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Influence of school characteristics on computational thinking: A supervised machine learning approach

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Abstract
This study explores the influence of schools' general characteristics, and their information and communication technology (ICT) capabilities on students' computational thinking. The computational thinking achievements of 31,823 students who participated in a large-scale comparative study in 1412 schools and across nine countries/regions were analyzed using supervised machine learning. Five classification rules were triangulated to determine how 22 schools' general characteristics and their ICT capabilities predicted students' computational thinking achievements. Data analysis showed no predictive relationship between schools' ICT capabilities and computational thinking. However, some classification rules predicted higher computational thinking achievement for students from affluent schools. The discussion amplifies the need for proper incorporation of ICT in schools with recommendations for more research on the nuanced relationship between schools' characteristics and computational thinking development.

Keywords Computational thinking · Data mining · ICT · Machine learning · School · Technology

1 Introduction

Computational thinking (CT) is often associated with Wing's (2006) call for computer science educators to teach learners in other domains 'ways to think like a computer scientist' (p. 35). Wing's suggestion has been strengthened in a recent systematic review that explored how CT has been operationalized (Ezeamuzie & Leung, 2022). The findings showed that concepts and practices in computer science

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have been harnessed to solve problems in other domains. The heightened importance of CT is derived from its propensity to make people better problem solvers — an instructional goal that Robert Gagné, the pioneer of conditions of learning, described as the crux of education (Gagné, 1985). Although theories of problem-solving are amorphous (Jonassen, 1997, 2000; Mayer, 1998), the quest to understand CT as a problem-solving strategy is aptly supported by Jonassen's (2000) assertion that 'most educators regard problem-solving as the most important learning outcome for life' (p. 63).

The importance of CT is demonstrated in the increasing multidimensional inquiries about its framework (Ezeamuzie & Leung, 2022), research towards designing effective CT instructional approaches (Ezeamuzie, 2023), and disentangling ambiguity in CT assessments (Tang et al., 2020). Wing (2006) suggested that CT should be ranked in similar importance with time-honoured literacies of writing, reading and arithmetic. Whilst such elevation of CT may be contentious, noteworthy positives have been associated with the acquisition of CT. Several studies have shown that CT enhances self-management, social skills, communication, confidence, and collaboration (Denner et al., 2019; Popat & Starkey, 2019). Also, CT is positively associated with cognitive skills such as mathematical thinking, natural language literacy, reasoning, creativity, and metacognition (Scherer et al., 2019). The benefits of developing CT skills are apparent. CT has been incorporated into major curricula such as the Next Generation Science Standards in the United States (National Research Council, 2013) and the national curricula of the European Ministries of Education (Bocconi et al., 2016). In addition, the importance of CT has been highlighted in large-scale international comparative studies. Notably, the Programme for International Student Assessment (PISA) and International Computer and Information Literacy Study (ICILS) have incorporated CT into their twenty-first century assessment frameworks (Fraillon et al., 2019; Organisation for Economic Co-operation & Development, 2018).

The lucidly supported benefits of CT and concomitant awareness in learning communities have also evoked questions about factors that promote CT development. In this regard, studies on CT have focused on issues such as the influence of learning environments (Noh & Lee, 2020; Zhang & Nouri, 2019), instructional strategies (Hsu et al., 2018; Lye & Koh, 2014; Scherer et al., 2020) and other micro-level learners' features such as attitude, gender, age, and programming experience (Ezeamuzie, 2023; Sun et al., 2022). However, there are broader factors that may influence students' CT skills such as classroom, school, home environment, and wider community contexts (Fraillon et al., 2019).

To address these critical gaps in CT discourse, this study examines how schools' general characteristics and their information and communication technology (ICT) capabilities support CT development. Prior studies have shown that incorporating ICT into learning affects students' performance. In a meta-analysis ($n = 110$), Sung et al. (2016) found that about 70% of learners who use mobile devices (such as laptops) for learning performed significantly better in cognitive-based learning outcomes. An earlier second-order meta-analysis of 25 meta-analytic studies found that the use of computer technology impacts students' achievements positively (Tamim et al., 2011). Given the antecedent between ICT and learning outcomes, the explicit research question underpinning this enquiry is –

Research Question – How do schools' general characteristics and their ICT capabilities influence students' CT achievements?

In this study, CT is interpreted from the definition adopted in the second edition of ICILS (a.k.a. ICILS-2018) large-scale comparative study.

> Computational thinking refers to an individual's ability to recognize aspects of real-world problems which are appropriate for computational formulation and to evaluate and develop algorithmic solutions to those problems so that the solutions could be operationalized with a computer (Fraillon et al., 2019, p. 27).

2 Literature review

2.1 Deconstructing computational thinking

Wing (2006) hypothesized that the thinking styles of computer scientists could support solving problems in non-computer science domains. Although Wing's assertion has been cited severally as a pioneering phase in CT research and development (Grover & Pea, 2013; Shute et al., 2017), the call for harnessing the cognitive practices in computer science for solving problems in other domains is not peculiar to Wing (Tedre & Denning, 2016). A similar rationale underlies Papert's (1980) work on procedural thinking, which encapsulates the epistemic development in children when they *teach computers to think*. Even in the 1960s, computer scientists had encouraged the transfer of problem-solving approaches to other domains. For instance, Alan Perils, the first recipient of the distinguished A. M. Turing Award from the Association for Computing Machinery, advocated learning programming by all students as an element of liberal arts education (Perils, 1962, as cited in Guzdial, 2008). Also, Donald Knuth – another renowned computer scientist, hypothesized that learners' understanding of tasks is enhanced when they translate the problems' solutions into machine-interpretable formats (Knuth, 1974). Therefore, even when these literacies were not explicitly described as 'computational thinking', the works of Papert, Perils, and Knuth highlighted the association between computer science practices and human cognition (Bull et al., 2020).

The above historical accounts on the transfer of computer science practices into solving problems underlie the current CT discourse. However, what it means to think like a computer scientist remains a challenge. In Wing (2006), CT was linked to practices such as abstraction, decomposition, data interpretation, heuristic reasoning, recursive thinking, system thinking and parallel processing. This framing has been criticized as loose and overly broad (Mannila et al., 2014). But alternative perspectives suggested that Wing's framing of CT should be interpreted as a nudge to explore the benefits of computer science in other domains and a 'shorthand' for making computer science accessible to all students (Nardelli, 2019, p. 32). Subsequently, many frameworks have been proposed for learning and instruction such as the CT model of the International Society for Technology in Education (Barr & Stephenson, 2011; Barr et al., 2011) and Computing at School (Csizmadia et al., 2015). Also, several researchers have suggested alternative models to articulate the dimensions of CT (e.g., Brennan & Resnick, 2012; Selby & Woollard, 2013; Shute et al., 2017; Weintrop et al., 2016). While there are some overlaps, these frameworks differ in their dimensions and reflect the difficulty in describing the complex thinking styles of computer scientists (Ezeamuzie & Leung, 2022).

The non-consensus on CT makes comparing learning and assessment across studies challenging (Ezeamuzie, 2023). Whereas a consistent definition may appeal to educators, Ezeamuzie and Leung (2022) described such missions as uphill tasks and recommended that researchers investigate how dimensions of CT augment everyday problem-solving. These recommendations are consistent with Nardelli (2019), who envisaged that focusing on the theories may derail the agenda of making computing accessible to all. Another remaining trouble spot deals with how to distinguish between CT and computer programming. Wing (2006) described CT explicitly description as 'conceptualizing, not programming' (Wing, 2006, p. 35). However, many studies operationalized CT by assessing learners' programming knowledge (Ezeamuzie & Leung, 2022; Lye & Koh, 2014).

2.2 Computational thinking as an outcome of multilevel contextual factors

The underpinning framework for this study is derived from ICILS–2018 contextual framework (Fraillon et al., 2019). ICILS–2018 framework mapped CT as an outcome of multilevel contextual factors. Figure 1 shows the framework with four contextual levels: wider community, school/classroom, home environment, and individual levels.

The wider community context deals with external variables such as the technology development index of a country, government policies, and the features of the regional educational system. For example, several national and local educational policies predicted students' CT development (Ezeamuzie et al., 2024). Other levels of the contextual determinant of CT include school/classroom setup (e.g., learning environment designs and availability of technology in school) and home environment (e.g., parent education and family composition). The individual context describes how distinct students' features may influence CT development. Examples include studies that examined the influence of students' gender, academic grade, and prior knowledge on CT (Ezeamuzie, 2023; Grover et al., 2019).

Although the different contexts are mapped to different levels (see Fig. 1), they interact with one another. For instance, students' CT development may be attributed to multiple contextual levels such as home, school, and the wider community. In addition, each level of the framework has two components –process and antecedents.

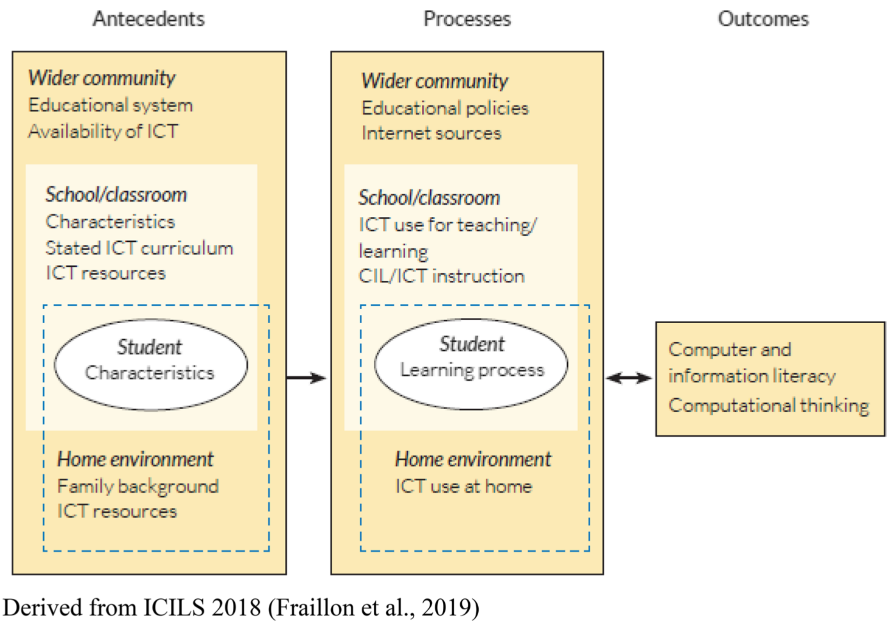

Fig. 1 Contextual framing of computational thinking as an outcome of multilevel contextual factors

The process and antecedents refer to features in the different contexts that have direct and indirect influences on the development of CT, respectively. This study examined the influence of school characteristics on CT development.

2.3 School contextual influence on computational thinking

In the first edition of ICILS (Fraillon et al., 2013), a latent analysis of school-level characteristics from 1727 schools showed that students' digital literacy attainments were distinguishable when schools were clustered by their ICT infrastructure, school vision, and teacher professional development (Gerick, 2018). This finding is consistent with an earlier study by Tondeur et al. (2008), which interviewed primary school principals ($n=53$) and surveyed their teachers ($n=574$). Tondeur et al. (2008) found that teachers' ICT use in the classroom is significantly influenced by school policies. The positive relationship between school characteristics, teachers' attitudes to ICT use, and students' digital literacy is also evident in other learners' outcomes. A second-order meta-analysis aggregated the findings of 25 meta-analytic studies on the use of computer technology in schools across 40 years (Tamim et al., 2011). Findings from the second-order meta-analysis revealed that the use of computer technology impacts students' achievements positively. However, some studies reported opposing perspectives on the effect of technology. For instance, McKnight et al. (2016) argued that ICT is not a determinant of successful learning but a thoughtful and careful implementation of ICT.

How school characteristics affect the development of CT remains unclear. Most CT research focused on the influence of learning environments (Hsu et al., 2018; Lye & Koh, 2014; Scherer et al., 2020), instructional approaches (Hsu et al., 2018; Lye & Koh, 2014; Scherer et al., 2020) and learners' features such as attitude, gender, age, and programming experience (Ezeamuzie, 2023; Sun et al., 2022). ICILS-2018 explored how different multilevel contextual variables influenced CT skills (see Fig. 1). However, the relationships between the school characteristics and CT were not explored (Fraillon et al., 2019). To address the knowledge gaps, the school characteristics refers to variables captured in the ICILS-2018. In this study, the characteristics are analysed in two broad categories – (a) ICT Capabilities and (b) General Characteristics.

School ICT capabilities refer to characteristics such as the teaching of ICT, the provision of innovative ICT teaching tools, the availability of ICT devices for learning, the expectation to use ICT and the priority accorded to ICT use in a school. The attitude of school leaders towards ICT matters too. For instance, a large-scale investigation on the role of ICT in mathematics and science classrooms revealed that school principals' views and support of ICT influenced its use in teaching and learning (Pelgrum, 2008). ICT has been increasingly adopted as standard practice in education (Fraillon et al., 2019). However, Gerick et al. (2017) found that the correlation between ICT and students' learning outcomes varied significantly across different educational systems. Hence, understanding the impact of school ICT capabilities on students' CT development remains a gap.

The general school characteristics comprised the school-wide attributes that were collected in ICILS-2018. These include the number of students, number of teachers, student–teacher ratio, socioeconomic status, number of grade levels, and number of students in target grade (i.e., Grade 8).

3 Research design

Data in this study was collected in ICILS-2018 and comprised a sample of 46,561 students in Grade 8 across 14 countries/regions. ICILS examines students' preparedness for life in a technology and information-driven society. ICILS-2018 was organised by the International Association for the Evaluation of Educational Achievement (IEA) – an independent research organization that has overseen large-scale comparative studies including Progress in International Reading Literacy Study (PIRLS), Trends in International Mathematics and Science Study (TIMSS), and International Civic and Citizenship Education Study (ICCS) for more than sixty years.

The CT achievements of 31,823 students in 1412 schools across eight countries (Denmark, Finland, France, Germany, Luxembourg, Portugal, South Korea, United States) and one region (North Rhine-Westphalia of Germany) were examined. Students completed two parts of CT tests that comprised 17 questions and 39 score points. Part 1 focused on *conceptualizing problems* through a 25-min automated bus task that assessed students' ability to analyse problems, understand digital systems and represent data. Part 2 focused on *operationalizing solutions* in a 25-min farm drone task. The drone task measured students' ability to plan, develop and evaluate algorithmic solutions.

To account for the difference in item difficulties across the 39 score points, students' CT achievements were standardized through the Rasch item response theory with a global mean ($M = 500$), and standard deviation ($SD = 100$). About 99.7% of the students have CT scores between 200 and 800. The minimum and maximum CT scores were 81.7 and 872, respectively. CT scores were categorized into three classes of achievements (lower, middle, and upper) with thirteen items in each class. Items in each class were ordered by their scaled difficulty (Fraillon et al., 2020a, p5).

The *lower* class represents students with less than 459 points. Students in this class ($n = 10{,}973$; 34.5%) demonstrated the ability to use simple sequences in algorithmic problems. However, the lower class created inefficient algorithmic solutions for tasks of medium complexity. The *middle* class represents students with CT scores between 459 and 589 points. These students ($n = 15588$; 49.0%) understood the application of CT in real-life problem-solving, created iterative algorithms and designed efficient solutions for medium-complexity tasks. However, the middle class created inefficient solutions for high-complexity problems that require multiple levels of iterations and decisions. The *upper* class represents the band of students with CT scores greater than 589 points. Students in the upper class ($n = 5262$; 16.5%) had a firm grasp of CT as a generalizable problem-solving approach and developed efficient algorithms in high-complex tasks.

The characteristics of the 1412 participating schools were collected through an online survey addressed to the school principals and ICT coordinators. The school-level data were combined with students' CT achievement as described in 'merging files from different levels' using the IEA IDB Analyzer (Mikheeva & Meyer, 2020, p. 27). Details of the research design and data management strategies are documented in the assessment framework (Fraillon et al., 2019), technical report (Fraillon et al., 2020a), international report (Fraillon et al., 2020b), and database user guide (Mikheeva & Meyer, 2020).

The consolidated data from the school characteristics and students' CT achievements yielded a dataset with more than 700 attributes. With a focus on the schools' ICT capabilities and general characteristics as plausible predictors of CT, unrelated and redundant attributes were removed. These included attributes with zero information gain (e.g., unique identifiers of countries, schools, and students), students' questionnaires and test items, individual items in the school questionnaire, sampling weights, and variance estimations. On the other hand, attributes derived from the aggregation of school questionnaire items and students' CT achievements were retained for data analysis (Supplementary 1).

Table 1 shows the 22 school characteristics that are potential predictors of CT in two broad categories – (a) general characteristics (G01, G02, G03, G04, G05, G06) and (b) ICT capabilities (T01, T02, T03, T04, T05, T06, T07, T08, T09, T10, T11, T12, T13, T14, T15, T16). ICILS-2018 used Rasch item response theory to derive T07, T08, T09, T10, T11, T12, T13, T14, T15, and T16. The values of these attributes were represented with an international mean ($M = 50$) and standard deviation ($SD = 10$). The 'low' label was assigned when the value of the characteristic was less

Table 1 Summary of ICILS 2018 school-level data

Code: School Attribute	ICILS Code	Value (Students coverage) [a]	Description
General Characteristics			
G01: Number of students	P_NUMSTD_CAT	1–300 (9.1%); 301–600 (27.5%); 601–900 (26.4%); greater than 900 (25.5%); missing (11.5%)	Number of students in school (School size)
G02: Number of teachers	P_NUMTCH_CAT	1–25 (11.6%); 26–50 (34.2%); 51–75 (21.0%); greater than 75 (20.2%); missing (13.0%)	Number of teachers in school (School size)
G03: Student–teacher ratio	P_RATTCH	1–10 (22.4%); 11–20 (60.4%); greater than 20 (2.8%); missing (14.4%)	Number of students per teacher in the school. The value is the inverse of the original ICILS code, which measured 'teacher to student' ratio
G04: Socioeconomic Status [b]	P_COMP	affluent (30.1%); neutral (13.8%); disadvantaged (43.4%); missing (12.7%)	School composition by student socioeconomic background
G05: Number of Grade levels	P_NGRADE	1–6 Grades (48.4%); 7–14 Grades (41.1%); missing (10.5%)	Number of grade levels in school (School size)
G06: Number of students in target group	P_NUMTAR_CAT	1–100 (30.4%); 101–200 (34.9%); greater than 200 (22.4%); missing (12.3%)	Number of students in the 8th grade – the target grade (School size)
ICT Capabilities			
T01: ICT experience	C_EXP	never (5.0%); less than 5 (11.5%); 5–9 (25.7%); greater than 9 (45.5%); missing (12.3%)	The number of years that schools have used ICT for teaching and learning
T02: Teaching of Computing in target grade	II2G14	yes (40.6%); no (46.5%); missing (12.9%)	Whether computing or similar subject is taught as a standalone subject at the target grade (Grade 8)
T03: Provision of personal digital device for teachers	II2G08	yes, for every teacher (27.9%); yes, but not for all teachers (14.9%); no (44.9%); missing (12.3%)	Whether school provides teachers with personal digital device?
T04: Student–ICT devices available for students' use ratio	C_RATSTD	at least 1 (9.1%); less than 5 (31.4%); 5–20 (28.5%); greater than 20 (5.5%); missing (25.5%)	Number of students per ICT device (only the ICT devices that are available for students' use)
T05: Student–smartboard ratio	C_RATSMB	at least 20 (17.2%); 21–50 (13.3%); 51–100 (9.9%); greater than 100 (24.8%); missing (34.8%)	Number of students per smartboard
T06: Student–ICT devices ratio	C_RATDEV	at least 1 (11.5%); less than 5 (41.4%); 5–20 (21.1%); greater than 20 (1.3%); missing (24.7%)	Number of students per ICT device (all usable ICT devices in the school)

Table 1 (continued)

Code: School Attribute	ICILS Code	Value (Students coverage) [a]	Description
T07: Expectation for teachers to use ICT[c]	P_EXPLRN	low (57.1%); high (32.0%); missing (10.9%)	Expectation for teachers to use ICT in learning activities
T08: Expectations for teacher to collaborate with ICT [c]	P_EXPTCH	low (44.5%); high (44.5%); missing (10.9%)	Expectations for teachers to collaborate with ICT
T09: Priorities for increasing ICT hardware resources[c]	P_PRIORH	low (47.2%); high (41.1%); missing (11.8%)	Priority given to increasing ICT hardware resources to facilitate teaching and learning?
T10: Priorities for increasing ICT pedagogical support [c]	P_PRIORS	low (48.9%); high (39.5%); missing (11.6%)	Priority given to increasing ICT professional learning resources, software and supports to facilitate teaching and learning?
T11: Availability of ICT resources at school [c]	C_ICTRES	low (43.3%); high (44.7%); missing (12.0%)	Availability of ICT resources at school
T12: Hinderance to learning related to computer and network resources [c]	C_HINRES	low (50.7%); high (36.4%); missing (12.9%)	Computer and network resource hinderances to use of ICT in teaching and learning
T13: Hinderance to learning related to pedagogical resources. [c]	C_HINPED	low (43.4%); high (43.8%); missing (12.8%)	Pedagogical resource hindrances to the use of ICT in teaching and learning
T14: Principal's view on ICT use[c]	P_VWICT	low (43.5%); high (45.6%); missing (10.9%)	Principal's view on using ICT for educational outcomes
T15: Principals' general use of ICT [c]	P_ICTUSE	low (45.8%); high (45.8%); missing (8.4%)	Principals' use of ICT for general school-related activities
T16: Principals' communication use of ICT [c]	P_ICTCOM	low (38.5%); high (53.0%); missing (8.5%)	Principals' use of ICT for school-related communication activities

[a] Students coverage is the percentage of student participants that were enrolled at schools where each of the school attribute's values were reported. For example, G04 (Socioeconomic Status) depicts the percentage of students that are in affluent, disadvantaged, and neutral in schools. The focus is on school characteristics (not to be interpreted as the number of students that are affluent, disadvantaged, or neutral)

[b] The 'affluent' category represents schools that have more affluent than disadvantaged students. Similarly, the 'disadvantaged' schools have more disadvantaged students than affluent students. The 'neutral' category has neither more affluent nor more disadvantaged students

[c] The 'low' and 'high' value depicts scores of less than 50pts and greater than 50pts, respectively

than the international mean. Conversely, a 'high' label was assigned when the value of the characteristic was greater than or equal to the international mean.

4 Educational data mining approach

First, a multiple linear regression was conducted using the stepwise method to unearth how school characteristics predict CT. The stepwise method is an iterative forward and backward approach that enters a predictor that makes significant contributions to the model, re-analyzes the model, and removes predictors that do not meet the model's requirements. Unequal variability from the multi-level effect of the school-level data was corrected with the final school weight variable 'TOTWGTS' (Mikheeva & Meyer, 2020, p. 27). Less than 9% of the variability of the CT achievement was explained by the resultant model (F (16, 17,758) = 106.315, $p < 0.001$, $R^2 = 0.087$). The strength of the linear relationship between the predictors and CT was computed with Pearson correlation (Table 2). The weak multiple linear regression was consistent with the weak correlation between the school characteristics and CT. The school characteristics that correlated significantly with CT ($p < 0.05$) had absolute Pearson's correlation coefficient between 0.021 in G5 (number of grade levels) and 0.239 in G4 (Socioeconomic status). Given the weak regression and correlation, data mining procedures were executed to gain additional insight into the school characteristics' prediction of CT achievements.

Data mining denotes experimental approaches for discovering the relationship between attributes of an object from a large dataset. Often iterative, it embodies well-designed logical and statistical processes to predict relationships and outcomes; and has been applied in educational interventions. Examples include the prediction of pre-service teachers' CT skills from their learning behaviour (Jin & Cutumisu, 2023), learners' level of satisfaction in a massive open online course (Hew et al., 2020), learners' academic performance from their activities in a learning management platform (Romero et al., 2013), and the relationship between learners' demographic distribution and academic performance (Rizvi et al., 2019). Figure 2 shows three stages of data mining operations that guided the analysis. An open-source software package for data mining and machine learning '*Weka 3.8*' was used in the analysis (Witten et al., 2016).

4.1 Instance selection

The accuracy of machine classifiers is inversely related to the number of options in the class attribute (Witten et al., 2016). In this study, the dependent variable (i.e., CT achievements) is the class attribute. The 'middle' class instances may decrease the classifiers' accuracy. Therefore, parallel experiments were executed with the data instances that were mapped to only the 'lower' and 'upper' classes.

Data was shuffled with Weka's instance randomization filter to prevent selection bias and two datasets were created – (a) *class3data* and (b) *class2data*. *Class3data* ($n = 31{,}823$) contains data on students with lower, middle, and upper CT

Table 2 Correlation matrix of the attributes and computational thinking (CT) achievements

General Characteristics	G01	G02	G03	G04	G05	G06										
Pearson's r	-0.024	-0.079	0.121	-0.239	-0.021	–										
ICT Capabilities	T01	T02	T03	T04	T05	T06	T07	T08	T09	T10	T11	T12	T13	T14	T15	T16
Pearson's r	–	–	-0.09	0.022	-0.039	–	0.082	0.124	–	–	0.112	–	-0.028	0.047	0.03	0.033

– attribute is not significantly correlated with CT ($p=0.05$)

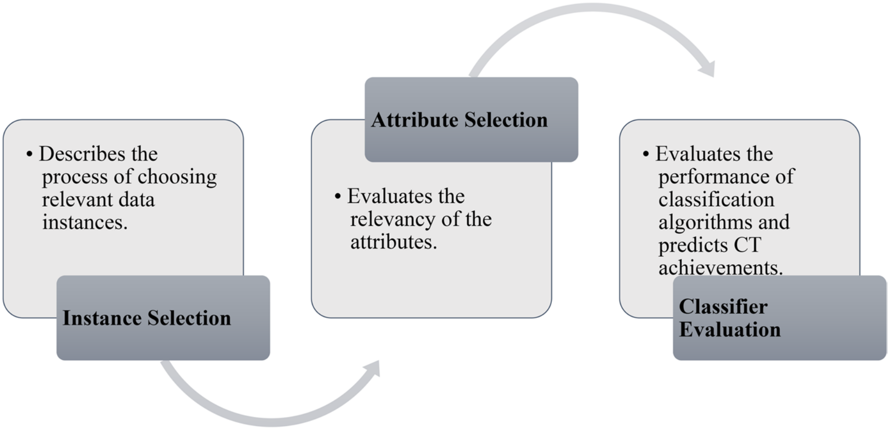

Fig. 2 Data mining approach for predicting relationship between school characteristics and students' computational thinking achievements

achievements (Supplementary 1). *Class2data* ($n=16,235$) excluded the middle CT achievers (Supplementary 2). The performances of the classifiers were evaluated with the two datasets – *class3data* and *class2data* in the subsequent data mining operations.

4.2 Attribute selection

This examined the relevancy of the attributes (i.e., school characteristics) in predicting students' CT achievement. Attributes' relevancy was evaluated with (a) filter-based rankers and (b) search for an optimal subset of attributes. A similar approach was adopted in Romero et al.'s (2013) investigation of how learners' behaviour predicts students' performance in an online discussion forum.

Filter-based rankers – Weka's *ChiSquaredAttributeEval, InfoGainAttributeEval* and *GainRatioAttributeEval* were executed. *ChiSquaredAttributeEval* measures Chi-squared statistics as a test of the relationship between attributes (i.e., school characteristics) and class (i.e., CT achievements). *InfoGainAttributeEval* and *GainRatioAttributeEval* rank attributes by comparing the information gain and gain ratio, respectively.

- Info Gain (Class, Attribute) = H(Class) – H(Class | Attribute)
- Gain Ratio (Class, Attribute) = (H(Class) – H(Class | Attribute)) / H(Attribute)
- H is the Entropy

Search for optimal subsets of attributes – this compares the predictive ability of a set of attributes. Weka's *WrapperSubsetEval* was used to evaluate the relevance of attributes when wrapped in different classifiers. The following classifiers were wrapped in the evaluation: Random Tree, Random Forest, J48, Decision Stump, Hoeffding Tree, ZERO, ONER, PART, JRIP, and Decision Table. For each of the wrapped classifiers, the attribute space was searched using the bi-directional method and evaluated through tenfold cross-validation. The bi-directional or evolutionary technique starts a search at any point, transverses the feature space in both backward and forward directions, and examines all attributes for deletions and additions at all points. The details of the above selection techniques and classifiers are described in the Weka guidebook (Witten et al., 2016).

4.3 Classifier evaluation

The performances of classifiers in predicting the influence of the attributes (i.e., school characteristics) on students' CT achievement were evaluated. Rule-based and tree-based classifiers were chosen to display predictions in visualized and logical formats. Tree pruning and a 5% minimum instance coverage rule were set to avoid over-fitting (i.e., a scenario where the classifier fits the training data, but depreciates in performance with unseen data). Classifiers were evaluated with tenfold stratified cross-validation (i.e., splitting the dataset into 10 identical subsets with similar class distribution and one subset formed the test data in each of the 10 iterations).

The classifiers' performance was reported with three metrics: accuracy, precision, and recall. Figure 3 shows the confusion matrix. Accuracy represents the percentage of correctly classified instances (i.e., the sum of the correct classification / total number of instances in the test). Precision represents the percentage of correct prediction when a class is predicted (i.e., number of correct predictions of a class / total number of times the class was predicted). Recall represents the percentage of the class that was correctly predicted, within an actual class (i.e., the number of correct predictions of a class / total number of actual instances in the class).

	Predicted: U	Predicted: L
Actual: U	T_U	F_L
Actual: L	F_U	T_L

Note.
U = Upper, L = Lower, T = True Prediction, F = False Prediction
Accuracy = $(T_U + T_L) / (T_U + F_U + T_L + F_L)$
Precision $_{Upper}$ = $T_U / (T_U + F_U)$; Recall $_{Upper}$ = $T_U / (T_U + F_L)$
Precision $_{Lower}$ = $T_L / (T_L + F_L)$; Recall $_{Lower}$ = $T_L / (T_L + F_U)$

Fig. 3 Confusion matrix of a two-class (upper, lower) computational thinking achievement

5 Results

5.1 Outcome of attribute selection

The results of the attribute selection and the descriptions of the underlying classifiers are enclosed in Supplementary 3. In summary, the wrapper-based attribute selection processes generated empty subsets of attributes except *OneR*. In *OneR*, socioeconomic status (G04) was selected as a relevant predictor in the binary-class CT dataset (i.e., *class2data)*. For the filter-based analysis, Fig. 4 shows the attribute ranking as the average of the filter-based techniques.

The high-ranked attributes (i.e., predictors appearing in the top 25%) included socioeconomic status (G04), student–teacher ratio (G03), number of teachers (G02), provision of personal digital devices for teachers (T03), expectations for teachers to collaborate with ICT (T08), and availability of ICT resources at school (T11).

Conversely, the following attributes were in the bottom 25% of the predictor list: number of grade levels (G05), ICT experience (T01), teaching of computing in target grade (T02), priorities for increasing ICT hardware resources (T09), priorities for increasing ICT pedagogical support (T10), hinderance to learning

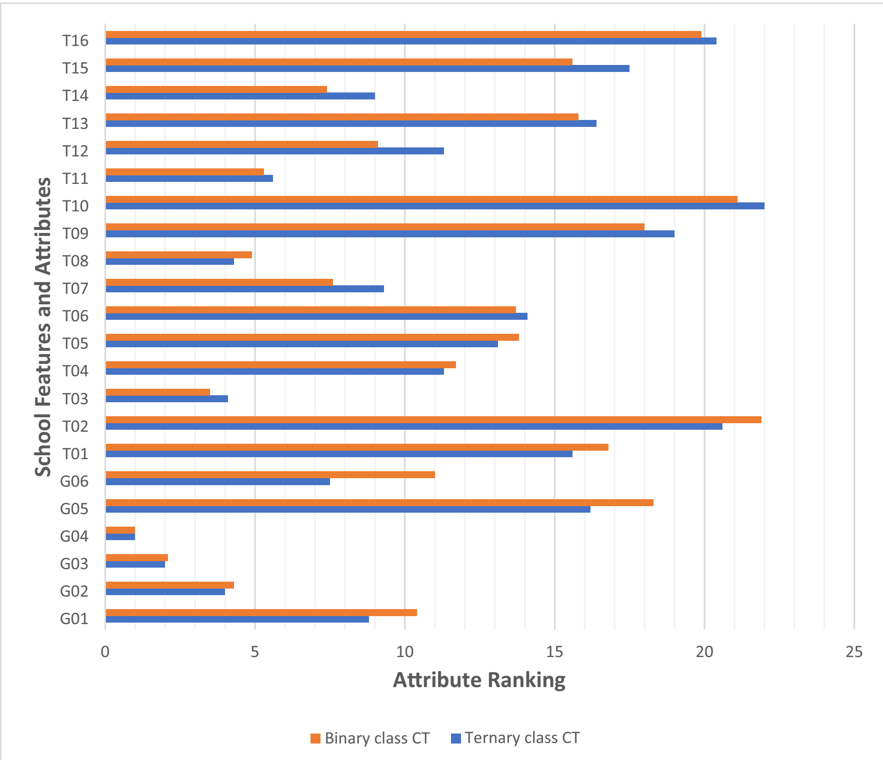

Fig. 4 Average attribute ranking across the binary and ternary class dataset

related to pedagogical resources (T13), principals' general use of ICT (T15), and principals' communication use of ICT (T16).

5.2 Outcome of classifier evaluation

Supplementary 4 contains the performance metric of the classifiers. The performance was computed with the following predictors – (a) all the attributes, (b) top 25% ranked attributes and (c) top 50% ranked attributes. In general, the accuracy of classifiers executed with the binary-class dataset (i.e., *class2data*) ranged between 67.6% to 75.9% and was significantly higher than the ternary class dataset (i.e., *class3data*) with classifiers' accuracy between 49% to 54.1%. This outcome justifies the rationale for a parallel evaluation of the classifiers without the *middle* CT achievers. Table 3 shows the accuracy, precision, and recall for the binary-class dataset. The precision and recall of the lower class were considerably higher than the upper CT class. This indicates that the models predicted lower CT achievers better than upper achievers.

Table 3 Performance evaluation of the classifiers (binary-classed CT dataset)

Classifier	Accuracy (%)	Precision (%)		Recall (%)	
		Lower	Upper	Lower	Upper
ZERO [a]	67.6	67.6	–	100	0
One Rule [a]	68.7	74.6	52.2	81.4	42.4
PART [a]	70.5	73	58.6	89.5	31
JRip [a]	70.6	73.2	58.6	89.1	32.1
Decision Table [a]	75.9	79.5	65.9	86.8	53.3
Random Tree[b]	68.1	68.7	55.3	96.8	8.2
Random Forest[b]	68.3	68.2	75.2	99.5	3.1
Decision Stump[b]	67.6	67.6	–	100	0
Hoeffding Tree[b]	71.1	75.9	56.9	83.8	44.5
J48[b]	70.9	73.4	59	89.1	32.8
REP Tree[b]	71	73.7	59	88.7	34

[a] Rule-based, [b] Tree-based

```
JRIP rules:
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(G04:P_COMP_c = affluent) and (G03:P_RATTCH_c = 11–20) => CT_c=upper (2881.0/1194.0)
 => CT_c=lower (13354.0/3575.0)

Number of Rules : 2
```

Fig. 5 Rules generated by JRIP classifier

5.3 Interpretating classifier outputs

High accuracy is desirable for interpreting the outputs of classifiers. However, what constitutes acceptable accuracy is subjective. Following a similar threshold in predicting CT from policies (Ezeamuzie et al., 2024), 70% accuracy was designated the cut-off for interpreting the rules. The DecisionTable classifier was excluded because of overfitting – classifier does not support pruning and yielded 1224 rules. Figures 5, 6, 7, 8, and 9 show the generated rules and trees. Notations in rule-based and tree-based classifiers are interpreted as *if-else-then* rules.

JRip classifier Fig. 5 shows the JRip classifier with two rules. The ‘ = > ’ represents the THEN operator. Rule 1 states that ‘IF G04 = affluent AND G03 = 11 – 20, THEN CT = upper’. Implicitly, students are predicted to attain upper CT levels when majority of students in the school come from affluent socioeconomic status (G04) and the student–teacher ratio (G03) is between 11 and 20. Rule 2 predicted lower CT achievement if the first rule is not satisfied.

PART classifier Fig. 6 shows the PART classifier with four rules. The ‘:’ represents the THEN operator. Rule 1 predicted lower CT levels when majority of students in the school come from disadvantaged socioeconomic status (G04). Rule 2 predicted upper CT achievement for students from schools where majority of students come from affluent socioeconomic status (G04) and the student–teacher ratio (G03) is between 11 and 20. Rule 2 is equivalent to JRip’s Rule 1 (Fig. 5). Rule 3 predicted lower CT achievement when the student–teacher ratio (G03) is less than 10. Rule 4 predicted lower CT achievement when the preceding rules were not satisfied.

```
PART decision list
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G04:P_COMP_c = disadvantaged: lower (8778.25/1926.5)

G03:P_RATTCH_c = 11-20 AND
G04:P_COMP_c = affluent: upper (3394.04/1550.57)

G03:P_RATTCH_c = 1-10: lower (2043.13/609.52)

: lower (2019.58/882.51)

Number of Rules  :      4
```

Fig. 6 Rules generated by PART classifier

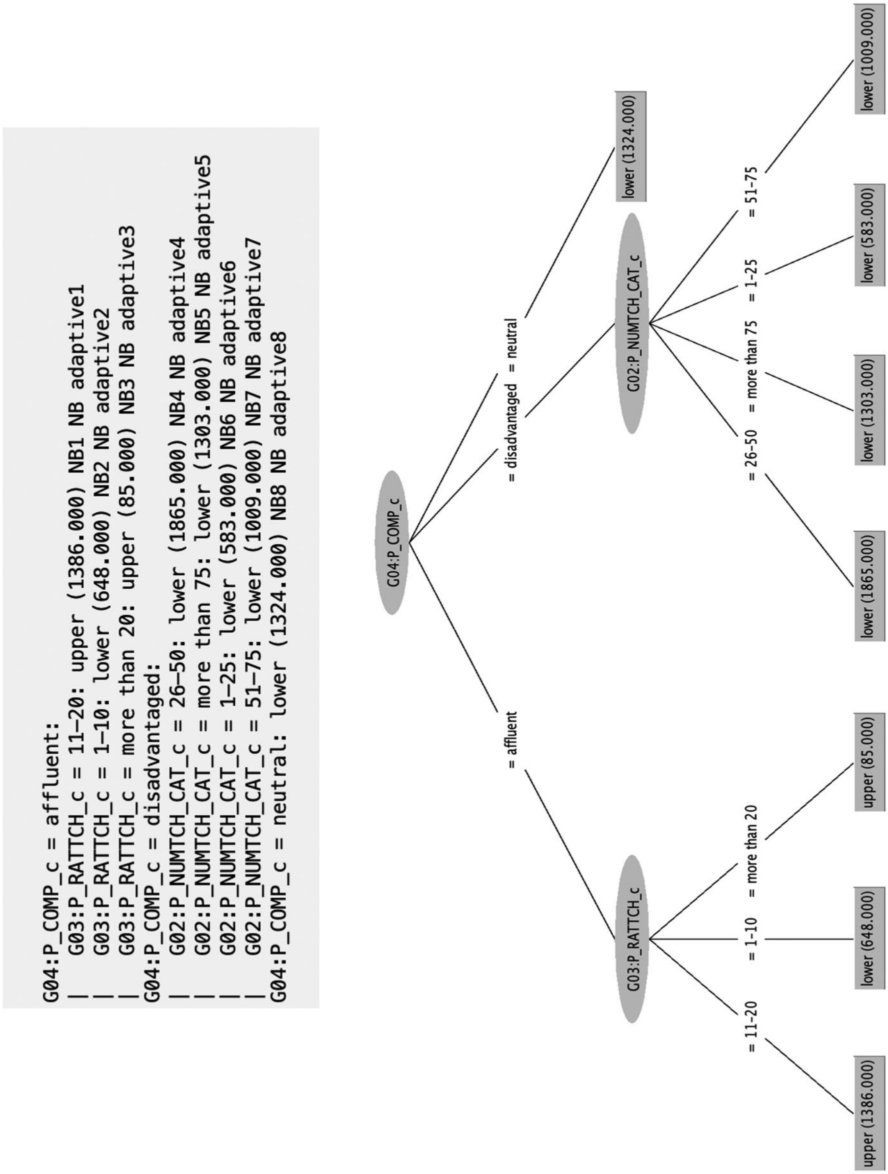

Fig. 7 Tree generated by Hoeffding Tree classifier

Tree-based classifiers – Hoeffding Tree (Fig. 7), J48 (Fig. 8), and REP Tree (Fig. 9) met the 70% accuracy cut-off. Trees have nodes (the attributes) and branches (the value of the attributes). The root node is the topmost oval in the Figures and branches to the leaf nodes. For instance, socioeconomic status (G04) is the root node of Hoeffding Tree (Fig. 7) and has three branches: *affluent*, *disadvantaged*, and

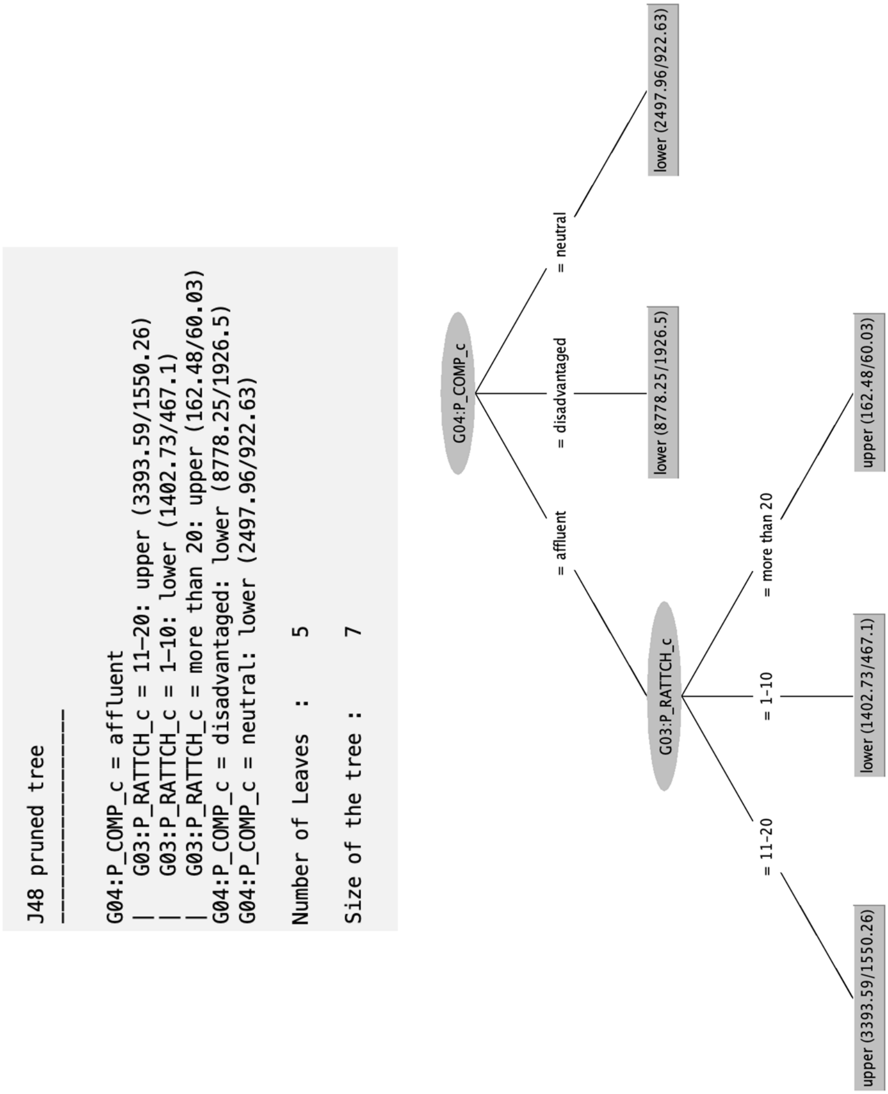

Fig. 8 Tree generated by J48 classifier

neutral. Every path from the root terminates in a decision node with either lower or upper CT. Rules are generated by tracing the paths from the root node to the decision nodes. For example, the leftmost path in Hoeffding Tree (Fig. 7) predicted upper CT achievement when majority of students in the school come from affluent socioeconomic status (G04) and the average student–teacher ratio (G03) is between 11 and 20 or greater than 20.

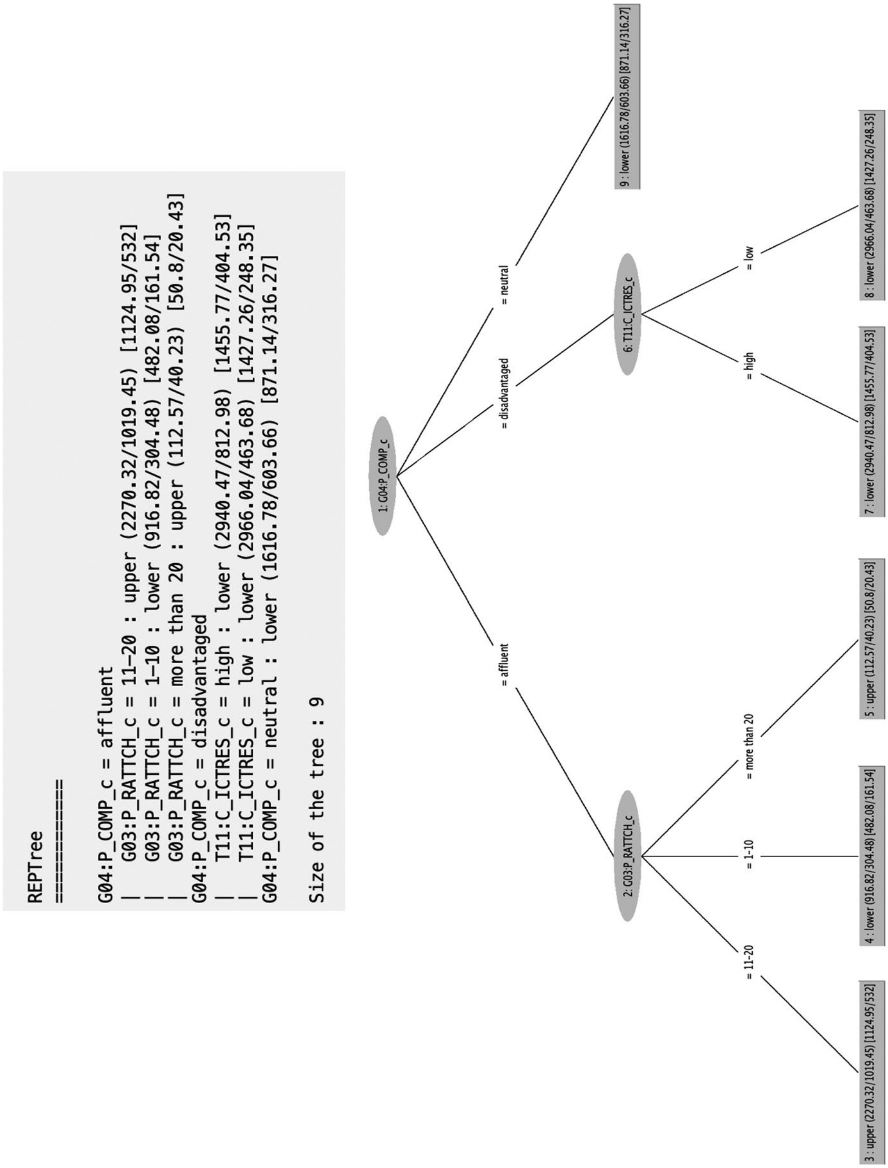

Fig. 9 Tree generated by REP Tree classifier

6 Discussion

The outputs from the rule-based and tree-based classifiers were triangulated. No definite prediction could be drawn from the school characteristics except for the socioeconomic status (G04) and student–teacher ratio (G03).

6.1 Socioeconomic status

According to the classifiers (see Figs. 5, 6, 7, 8, and 9), students have higher tendency to develop CT skills in schools where majority of the students come from affluent socioeconomic status. This finding may raise concerns about equity and inclusiveness for learners from disadvantaged schools or low socioeconomic status. One logical extrapolation of this finding suggests that students from affluent socioeconomic status are more likely to attend schools that have quality ICT infrastructure to support learning. However, more substantiation is required to understand the interplay of socioeconomic status and CT achievements. The findings that the socioeconomic status (G04) affects CT may not be generalizable as it was derived from classification rules with marginal accuracy and weak recall for upper CT achievers. Also, there are contrasting studies like the investigation on web-mediated parents-child home learning that showed family socioeconomic status had no moderating effect on students' CT skills (Li & Yang, 2023).

6.2 Student–teacher ratio

The classifiers generated some interesting rules about the student–teacher ratio (G03) too. The Prediction of higher CT achievement for students in schools that have majority of their students from affluent socioeconomic status, is also hedged in the 'AND' logical conjunction with the student–teacher ratio (G03). Higher CT achievement is predicted when the student–teacher ratio (G03) is between 11 and 20 (see Figs. 5, 6, 7, 8, and 9), and when the student–teacher ratio (G03) is greater than 20 (see Figs. 7, 8, and 9). On the other hand, the classifiers predicted lower CT achievements when the teacher supported fewer students. This prediction may not be consistent with the expectation that small classroom would make for personalized attention and improved learning. One plausible explanation that can be adduced is that schools with low student–teacher ratio were likely supporting special educational needs. Since the underlying cause of this variance is unclear, more investigations are required in future studies.

6.3 School ICT capabilities

The lack of insight into the influence of school ICT capabilities on CT development is interesting, or perhaps a concern in this study. No definitive prediction could be deduced from the ICT experience of a school (T01). In other words, the number of years that a school have used ICT for teaching and learning may not translate to the level of students' CT achievement. Though surprising, some prior studies found that students' prior experience in ICT (Shih et al., 2006) and programming (Ezeamuzie, 2023) did not enhance their abilities to solve CT-related tasks.

Teaching computing (T02), providing digital devices for teachers (T03), and the availability of ICT devices to students (T04, T05, T06, T11) did not predict CT achievement. Likewise, no definitive prediction could be deduced from the expectation to use ICT (T07, T08), priority for ICT in learning (T09, T10), hindrances to ICT use (T12, T13) and school leadership's attitudes towards the use of ICT (T14, T15, T16). The above findings contradict the perceived connection between school ICT and CT. Anecdotally, there is a perception that ICT resources are enablers of CT. Most CT interventions have underlying ICT platforms such as computers, robotics, and micro-controllers. For example, Agbo et al. (2022) evaluated how virtual reality environments supported the development of minigames for fostering CT skills. More so, Ezeamuzie and Leung (2022) found that ICT and CT share blurred boundaries in most empirical studies, where CT is often associated with computer programming.

Prior studies that synthesized the effect of ICT on learning such as the meta-analysis by Sung et al. (2016) and a second-order meta-analysis by Tamim et al. (2011) found that the use of ICT has positive impacts on students' learning, albeit moderately. In contrast, this study found that schools' ICT capabilities seem insufficient in enhancing students' CT skills. McKnight et al. (2016) had a similar observation that the ordinary presence or use of ICT alone is not a determinant of successful learning. Therefore, schools need to incorporate CT into their curriculum in meaningful ways and prompt teachers to interrogate their ICT practices. Future work is required to identify the nuanced relationship between school ICT capabilities and students' CT development.

6.4 Limitations

The first threat to the validity of the result is inherited from the underlying data. School characteristics were snapshots from the participating schools. Hence, the data did not account for the historical developments in schools across the years, which may be probable moderators in students' CT achievements. For instance, schools that reported active availability of ICT might have varied experiences in their usage.

The second limitation is the weak performance of the classifiers. What constitutes an acceptable accuracy level is subjective. However, higher accuracy, recall and precision are desirable for enhanced confidence in emerging rules. Specifically, the weak recall of the upper CT class implies that the models could not predict CT development reliably.

The third issue deals with the multi-dimensional framing of CT. Students' CT achievements were assessed as *conceptualizing problems* (in an automated bus task that probed understanding of digital systems and representation of data) and *operationalizing solutions* (in a farm drone task that measured students' ability to develop and evaluate algorithms). CT framing by ICILS represents one approach and differs from others such as alternative arguments in favour of broadening CT to everyday problem-solving (Ezeamuzie, 2023; Ezeamuzie et al., 2022; Standl, 2017).

7 Conclusion

Despite the limitations, this study unearthed valuable knowledge and research gaps. CT is still a crystallizing literacy and the multiple conceptualizations may not be faulted per se. Also, 70% cut-off accuracy for interpreting the classifiers' results is superior to the accuracy of basic classifiers such as ZERO (67.6%) and OneR (68.7%), which predicted classes with the highest count and minimum-error attribute, respectively (Witten et al., 2016). The weak predictions may not imply that school characteristics are not relevant. Rather, it opens fronts for future research and discussion on the nuanced interactions of school characteristics and CT skills.

Tying back to the research question – how schools' general characteristics and ICT capabilities influence students' CT achievement, data from 31,823 students in 1412 schools across 9 regions were collated, analysed, and triangulated. Twenty-two dimensions of school characteristics framed in two categories – general characteristics ($n = 6$) and ICT capabilities ($n = 16$), were analyzed as potential predictors of CT. A preliminary multiple linear regression analysis resulted in a weak model, explaining less than 9% of the variability of CT achievement. Similarly, the correlations between the school characteristics and CT were weak. Consequently, data mining procedures were implemented to further explore the relationship.

No predictions were deduced from school characteristics on CT achievement except for the socioeconomic status and student–teacher ratio. The plausible rules that predicted higher CT achievement for learners from affluent schools and high student–teacher ratio should be interpreted with caution. The finding may not be generalizable as the classifiers were moderately accurate. In addition, some confounding explanations existed.

Nonetheless, this study adds to our knowledge of the interaction between school characteristics and students' CT achievement. Ordinary presence or use of ICT in schools is not a definitive determinant of successful learning. With the continuous emphasis on developing problem-solving skills in schooling, it is important to uncover how school characteristics and ICT influence the development of CT – a genre of problem-solving skill for everyone that is rooted in computer science.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10639-024-12644-9.

Data Availability The data supporting this study's findings are available for free and can be accessed from the ICILS-2018 database [https://www.iea.nl/data-tools/repository/icils].

Declarations

Conflicts of interest The authors have no relevant financial or non-financial interests to disclose.

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