Capital in Computing Education: Investigating Factors Underlying Participation

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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 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: $X^2 p$ = 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.

CCS CONCEPTS

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

KEYWORDS

Computing education; broadening participation; capital

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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]. Vrieler 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 student 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.

Table 1: Survey instruments and constructs

Authors	Relevant constructs
Archer et al. [1]	Science capital
Dorn & Elliot Tew [8]	Computing attitudes
Vekiri & Chronaki [34]	Self-efficacy, Social support
Nguyen & Lewis [30]	Self-efficacy
Lewis et al. [23], Bell-Watkins et al. [2], Moudgalya et al. [27]	Identity, Sense of belonging
Hur et al. [15]	Career aspirations
Grande [12]	Role models, Social support

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

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:

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

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

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 Karlstads 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. Then, two duplicate survey responses 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.

Table 2: Survey participants by university

University	Count
Uppsala University	269
KTH Royal Institute of Technology	88
Linköping University	57
Mälardalens University	16
Karlstads University	1
Lund University	1

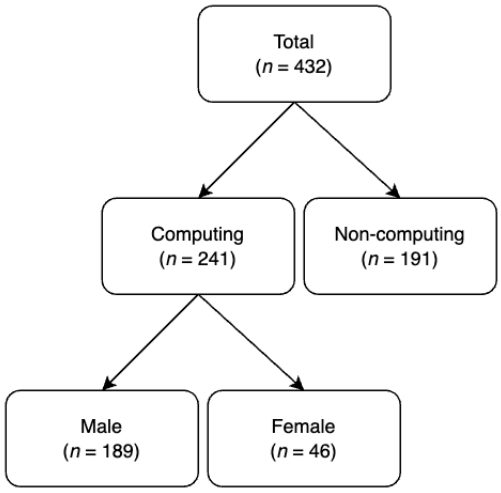

Figure 1: Groups used for comparison

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.

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 predicts or 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

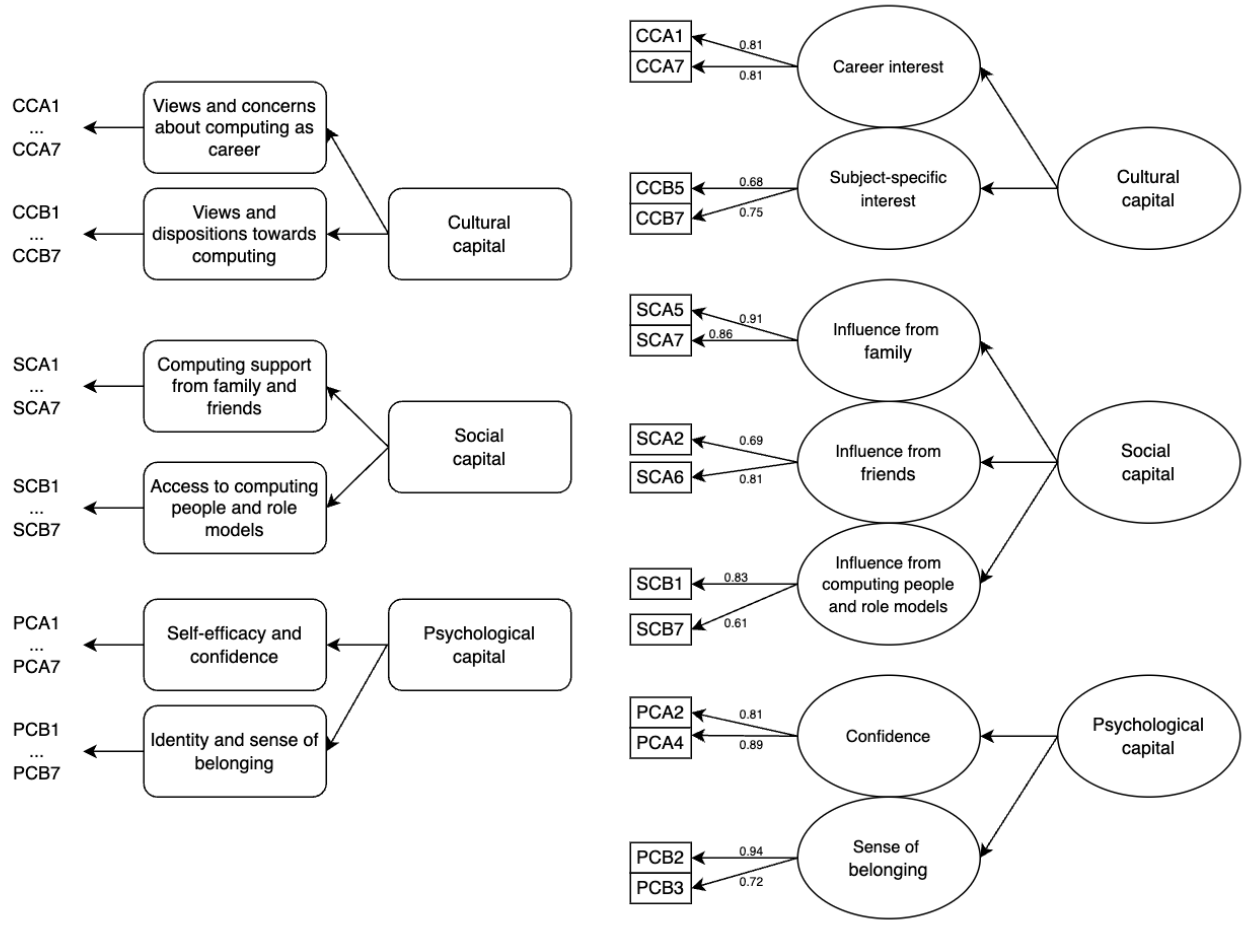

Figure 2: Pre-validated and validated survey structure

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

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

Capital	Factor	Item	Male computing Median (n = 189)	Female computing Median (n = 46)	Mann-Whitney U test p-value	Computing Median (n = 241)	Non-computing Median (n = 191)	Mann-Whitney U test p-value
Cultural	Career interest	CCA1	5	5	0.5	5	3	**<0.01***
		CCA7	5	4	0.6	5	4	**<0.01***
	Subject-specific interest	CCB5	5	5	0.4	5	4	**<0.01***
		CCB7	5	5	1	5	4	**<0.01***
Social	Influence from family	SCA5	3	3.5	0.4	3	3	0.4
		SCA7	3	3	0.5	3	3	0.3
	Influence from friends	SCA2	4	4	**0.03***	4	4	0.8
		SCA6	4	3	**<0.01***	4	3	**<0.01***
	Influence from computing people and role models	SCB1	5	4	**<0.01***	4	4	**<0.01***
		SCB7	5	4	0.4	5	4	**0.05***
Psychological	Confidence	PCA2	5	4	**0.01***	5	4	**<0.01***
		PCA4	5	5	0.08	5	4	**<0.01***
	Sense of belonging	PCB2	4	4	**<0.01***	4	3	**<0.01***
		PCB3	4	4	**<0.01***	4	3	**<0.01***

* Indicates significance at the 0.05 level.

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.

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