Computing media consumption</td>
<td>5.6</td>
<td>12.8</td>
<td>&lt; 0.001***</td>
<td></td>
</tr>
<tr>
<td>Computing support from family and friends</td>
<td>4.1</td>
<td>5.2</td>
<td>0.36**</td>
<td></td>
</tr>
<tr>
<td>Participation in computing activities</td>
<td>0.6</td>
<td>0.3</td>
<td>*</td>
<td>0.21</td>
</tr>
<tr>
<td>Computing attitudes and values</td>
<td>1.4</td>
<td>1.6</td>
<td>0.6</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>43.8</td>
<td>58.1</td>
<td>0.002***</td>
<td></td>
</tr>
</tbody>
</table>

*data not normally distributed for this construct
**unequal variances t-test
***$p$-value is statistically significant with a threshold of $p \leq 0.05$

Students’ scores ranged from 29 to 76.5 with a mean score of 50.4 and a standard deviation of 12.8. This distribution of scores was then used to divide the students into three groups of equal range, indicating a low, medium, or high score. As can be seen in Table II, 91.6% of male students scored medium or high, in contrast to 64.7% of female students whose score fell into the low range.

Table IV

<table>
<thead>
<tr>
<th>Score distribution by gender, © 2024 IEEE</th>
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<tbody>
<tr>
<td>Low (29 - 45)</td>
</tr>
<tr>
<td>Medium (46 - 61)</td>
</tr>
<tr>
<td>High (62 - 76.5)</td>
</tr>
</tbody>
</table>

VI. DISCUSSION

Understanding the factors that drive participation in computing is crucial due to the limited diversity in the field and the growing need for individuals with computing-related qualifications. In line with previous studies, which highlight the high demand for computing skills in the job market [1], participants in this study are motivated to study bioinformatics and computing for its potential career benefits. Unlike previous studies, which report negative stereotypes associated with computing [5], the students in this study held positive beliefs and values when it comes to computing. They exemplified this through providing examples of using computing in everyday life, and all of them supported mandatory computing education, for instance in high school or during their biology education. Previous research also suggests that there are differences in male and female self-efficacy in computing [4], and similarly, this research observed gender differences for the construct computing knowledge and skills ($p = 0.03$). More generally, the students reported levels of discouragement in their studies, by perceiving themselves as not good enough for computing studies, or for future careers. These findings are the result of adapting science capital research to computing education. From a methodological perspective, the survey was useful for exploring initial factors for participation, while the follow-up interviews made it possible to further explore these factors in-depth. In addition, the interviews allowed the researchers to discuss survey design and findings with the students. The interviews confirmed three themes from the survey results, namely seeing the value of computing, positive beliefs about computing, and low levels of computing confidence, in addition to revealing an additional theme, perceived gap between ability and future career. The researchers therefore recommend the interview in this type of research for its potential to increase reliability and validity of the survey instrument, to improve the survey design, and to provide additional depth to the survey findings.

VII. LIMITATIONS

Since the goal of this study is to develop new research instruments, some limitations are observed which will need to be worked on for future research. Through this study the researchers found that the score distribution per survey construct was uneven. While this reflects social reality to
some extent, in which not every resource is equally valuable or influential [7, p. 928], future refinements of the survey should take into consideration adding more questions for some research constructs. As for reliability testing of the survey items, it is important to increase the sample size to acceptable levels for testing. It should be noted, however, that the original survey [7], and the computing education version in [16], both reported acceptable levels of reliability.

VIII. CONCLUSION AND FURTHER WORK

The aims of the current study were to evaluate how science capital can be adapted to computing, and how such studies can help to understand factors underlying participation in computing education. In this study, it was found that students are motivated by career opportunities, as well as positive beliefs and values when it comes to studying a programme involving computing, but were discouraged by low levels of computing confidence, and a perceived gap between skills and future career. In a second round of data analysis, gender differences among survey results were observed among this cohort of students ($p = 0.002$), in particular for computing knowledge and skills ($p = 0.03$) and for computing media consumption ($p < 0.001$).

What is interesting from these findings is that while students have access to varying degrees of capital, they are all part of the same educational programme. In light of knowing this, questions then remain in what way capital is used to study computing, and how it leads to different educational achievements. While this research identified areas where differences can be observed, an outcome measure is missing, such as employment after graduation. Future research could, for example, investigate if there is a correlation between higher levels of capital during studies, and employment in the first year after graduation. Qualitative studies, on the other hand, could focus more on the ways students make use of their different forms of capital to generate educational and professional advantages.

From a methodological perspective, it can be said that both research instruments developed for this research proved useful, and complemented each other well, for a variety of purposes. The interviews provided depth to, and validated, the survey findings, while improving the instrument quality of the survey. Some additional adjustments need to be made to the research instruments, such as adding additional questions for some of the constructs in the survey. While it is currently possible to compare scores based on independent variables, such as gender, it is less meaningful to compare between the dependent variables due to uneven score distribution. Mitigating this issue would allow for additional analyses, providing further insight into factors, and the weight of each factor, that contribute to students’ engagement with computing education. The next step is to repeat this study with new cohort of students from a variety of computing-related disciplines. The goal of increasing the sample size is to make the sample more reflective of the general population, allowing for more meaningful comparisons between gender groups, and reliability testing for the survey items. For validity purposes, it would also be interesting to compare students in a computing-related discipline, to those from other disciplines. If this survey is measuring what it is supposed to measure, then logically it would follow that students in a computing-related discipline would score higher on the survey than those from other disciplines. Again, further research could confirm this.

Based on the findings and the discussion the authors recommend actions to be taken to encourage more students from a variety of backgrounds to study computing and to even out the gender imbalance. Teachers need to be aware and should act on the lack of confidence in computing among students, for instance by encouraging and increasing the self-efficacy of students when it comes to computing. In addition, students should be made aware of the diversity of the field of computing and careers, knowing that there is a place for everyone. Ultimately, the goal of such efforts is to broaden participation in computing.

ACKNOWLEDGMENTS

The authors would like to thank Tina Vrieler for her input on the study design and providing comments on the paper. In addition, the authors express their gratitude to Bedour Alshaigy for her continuous support and enthusiasm.

REFERENCES


**IX. BIOGRAPHIES**

**Thom Kunkeler** is a PhD student in Computing Education Research at the Department of Information Technology, Uppsala University, Sweden. His research is focused on capital development in the computing classroom, aiming to understand why people engage with computing, and what they aspire to do with it. His goal is to inspire more young people, in particular those from underserved communities, to participate in computing education.

**Aletta Nylén** is Head of the Computing Education Research unit at the Department of Information Technology, Uppsala University, Sweden. Coming from a background in theoretical computer science, Dr. Nylén has turned her research interests towards computing and engineering education. She has a special interest in curriculum design aimed at supporting students’ professional development. With this goal her research spans topics such as students’ motivations and preconceptions as they engage in computer science studies, as well as their progressive competence development.
ABSTRACT
Computing education in Western countries has traditionally been characterised by low levels of participation and diversity among its student population. In order to broaden participation in the field, it is fundamental to understand why students engage with the subject, and what they aspire to get out of their education. One approach is to use the Bourdieusian concept of capital, referring to the legitimate, valuable and exchangeable resources that individuals use to generate social advantage within specific fields. This paper presents a survey developed to measure forms of capital which enable students to participate in computing-related fields, and succeed in it. The sample included 432 students from 6 large-scale universities in Sweden. Using Confirmatory Factor Analysis, the hypothesised survey structure was assessed in terms of model fit to the observed data, and adjusted to achieve a survey with high internal consistency among the items and factors (robust: \( \chi^2 = 0.119; \) CFI/TLI = 0.97/0.95; RMSEA = 0.06; SRMR = 0.041). Using the proposed model, group differences were observed using the Mann-Whitney U test. Using a significance threshold of 0.05, differences between computing (\( n = 241 \)) and non-computing (\( n = 191 \)) students were observed 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.

KEYWORDS
• Social and professional topics → Computing education.

1 INTRODUCTION
A persistent problem in computing education and careers in Western countries has been the underrepresentation of disadvantaged groups, in particular as it relates to race, gender, and ethnicity [25]. Despite research and policy efforts to broaden participation in the field [31], the participation problem persists, in part due to a lack of understanding of why students engage with computing education, and what they aspire to get out of it. This paper sets out to understand the many factors that drive demographic participation in computing education, which include social, cultural, and individual factors. Drawing inspiration from Bourdieu’s sociocultural theory, this paper acknowledges the multifaceted nature of capital, legitimate, valuable, and exchangeable resources that can be used to generate social advantage within specific fields. Moving beyond the economic dimensions of capital, Bourdieu popularised social and cultural forms, for example being a member of an influential family, or having skills, habits, and tastes that are considered to be valuable and exchangeable. In computing education, studies on capital have shown gender differences in computing motivation and aspirations among young people [35]. Other recent work shows how capital serves as both a motivation and a barrier to students entering the field of computing education [21]. While research in this area has been fruitful for understanding factors underlying participation, validated research instruments in this domain are missing. This research paper fills that gap by developing a survey instrument on capital in computing education based on existing literature and expert review, before testing the fit of the hypothesised survey structure to the observed data using Confirmatory Factor Analysis (CFA) [18]. The following research questions are to be answered:

RQ1 What is the factor structure of the survey, and how well does it represent the underlying latent constructs?

Then, using the validated survey structure and 432 student responses from multiple large Swedish universities, the following question will be answered:

RQ2 What group differences can be observed for the forms of capital in computing education and how does this relate to participation in the field?

Through careful survey design and CFA, this study proposes a validated survey structure which can be used for studying capital in computing education. Using the proposed model, differences between computing and non-computing students were observed for 11 out of 14 survey items, whereas differences between male and female computing students were observed for 6 items. The results suggest that the proposed forms of capital are related to participation in computing education, and that this relationship is stronger...
for male computing students. This paper also acknowledges the cultural context of Sweden in which the study is situated and discusses how that may relate to survey validation outcome and test results. Future work should therefore build on the methodology proposed here, and replicate the study in other cultural contexts. Ultimately, the goal is to broaden participation in computing education, by developing a cross-cultural understanding of why students engage with the subject, and what they aspire to get out of their education.

2 RELATED WORK
Over the past few years, studies on capital in computing education have emerged as a response to widening inequalities in computing education and careers [19–21, 35]. Capital in this context can be understood as a legitimate, valuable, and exchangeable resource [3]. Social capital, for example, can be understood in terms of connections, such as membership to a group, like family or school. Cultural capital, on the other hand, refers to resources such as educational qualifications, dispositions, knowledge, and skills. From a social reproduction perspective, it is important to study capital as it has been linked to enduring educational inequality [4]. That is, in order to broaden participation in education, it is fundamental to understand what forms of capital are required for participation, and how this enables one to succeed in a given field.

In computing education, attempts to measure capital stem from established research in science education [1]. Vriele et al. [35] adapted the original science capital survey in order to explain differential patterns of computer science aspiration, appreciation and educational participation among young people. By studying 115 boys and 39 girls aged 9–16 at a computing summer camp, the authors found that similar parental support was perceived by both genders, although girls are less likely to appreciate computing and to aspire to study computing or work in a computing-related field.

Similarly, Kunkeler & Nylén [21] used the survey to understand why biology students switch to bioinformatics, a programme involving computing. Using a mixed methods approach including 35 students, they find that the students are driven by career opportunities, as well as positive beliefs and values when it comes to computing, while perceiving barriers such as low levels of computing confidence, and a gap between their skills and future careers.

On a theoretical level, a literature review by Kallia & Cutts [19] of 147 academic publications identified nine forms of capital in computing education spanning across cultural, social, and psychological domains. Considered dimensions are, for example, having access to a supportive environment, possessing knowledge and skills, and experiencing a sense of belonging to the field of computing. In the academic literature, these forms of capital have shown to affect students’ participation in the subject.

Yet, a connection between a theoretical model and empirical evidence is missing. That is, no effort has been made to test a hypothetical model of capital in computing education with empirical evidence, which is fundamental to theory development. This research paper establishes that connection by designing a survey based on the framework as developed by Kallia & Cutts [19], before assessing the hypothesised survey structure with the data collected in this study.

3 METHODOLOGY
Empirical data used to answer the research questions was collected using a survey. Since no existing validated survey instrument was identified, an entirely new research instrument was designed. A theoretical framework on capital in computing education by Kallia & Cutts [19] was used as hypothetical structure of the survey. Then relevant constructs from previous survey research were identified and used as a basis for the new survey as shown in Table 1. It should be noted that for the construct Access to computing people and role models no survey instrument could be found, and thus the survey items were co-designed with an expert in this area. The survey included an Attention-Check question halfway through the survey to ensure that the respondents carefully read the questions. Once the first draft of the survey was complete, it was cross-validated by one of the authors of the original theoretical framework [19], by mapping each of the survey items to a construct on the framework. The full survey instrument can be found in a supplementing report [22].

3.1 Pilot study
To ensure that the survey was readable and devoid of ambiguity, a pilot study with four students with computing and non-computing backgrounds was conducted. In particular, the researchers wanted to make sure that the survey was understandable to students from a non-computing background, as the survey mostly included statements related to computing. An informal interview revealed that while the non-computing students did not feel like the survey was “for them”, they understood that their data would be used for comparison purposes, as was explained in the survey information. Other feedback related to the formulation of some statements in the survey, and minor adjustments were made accordingly. In addition, one of the computing students felt that some of the statements were repetitive. However, this is what the researchers intended, as the goal of the survey validation process was to find out which survey items work best together for a given construct. In short, the pilot study allowed the researchers to test the survey instrument with a small group of students, confirming survey design decisions and

Table 1: Survey instruments and constructs

<table>
<thead>
<tr>
<th>Authors</th>
<th>Relevant constructs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Archer et al. [1]</td>
<td>Science capital</td>
</tr>
<tr>
<td>Dorn &amp; Elliot Tew [8]</td>
<td>Computing capital</td>
</tr>
<tr>
<td>Vekiri &amp; Chronaki [34]</td>
<td>Self-efficacy, Social support</td>
</tr>
<tr>
<td>Nguyen &amp; Lewis [30]</td>
<td>Self-efficacy</td>
</tr>
<tr>
<td>Lewis et al. [23],</td>
<td>Identity, Sense of belonging</td>
</tr>
<tr>
<td>Bell-Watkins et al. [2],</td>
<td></td>
</tr>
<tr>
<td>Moudgalya et al. [27]</td>
<td></td>
</tr>
<tr>
<td>Hur et al. [15]</td>
<td>Career aspirations</td>
</tr>
<tr>
<td>Grande [12]</td>
<td>Role models, Social support</td>
</tr>
</tbody>
</table>
readability, whilst making some minor adjustments to the survey statements.

3.2 Sample

3.2.1 Sample size calculation. Since it is unclear what the population of computing students in Sweden is in a given year, some estimations had to be made in order to calculate the minimum sample size needed for this research. Given a total student population in Sweden N of 372,414 in 2022 [9], a maximum population proportion of $p = 0.5$ was assumed since it was unclear how many of those students were in a computing-related field, such as computer science, information technology, or data science. Then, with a $Z$-score of 1.96 for a confidence level of 95%, and a margin of error ($e$) of 5%, the following formulae [16] were used:

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

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

Where $n_f = 384$ 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 455 students from 6 Swedish universities. Respondents were recruited via a contact person at their respective university. They were sent an invitation to participate in the survey, including an information sheet with regards to the data collected, processing and handling. It should be noted that one respondent reported being at Karlstad University and one at Lund University, despite no recruitment efforts there, possibly because these students recently switched study programmes. They were included in the sample as no threat to survey validation was identified. The data collection was reported to the university’s data protection officer and considered to be non-sensitive in nature. A GDPR-compliant survey tool, hosted by the 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 [26].

First, 21 respondents which incorrectly answered the Attention-Check question were removed from the dataset. These responses were placed in a short period of time and so the researchers were able to deduce that the respondents submitted the same form twice. This resulted in the sample as can be found in Table 2.

Finally, missing values were handled using the median imputation method. This method was justified as the percentage of missing values was extremely low, namely 0.15%. Then, data inversion was applied to the three negative statements found in the survey.

3.2.4 Data used for analysis. The sample in Table 2 ($n = 432$) can be divided into computing ($n = 241$) and non-computing ($n = 191$) students. Of the 241 computing students, 189 answered to be of the legal gender male, 46 female, and 6 chose prefer not to stay. The groups found in the sample and used for data analysis are visualised in Figure 1.

3.3 Data analysis

Since the data was ordinal in nature, the Mann-Whitney $U$ Test was used to compare group differences [24]. Given two groups $Y_0$ and $Y_1$, and a probability $P$, the Mann-Whitney $U$ test can be expressed:

$$P(Y_0 > Y_1) = P(Y_0 < Y_1)$$

If this equality holds, it implies that no group systematically chooses larger values than the other group. The tests were performed in the statistical software environment of R using the coin library [14] with a significance threshold of 0.05.

3.4 Validity and Reliability

In survey research, the validity of measurement refers to how well the answer to a question corresponds with the true value for the construct that is being measured [6]. Reliability refers to the consistency and stability of measurement over time and across different conditions [7]. What follows below are descriptions of how forms of validity and reliability were addressed in the context of this research.

<table>
<thead>
<tr>
<th>University</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uppsala University</td>
<td>269</td>
</tr>
<tr>
<td>KTH Royal Institute of Technology</td>
<td>88</td>
</tr>
<tr>
<td>Linköping University</td>
<td>57</td>
</tr>
<tr>
<td>Mälardalens University</td>
<td>16</td>
</tr>
<tr>
<td>Karlstads University</td>
<td>1</td>
</tr>
<tr>
<td>Lund University</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 2: Survey participants by university

![Figure 1: Groups used for comparison](image-url)
3.4.1 Face validity. Face validity is a type of validity assessment in survey research that examines whether a survey instrument appears, on its face, to measure what it is intended to measure [29]. In the context of this study, the draft survey instrument was sent to the author of the original capital in computing education research [19], who then proceeded to cross-validate each survey item with a construct of the framework. In addition, a pilot study was conducted with four students to gather feedback on the clarity, relevance, and appropriateness of the survey items. While some minor changes were made for readability purposes, the survey remained unchanged in terms of content and structure.

3.4.2 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 [10]. In other words, it refers to the representation of the research sample with regards to the population of computing students in Sweden. As can be seen in Table 2, the sample included multiple large Swedish universities. In particular Uppsala University and KTH Royal Institute of Technology recruit students from all over Sweden, further adding to the external validity of the sample. And, while it is uncertain what the gender balance of computing students in Sweden is, Bradley et al. [5] report between 11.4% to 20.5% for the years 2020-2022 at Uppsala University. In this study, 46 out of 235 computing students were female (19.6%), closely resembling that distribution. In addition, the sample size of 235 computing students in this study was larger than the minimum sample size of 196 as calculated in Section 3.2.1.

3.4.3 Construct validity. Construct validation refers to the process of simultaneously validating measures of psychological constructs and the theories of which the constructs are a part [33]. In this regard, content validity assesses whether the measurement covers the full construct. To achieve this goal, the survey instrument was based on existing literature, as can be seen in Table 1, and seven survey items were added for each construct, each measuring the construct in related, yet slightly different ways. Criterion validity, on the other hand, assesses whether the measurement correlates with a specific outcome. In the context of this study, this type of validity was evaluated by comparing computing and non-computing students. If the survey measures what it is supposed to measure, then from a criterion validity perspective it should follow that differences can be observed between the student groups. Once the data had been collected, CFA was used to test the fit of the hypothesised survey structure to the observed data [18]. In the context of survey research, factor analysis can be used to confirm that the survey items align with the intended constructs or dimensions, ensuring that the survey is measuring what it is designed to measure. If the factor analysis reveals that the survey items load well onto distinct factors that align with the theoretical constructs, it provides support for the construct validity of the survey. If, on the other hand, the factor analysis does not yield clear and interpretable factor structures, it may suggest issues with the construct validity of the survey instrument. In addition, an advantage of CFA in construct validity research is the possibility of directly comparing alternative models of relationships among constructs, a critical component of theory testing [36]. The CFA was performed using the statistical software library lavaan in R [32].

3.4.4 Reliability. In the context of survey validation, internal consistency reliability assesses the consistency of responses across different items within the survey [13]. While CFA does not directly address reliability, it can indirectly contribute to an internal consistency of the survey structure. That is, if CFA reveals that a set of items load well onto a single factor, it suggests that those items are measuring a coherent and internally consistent construct.

3.5 Confirmatory Factor Analysis

Since the model involved ordinal data, the Weighted Least Squares Mean and Variance (WLSMV) adjusted method was used for the CFA [28]. Then, using the Diagonally Weighted Least Squares (DWLS) estimator, the pre-validated survey structure in Figure 2 did not converge. The error log revealed that the covariance between the Cultural Capital factors was too high, meaning that they had to be merged before proceeding. Based on this information and a balance between data-driven and theory-driven model adjustment, the authors carefully removed survey items with low factor loadings (≤0.4), adjusted the scope of the factors, and ran multiple models. In terms of Social Capital, for example, the data suggested to split the factor Computing support from family and friends into separate factors, which also made sense from a theoretical perspective, as family and friends are distinguishable variables. For most of the other factors, the scope had to be adjusted in order to fit the empirical data. This meant that the factors were too broad and included statements were the model-implied data did not match the observed data. By adjusting the scope of the factors and reducing the amount of survey items, the researchers wanted to make sure that the survey items aligned with the factors, thereby ensuring that the survey is measuring what it is designed to measure. The factor structure that achieved the most optimal CFA results is illustrated in Figure 2.

Using the optimised model, the chi-square test of model fit was conducted to assess the goodness of fit between the model and the observed data. The results indicated a non-significant chi-square statistic (robust X^2 = 68.69, df = 56, p = 0.119), suggesting that, based on the conventional significance level of 0.05, there is insufficient evidence to reject the null hypothesis of exact model fit [7]. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) both exceeded 0.90, with robust values of 0.97 and 0.95 respectively, suggesting good fit according to conventional guidelines. The Root Mean Square Error of Approximation (RMSEA) had a robust value of 0.06 with a 90% confidence interval of [0.016, 0.092], indicating that the model provides a reasonable approximation of the population covariance matrix. The point estimate of 0.06 falls below the commonly recommended threshold of 0.08, suggesting good fit. Furthermore, the upper limit of the confidence interval, 0.092, remains within an acceptable range, reinforcing the confidence in the adequacy of the model fit. Lastly, the Standardised Root Mean Square Residual (SRMR) was 0.041, falling below the commonly recommended threshold of 0.08, suggesting good fit.

4 FINDINGS

To compare the distributions of the validated survey items between the groups, a Mann-Whitney U test was conducted. Table 3 shows the median value on each survey item per group, in addition to the...
Figure 2: Pre-validated and validated survey structure

associated test $p$-value. Groups are said to be statistically significant different for a survey item using a significance threshold of 0.05.

4.1 Group differences by gender

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 social capital and psychological capital elements of the survey. No statistically significant group differences are observed for cultural capital, and social capital constructs such as Influence from family.

4.2 Group differences by field of study

The group differences by field of study are more noticeable, with an obtained $p \leq 0.05$ for 11 out of 14 survey items. In addition, the median values observed are further apart between the groups. Statistical significant group differences are observed for all forms of capital between the groups, but again some group differences are missing for survey items from social capital.

5 DISCUSSION

As expected, group differences were observed for computing and non-computing students, supporting the criterion validity of the survey design. In addition, this research explored gender differences between male and female computing students. While previous work has found differences in career interest [35] or subject-specific interest [5], this work observed no statistically significant group differences on these constructs. One interpretation is that there is closer alignment of career and subject-specific interest between male and female computing students, at least in the context of this study.

On the other hand, this research observed gender differences for constructs in social capital and psychological capital. Previous research has shown that male students experience larger peer support when it comes to computing education [34] and that women rate their role models as more important to them than men do [11]. Likewise, the results show that male computing students express to have more social interaction with their friends when it comes to computing, and female students express to have less access to
computing role models, which could be indicative of unequal participation in the subject.

Gender differences in computing education have also been observed in sense of belonging [23, 27] and confidence [30], and are shown to have a negative effect on female participation in the subject. Similarly, statistically significant differences are observed in the context of this study, showing the persistence of this phenomenon across studies and cultural contexts.

The results can be interpreted as follows. Differences in capital can be observed for computing and non-computing students, indicating a relationship between capital and participation in computing education. Then, for computing students, the relationship is stronger for male students, which corresponds with their higher level of participation in the field.

6 LIMITATIONS AND FUTURE WORK

While this work has addressed sample size and external validity, the geographical spread of the universities included in this survey could be improved. Looking at the map of Sweden, the universities are mostly located in the East of Sweden, and an effort can be made to include the North (Umeå and Luleå), the South (Malmö), and the West (Gothenburg). While doing so might not yield significant differences in the model or results, this would increase the representation of the sample in terms of the whole computing student population of Sweden. The authors also made the conscious decision not to include data related to race and ethnicity, concepts that are not widely used in Europe and are increasingly erased from legislation [17]. Instead, future work could replicate this study in other contexts, allowing for cultural-specific comparisons on computing education participation. This type of research is also desired for model fit comparison, providing insight into the validity of the research instrument developed, and how it can be adjusted across contexts. Doing so would allow for group comparison on a cultural level, providing cultural-specific insights into why students engage with computing.

7 CONCLUSION

In order to broaden participation in computing education, we need to understand why students engage with the subject, and what they aspire to get out of it. To this end, a survey was developed to measure forms of capital which enable students to engage and succeed in the field. Using CFA, the hypothesised survey structure was assessed in terms of model fit to the observed data, and adjusted to achieve a survey with high internal consistency among the items and factors. Using the proposed model, group differences were observed using the Mann-Whitney U test [24]. Using a significance threshold of 0.05, differences between computing and non-computing students are observed for 11 out of 14 survey items, whereas for male and female computing students, differences are observed for 6 items. The results suggest that there is a relationship between capital and participation in computing education, and that this relationship is stronger for male computing students. At the same time, it is important to acknowledge the cultural context in which this study took place, and how this affected the survey validation process and test findings. Replicating this study in other contexts would allow for comparisons on a cultural level, while also providing insights into the model developed here. Through these research efforts, the goal is to broaden participation in computing education, by developing a cross-cultural understanding of why students engage with the subject, and what they aspire to get out of their education.

8 ACKNOWLEDGEMENTS

The authors would like to thank Virginia Grande for their input on survey design, and Maria Kallia for cross-validating the survey with the original theoretical framework. In addition, the authors would like to express their gratitude to Shaobo Jin for his support with the statistical techniques used in this project.

### Table 3: Mann-Whitney U test results by group

<table>
<thead>
<tr>
<th>Capital</th>
<th>Factor</th>
<th>Item</th>
<th>Male computing Median (n = 241)</th>
<th>Female computing Median (n = 191)</th>
<th>Mann-Whitney U test p-value</th>
<th>Computing Median (n = 189)</th>
<th>Non-computing Median (n = 191)</th>
<th>Mann-Whitney U test p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cultural</td>
<td>Career interest</td>
<td>CCA1</td>
<td>5</td>
<td>5</td>
<td>0.5</td>
<td>5</td>
<td>3</td>
<td>&lt;0.01*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CCA2</td>
<td>5</td>
<td>4</td>
<td>0.6</td>
<td>5</td>
<td>4</td>
<td>&lt;0.01*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CCA7</td>
<td>5</td>
<td>5</td>
<td>0.4</td>
<td>5</td>
<td>5</td>
<td>&lt;0.01*</td>
</tr>
<tr>
<td>Social</td>
<td>Subject-specific interest</td>
<td>CCB5</td>
<td>5</td>
<td>5</td>
<td>1</td>
<td>5</td>
<td>4</td>
<td>&lt;0.01*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CCB7</td>
<td>5</td>
<td>5</td>
<td>0.4</td>
<td>5</td>
<td>4</td>
<td>&lt;0.01*</td>
</tr>
<tr>
<td></td>
<td>Influence from family</td>
<td>SCA5</td>
<td>3</td>
<td>3</td>
<td>0.5</td>
<td>3</td>
<td>3</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SCA7</td>
<td>3</td>
<td>3</td>
<td>0.4</td>
<td>3</td>
<td>3</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Influence from friends</td>
<td>SCA2</td>
<td>4</td>
<td>4</td>
<td>0.03*</td>
<td>4</td>
<td>4</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SCA6</td>
<td>4</td>
<td>3</td>
<td>&lt;0.01*</td>
<td>4</td>
<td>3</td>
<td>&lt;0.01*</td>
</tr>
<tr>
<td></td>
<td>Influence from computing people and role models</td>
<td>SCB1</td>
<td>5</td>
<td>4</td>
<td>&lt;0.01*</td>
<td>4</td>
<td>4</td>
<td>&lt;0.01*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SCB7</td>
<td>5</td>
<td>4</td>
<td>0.05*</td>
<td>4</td>
<td>4</td>
<td>&lt;0.01*</td>
</tr>
<tr>
<td>Psychological</td>
<td>Confidence</td>
<td>PCA2</td>
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<td>4</td>
<td>0.01*</td>
<td>5</td>
<td>4</td>
<td>&lt;0.01*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PCA4</td>
<td>5</td>
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<td>4</td>
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<tr>
<td></td>
<td>Sense of belonging</td>
<td>PCB2</td>
<td>4</td>
<td>4</td>
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<td>&lt;0.01*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PCB3</td>
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<td>&lt;0.01*</td>
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<td>3</td>
<td>&lt;0.01*</td>
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</tbody>
</table>

* Indicates significance at the 0.05 level.
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