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Information technology, mathematics achievement and educational equity in developed economies

Cheng Yong Tan and Khe Foon Hew

Faculty of Education, The University of Hong Kong, Pokfulam, Hong Kong

ABSTRACT

The present study examined how access to home and school IT resources impacted student mathematics achievement. Data comprised 144,395 secondary school students from 7,308 schools in 22 developed economies who participated in the Programme for International Student Assessment (PISA) 2012. Results of hierarchical linear modelling showed that after controlling for student and school covariates, student achievement benefited from their access to home IT resources (main effect), and from the access to both home IT resources and highly educated mothers (interactive effect). Furthermore, IT resource shortages in school had a detrimental impact on student achievement (main effect), and the shortage accentuated the negative effects of school shortage in qualified teachers on achievement (interactive effect). Lastly, the results showed that students with less home academic and cultural resources were more impacted by IT resource access when compared to peers from advantaged families.

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Introduction

There is an evolving consensus among policy-makers, scholars and educators in contemporary societies that effective schools should not just produce high levels of students' achievement (i.e. "educational quality"), but also spread the benefits of learning across different students (i.e. "educational equality") (Schleicher 2009). The fascination with students' achievement has propelled scholars to examine the different factors that enhance students' learning (Hattie 2009; Reynolds et al. 2014). For example, Hattie (2009) analysed more than 800 meta-analyses examining how different variables in the domains of student, home, school, teacher, curricular and teaching approaches contributed to achievement. In particular, a review of the extant literature indicates that many researchers have examined how the access to home and school resources may enhance students' achievement (Chiu 2010; Visser, Juan, and Feza 2015). The nature and scope of these resources are varied, including the access to different home resources on the one hand, and the availability of qualified teachers, teaching-learning materials, infrastructure and IT in school on the other.

CONTACT Cheng Yong Tan tancy@hku.hk

Among these myriad resources, many policy-makers, scholars and educators have touted the potential of IT in enhancing the learning experiences of students (Delen and Bulut 2011). Indeed, the immense interest in IT has culminated in the conceptualisation and implementation of system-wide master-plans to integrate IT with school teaching, curriculum and assessment in many countries. The leveraging of IT to enhance learning is especially prolific in developed countries, such as the economies of the Organisation for Economic Cooperation and Development (OECD 2010), given their high levels of basic universal education, more developed education systems and greater financial resources (Baker, Goesling, and LeTendre 2002; Mourshed, Chijioke, and Barber 2010). This state of affairs is interesting when juxtaposed against the evolving research evidence indicating that home resources may be more influential than school resources in influencing achievement (Baker, Goesling, and Letendre 2002).

Given the dearth of well-designed studies on the contribution of home and school IT resources, there is little evidence to-date to unequivocally support or refute the rhetoric that access to IT can enhance student achievement. For example, Cheung and Slavin's (2013) meta-analysis of 74 studies showed that educational technology applications generally were, on average, related with modest but positive mathematics learning outcomes. However, OECD's (2015) recently published analysis of PISA 2012 international data showed that home or school IT resources were not associated with enhanced mathematics achievement. Even experimental studies showed mixed evidence for the contribution of IT to student achievement (Leuven et al. 2007; Machin, McNally, and Silva 2007).

Accordingly, the aim of the present study is to examine, using data from PISA 2012, how IT access contributes to students' mathematics achievement using the social construction of technology perspective (Klein and Kleinman 2002). This perspective challenges the presumed determinism of IT in affecting student learning (Selwyn 2012). It underscores the notion of students' perceived affordances (or possibilities; Hutchby 2001), as a function of their familial socio-economic backgrounds, on how access to IT resources can frame their agentic actions and in turn facilitate their learning.

Literature review

Access to IT resources

Technological advancement has led to the concomitant domestication and deployment of IT in households and schools to support student learning (Berker et al. 2006). More specifically, families and schools are able to purchase IT resources, own them, and incorporate them into student daily learning routines (Silverstone and Hirsch 1992; Silverstone, Hirsch, and Morley 1992). In the process, parents, teachers and students seek to understand and harness the capabilities of IT resources to support students' learning.

Indeed, many researchers have pointed to the positive influence of IT resources (at home and school) on the teaching and learning of mathematics (Dix 2007; Pierce and Ball 2009). Because technology can increase the motivation of students, especially disinterested ones (Pierce and Ball 2009), the access to more IT resources in learning should yield better overall mathematics achievement. Some scholars contend that technology is "mere vehicles that deliver instruction but do not influence student achievement" (e.g. Clark 1983, 445). In other words, IT per se has no impact on student achievement; rather student learning depends on the instructional methods used. This position was, however, challenged by other scholars. Kozma (1994), for example, argues that Clark's position created an "unnecessary and undesirable schism" (16) between medium (e.g. IT) and method. Recently, Cheung and Slavin (2013) argue that due to the extraordinary developments in IT over the recent years, medium, content and instructional methods are often intertwined and impossible to be separated in practice.

It is important to stress that the present study does not attempt to explicitly determine the unique instructional methods of using IT per se, as this has been explored by other researchers such as Cheung and Slavin (2013), and Hattie (2009). Instead, we explore how the overall effect of access to home and school IT resources such as Internet connectivity, computer-based instructional software and computers may impact students' achievement. These resources provide students with enriched learning opportunities that may not be available otherwise. Students, for example, could look for information on the Internet outside school hours on how to factorise algebraic expressions, use instructional software such as *SRA Drill and Practice* to supplement traditional classroom instruction, or determine how graphs change according to different parameters using *Geometer's Sketchpad*. Technology is here to stay, and therefore we believe it is useful for policy and practice to know the overall relationship between access to these IT resources (both in school and home) and students' achievement.

A review of the extant literature shows mixed results on the relationships between home and school IT resources, and student achievement. First, some studies found that access to IT resources was not related to student achievement. For example, Wittwer and Senkbeil's (2008) study of 4660 German students who participated in PISA 2003 showed that students' access to home computers was not related to their mathematics performance. Other studies reported that either home or school IT resources contributed more or exclusively to student achievement. Du et al. (2004) provided one of the earlier cases of this claim. Results of their multiple regression analysis of 15,362 US tenth graders from the National Educational Longitudinal Study 2002 showed that home IT access was far more significant than school IT access for students' reading and mathematics achievement. Papanastasiou and Ferdig (2006) found a similar positive relationship between home IT access and mathematics achievement. Using the PISA 2000 US data-set, they performed a series of multiple regressions to explain students' mathematics literacy scores based on their access to computer, among other relationships. Their results suggested that computer use at home and students' socio-economic status (SES) was associated with higher mathematics achievement. A surprising result of the study was that using computer in schools was unrelated to students' scores. A more recent study of 4996 Turkish students by Delen and Bulut (2011) found that students' access to home IT resources was a stronger predictor of their mathematics performance than their access to school IT resources. A third group of studies documented that both home and school IT resources benefited student achievement. For example, Demir, Ibrahim and Serpil (2010) examined the relationships between mathematics achievement and the access to IT (e.g. educational software, Internet connectivity) and non-IT resources (e.g. textbooks, library materials) for a sample of 4942 Turkish students who participated in PISA 2006. ANOVA and MANOVA results indicated that IT access had a greater effect than access to non-IT resources on achievement. Students who accessed computers at home, and who had Internet connection and educational software outperformed those who lacked access to these IT resources. Furthermore, students in schools with Internet connectivity performed better than those in schools lacking in Internet access.

Socio-economic status

Beyond examining if IT access relates to students' achievement in the mainstream literature, there is also a burgeoning body of studies that addresses issues of differential impact of IT access on diverse students. Researchers conducting these latter studies are concerned with issues of digital divide and equity in cognisance of student diversity (Korupp and Szydlik 2005; OECD 2010). In particular, many of these researchers examine how students from families of different SES backgrounds benefit differentially from access to IT resources, but the results are mixed (Attewell and Battle 1999; Li and Ma 2010; OECD 2010; Cheung and Slavin 2013). For example, Attewell and Battle (1999) found that American eighth-graders who had access to home computers reaped more educational gains in mathematics achievement if they were also from higher-SES families. Results from PISA 2006 also showed that students from the higher-SES families were more confident in Internet tasks and also had higher science achievement than students from lower-SES families (OECD 2010). On the other hand, two recent meta-analyses showed that the impact of IT on school achievement was similar for students with different SES backgrounds (Li and Ma 2010; Cheung and Slavin 2013). More specifically, Li and Ma (2010) reported that IT had similar effects on mathematics achievement for students from low- and middle-SES families, while Cheung and Slavin (2013) provided evidence that students from low- and high-SES families benefited similarly from IT.

Familial capital

In view of the inconclusive results on the impact of IT access, the present study addresses the issue of how home and school IT access contributes to the achievement of students from different familial SES backgrounds. More specifically, it examines how students with different levels of SES-related familial capital benefit differentially from IT access. This family capital perspective is informed by recent evidence demonstrating the inadequacy of using traditional SES indicators (e.g. parents' education) to map social stratification in increasing complex societies (Savage et al. 2013). For example, Savage and colleagues (2013) showed using latent class analysis that there were seven social classes that are characterised by different combinations of economic, cultural and social capital in the UK. Indeed, Bourdieu (1986) asserts that it is difficult to understand the functioning of the social world without recognising the existence of different forms of economic and non-economic capital. For the purposes of the present study, three different forms of familial capital are examined: human, academic and cultural.

First, human capital is a form of institutionalised capital that is accumulated in parents who are highly educated (Bourdieu 1986). These parents are able to more effectively support their children in using IT productively in learning (Giacquinta, Bauer, and Levin 1993). The second form of familial capital examined – academic capital – measures the availability of objectified resources at home (e.g. books and study desk) that reflects a premium on learning and that facilitates achievement (Byun, Schofer, and Kim 2012; Xu and Hampden-Thompson 2012). These objectified resources are sometimes used as a proxy for family wealth, and there is research evidence that students from more affluent families may have higher school achievement than poorer students (Hattie 2009). Therefore, it is important to control for the level of home academic capital in the endeavour to examine the impact of IT access on achievement. The third form of familial capital examined in the present study – cultural capital – measures the cultural attitudes and dispositions (e.g. appreciation of the arts) in students that are consonant with those of school gatekeepers (e.g. teachers) (Bourdieu 1986). According to Bourdieu (1986), students who exhibit these attitudes and dispositions are perceived more favourably by teachers and therefore, these students benefit more in their learning.

The social construction of technology perspective suggests that the impact of technological engagement depends on the social milieu in which the engagement occurs (Klein and Kleinman 2002). The impact is enhanced when participants perceive or enjoy greater possibilities and a higher level of self-efficacy (Hutchby 2001, 2003). In the context of the present study, student access to the three forms of familial capital contributes to their perceptions of the myriad possibilities in which they can creatively engage with IT resources to support their learning. For example, access to academic resources at home affords students with more opportunities to engage in their learning and identify more areas where they can use IT to facilitate their learning. The scaffolding from more highly educated parents (human capital) contributes towards students' understanding of the nature of IT, including its enablements and constraints. This may improve students' self-efficacy in using these IT resources more effectively in schools. In schools, teachers may provide more opportunities for students who are perceived to be competent and to have greater learning potential, by virtue of their cultural capital, to use IT resources more critically to pursue higher order learning tasks. These multiple advantages coalesce to frame the scope of learning opportunities for students, improving learning for those endowed with more familial capital and compromising learning for those with less familial capital, with consequences for student agency in their interactions with IT resources (Hutchby 2001, 2003). These different forms of familial capital may shape students' agentic perceptions of "possibilities and impossibilities, freedoms and necessities, opportunities and prohibitions" (Bourdieu 1990, 54) related to the use of IT resources, which then influence their subsequent academic achievement. Therefore, the mixed results on the relationship between IT resources and student achievement may be explained by the moderating influence of familial capital.

Research objectives

The present study addresses two specific research questions:

(a) How is home and school IT access related to student achievement?
(b) How do different levels of student familial resources moderate the relationships between IT access and student achievement?

Mathematics represents an important domain of achievement given its relevance to science, technology, engineering and mathematics (STEM) careers in knowledge-based economies (KBEs) (Harris 2001). Therefore, the present study is designed to address the premise that students who have access to home IT resources to complement their school learning, and who have access to school IT resources are well placed to learn mathematics more optimally.

The research design also addresses three pertinent limitations of past research on the relationships between IT access and mathematics performance. First, it analyses data involving 144,395 students from 22 developed countries, thereby diminishing the threat of

Table 1. Summary of inter-correlations for variables.

Measures	1	2	3	4	5	6	7	8	9
1. MathPV	–	–.14**	.31**	–.18**	.26**	.31**	.24**	–.12**	–.16**
2. Repeat		–	–.07**	–.07**	–.03**	–.03**	–.06**	.05**	.00
3. MoEdu			–	–.21**	.34**	.28**	.23**	–.15**	–.17**
4. ClassSize				–	–.31**	–.24**	–.04**	.08**	.20**
5. Home IT					–	.44**	.22**	–.13**	–.21**
6. HomeEdu						–	.37**	–.08**	–.14**
7. HomeCul							–	–.06**	–.06**
8. ShortTr								–	.27**
9. ShortIT									–

Note. For all variables, higher scores are indicative of more extreme responses in the direction of the construct assessed.
**$p < .01$.

country-specific limitation leading to non-generalisable inferences. Second, it statistically accounts for student prior ability and the shortage of qualified teachers, thereby mitigating the potential confounding effects of these variables in the investigation of the relationships between IT access and mathematics performance (Dochy 1994; Goldhaber and Brewer 2000). Third, the use of HLM in the present study, unlike ANOVAs or regression analyses in some studies, enables the analysis of the complex data of students being nested in schools (Raudenbush and Bryk 2002; Richter 2006; Werblow and Duesbery 2009).

Method

Participants

Participants were students and school principals who participated in PISA 2012 conducted by OECD. PISA 2012 measured the proficiency of approximately 500,000 15-year-old students from 68 economies (OECD and non-OECD members) in applying their knowledge and skills learned in reading, mathematics, and science to authentic problems. These students also completed a Student Questionnaire asking them about various family characteristics, resources and processes that may be related to their learning. Principals completed a School Questionnaire asking them about various school and teacher characteristics, resources, and processes that may be associated with student learning. However, only the data from OECD economies were examined in the present study. Cases with missing data for any of the variables investigated were excluded. This resulted in a final sample of 144,395 students from 7,308 schools in 22 OECD economies comprising Australia, Austria, Belgium, Canada, Switzerland, Chile, Denmark, Finland, France, United Kingdom, Hungary, Ireland, Italy, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Portugal, Slovak Republic, Sweden, and United States of America.

Measures

Data on the following variables from the PISA 2012 data-set were used in the analysis.

In PISA 2012, students' mathematics achievement was the focal outcome variable of investigation. In PISA 2012, students were not administered the complete set of mathematics items by design, and therefore each item had missing responses. This made it impossible to estimate achievement scores for each student. To overcome this limitation, the results of

Table 2. Summary of means and standard deviations for variables.

Variables	*M* (SD)
MathPV	499.74(88.95)
Repeat	3.07(0.34)
MoEdu	4.22(1.05)
ClassSize	4.07(1.92)
Home IT	2.37(0.83)
HomeEdu	4.93(1.18)
HomeCul	1.55(1.10)
ShortTr	1.66(0.67)
ShortIT	1.99(0.80)

Note. Standard deviations in parentheses.

individual students were aggregated to produce scores for groups of students in PISA 2012. For each student then, the estimated distribution of mathematics scores of students similar to him or her in terms of responses to the assessment and background items was represented by a set of five "plausible values" (PVs) (Hopstock and Pelczar 2011). The five PVs were highly correlated with each other, and therefore, the mean of the five PVs was used as the dependent variable in the HLM analysis. This measurement approach has been employed elsewhere (e.g. Atar and Atar 2012; Tan 2015).

Three scales were constructed to measure the access to home resources using students' responses (1 = *Yes*; 0 = *No*). More specifically, Home IT measured the access to IT resources, and was computed by adding the responses pertaining to computer for school work, educational software, and Internet access. The second scale, HomeEdu, measured the access to academic resources and was computed by adding the responses for study desk, students' own room, quiet place to study, books for school work, technical reference books, and dictionary. The third scale, HomeCul, measured the access to cultural resources and was computed by adding up the responses for classic literature, poetry books, and art works.

Principals answered a series of questions regarding the impact of resource shortages on the school's capacity to provide instruction using a four-point scale (1 = *Not at all*, 2 = *Very little*, 3 = *To some extent*, 4 = *A lot*). For the purposes of the present analysis, seven items pertaining to the shortage of qualified teachers and IT resources in schools were subjected to exploratory factor analysis using principal component analysis. Results showed that two factors could be extracted, explaining a total of 71.58% of the variance. The first factor, comprising four items, measured the shortage of qualified teachers in different subjects in the school (*eigenvalue* = 2.76) and explained 39.47% of the variance. Therefore, a scale was constructed by averaging the responses to these items and named ShortTr ($\alpha = .85$). The second factor, comprising three items, measured the shortage of computers, Internet, and computer software for instruction (*eigenvalue* = 2.25) and explained 32.11% of the variance. Similarly, a scale was constructed by averaging the responses to the three items and named ShortIT ($\alpha = .83$).

A dummy variable, Sex, was coded as 0 for female and 1 for male students. Students also responded to three items indicating whether they had ever repeated a grade at the primary, lower secondary, and upper secondary level using a three-point scale (1 = *No, never;* 2 = *Yes, once;* 3 = *Yes, twice or more*). These responses were added up to form a measure of students' prior academic ability (Repeat).

Three indicators (parents' education, occupation, and income) have been used to measure SES in the literature. There is also evidence that these indicators are highly correlated with each other, with more educated parents enjoying work of higher occupational status and earning a higher income in advanced economies. In the present study, a variable (MoEdu) measuring mothers' education was used to measure students' familial SES (1 = *Did not complete primary education*, 2 = *Completed primary education*, 3 = *Completed lower secondary education*, 4 = *Completed upper secondary education that provided direct access to labour markets or to non-university tertiary education*, 5 = *Completed upper secondary education that provided access to university level or non-university tertiary education*). Mothers' as opposed to fathers' education was used because prior research showed that it was a more predictive variable of student achievement (Chiu and Khoo 2005).

ClassSize measured the average class size (principal-reported) for the modal grade for 15-year-old students in schools (1 = ≤ *15 students*, 2 = *16–20 students*, 3 = *21–25 students*, 4 = *26–30 students*, 5 = *31–35 students*, 6 = *36–40 students*, 7 = *41–45 students*, 8 = *46–50 students*, 9 = > *50 students*). The correlations, and means and standard deviations of the variables are summarised in Tables 1 and 2 respectively.

Procedure

PISA 2012 involved all 34 OECD and 31 partner economies (OECD 2013). All participating economies followed standardised procedures outlined in the technical standards and manuals provided. In addition, students, school principals and parents (in some economies) completed related questionnaires pertaining to student learning.

Results

Two-level HLM with restricted maximum likelihood estimation was employed to account for the correlations between mathematics achievement scores of students from the same school (Raudenbush and Bryk 2002). This technique allows for the investigation of student-level variables such as gender, prior ability, mother education, and home IT resources (level 1), and school-level variables such as average class size, shortages of teachers, and school IT resources (level 2) simultaneously. Models predicting students' mathematics achievement were first examined for the entire sample of students and schools. Centred independent variables were used in all the HLM models to enhance the interpretability of the results and to minimise the problem of multi-collinearity arising from the inclusion of interaction terms (to be discussed later).

The following set of six nested models was fitted:

- Model 1 – baseline with no predictors;
- Model 2 – levels 1 and 2 random intercepts model with student-level (Sex, Repeat, MoEdu) and school-level (ClassSize, ShortTr) control variables;
- Model 3 – levels 1 and 2 random intercepts model with the variables in Model 2 plus access to home IT resources (Home IT);
- Model 4 – levels 1 and 2 random intercepts model with the variables in Model 3 plus interaction term comprising access to home IT resources and maternal education (Home IT X MoEdu);
- Model 5 – levels 1 and 2 random intercepts model with the variables in Model 4 plus shortage of school IT resources (ShortIT);

- Model 6 – levels 1 and 2 random intercepts model with the variables in Model 5 plus interaction term comprising school IT shortage and school teacher shortage (ShortTr X ShortIT).

Model 6 can be mathematically represented as follows:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{Sex})_{ij} + \beta_{2j}(\text{Repeat})_{ij} + \beta_{3j}(\text{MoEdu})_{ij} + \beta_{4j}(\text{HomeIT})_{ij} + \beta_{5j}(\text{HomeIT X MoEdu})_{ij} + \epsilon_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{ClassSize})_j + \gamma_{02}(\text{ShortTr})_j + \gamma_{03}(\text{ShortIT})_j + \gamma_{04}(\text{ShortTr X ShortIT})_j + \text{U}_{0j}$$

where Y_{ij} = Mathematics achievement of student i from school *j*, β_{0j} and $\mathcal{E}_{ij}$ = Intercept and variation in estimated student's mathematics achievement within schools, respectively, β_{1j} to β_{5j} = parameter estimates of level 1 variables, γ_{00} = grand mean of student mathematics achievement, γ_{01} to γ_{04} = parameter estimates of level 2 variables and U_{0j} = between-school variation in intercepts from grand mean.

Impact of access to IT resources on achievement

HLM results (Table 3) for the null model (Model 1) showed that 53.27 and 46.73% of the variance in students' mathematics achievement occurred at level 1 (within-school) and 2 (between-school), respectively. These results supported the use of HLM models which took into account the non-independence of mathematics achievement scores of students who belonged to the same school.

When the various control variables were included in the model (Model 2), results showed that girls as compared to boys had lower achievement (Sex, $\beta = -19.57$), while students with more highly educated mothers had higher achievement (MoEdu, $\beta = 8.87$), $p < .01$. On the other hand, students with lower prior ability (Repeat, $\beta = -30.56$), and who studied in schools with larger class sizes (ClassSize, $\gamma = -5.49$) and with greater shortages of qualified teachers (ShortTr, $\gamma = -13.56$) had lower achievement, $p < .01$.

In Model 3, these control variables remained significant at the .01 level (Sex, $\beta = -19.70$; Repeat, $\beta = -30.29$; MoEdu, $\beta = 8.38$; ClassSize, $\gamma = -4.94$; ShortTr, $\gamma = -12.84$). Results also showed that students who had access to more home IT resources (Home IT, $\beta = 5.13$, $p < .01$) had higher achievement.

Model 4 extended the analysis in the previous model by examining the interactive effect between Home IT and MotherEdu. Results showed that the different variables examined in Model 3 remained significant at the .01 level (Sex, $\beta = -19.73$; Repeat, $\beta = -30.29$; MoEdu, $\beta = 8.74$; ClassSize, $\gamma = -5.04$; ShortTr, $\gamma = -12.95$). There were main and interactive effects for access to home IT resources. More specifically, students benefited from greater access to home IT resources (Home IT, $\beta = 5.78$, $p < .01$). Additionally, access to home IT resources at home provided extra benefits to students with highly educated mothers (Home IT X MoEdu, $\beta = 1.57$, $p < .01$).

In Model 5, the main effect of shortages of IT resources in teaching was examined. The results for the different independent and control variables examined were similar to those obtained in Model 4 (Sex, $\beta = -19.74$; Repeat, $\beta = -30.23$; MoEdu, $\beta = 8.68$; ClassSize, $\gamma = -4.19$; ShortTr, $\gamma = -8.80$; Home IT, $\beta = 5.65$; Home IT X MoEdu, $\beta = 1.66$), $p < .01$. Students

Table 3. Fixed effects estimates (top) and variance-covariance estimates (bottom) for models of the predictors of mathematics achievement (for all students).

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
			Fixed effects			
Intercept	490.21**(0.75)	500.85**(0.70)	501.18**(0.69)	500.67**(0.69)	501.09**(0.69)	501.79**(0.71)
Sex		−19.57**(0.37)	−19.70**(0.36)	−19.73**(0.36)	−19.74**(0.36)	−19.74**(0.36)
Repeat		−30.56**(0.55)	−30.29**(0.55)	−30.29**(0.55)	−30.23**(0.55)	−30.23**(0.55)
MoEdu		8.87**(0.20)	8.38**(0.20)	8.74**(0.21)	8.68**(0.21)	8.67**(0.21)
ClassSize		−5.49**(0.36)	−4.94**(0.35)	−5.04**(0.35)	−4.19**(0.35)	−4.09**(0.35)
ShortTr		−13.56**(1.02)	−12.84**(1.00)	−12.95**(1.00)	−8.80**(1.03)	−8.07**(1.05)
Home IT			5.13**(0.26)	5.78**(0.27)	5.65**(0.27)	5.64**(0.27)
Home IT X MoEdu				1.57**(0.18)	1.66**(0.18)	1.68**(0.18)
ShortIT					−12.52**(0.84)	−12.26**(0.84)
ShortTr X ShortIT						−4.40**(1.14)
			Random parameters			
Level 1 intercept	4300.86** (16.44)	4090.81** (15.64)	4086.20** (15.62)	4083.16** (15.61)	4081.60** (15.60)	4081.45** (15.60)
Level 2 intercept	3772.59** (69.43)	2968.12** (55.59)	2859.61** (53.86)	2871.48** (54.13)	2798.93** (52.63)	2795.00** (52.54)
% Level 1 variance	53.27	57.95	58.83	58.71	59.32	59.35
% Level 2 variance	46.73	42.05	41.17	41.29	40.68	40.65
% Reduction in Level 1 variance when compared to Model 2			0.11	0.19	0.23	0.23
% Reduction in Level 2 variance when compared to Model 2			3.66	3.26	5.70	5.83
−2 Restricted log likelihood	1,637,775.56	1,629,288.99	1,628,890.62	1,628,815.31	1,628,593.56	1.628.576.51

Note. Standard errors in parentheses.
$^{**}p < .01$.

in schools with greater shortages of IT resources in teaching had lower achievement (ShortIT, $\gamma = -12.52$, $p < .01$).

In Model 6, the interactive effect between shortages of qualified teachers and IT resources in teaching was examined. Results showed that all the other variables remained significant predictors (Sex, $\beta = -19.74$; Repeat, $\beta = -30.23$; MoEdu, $\beta = 8.67$; ClassSize, $\gamma = -4.09$; ShortTr, $\gamma = -8.07$), $p < .01$. There were both main (Home IT, $\beta = 5.64$) and interactive effects (Home IT X MoEdu, $\beta = 1.68$) for Home IT, $p < .01$. Additionally, students in schools experiencing shortages of IT resources in teaching had lower achievement (ShortIT, $\gamma = -12.26$, $p < .01$). Schools' shortages in IT resources also compounded the detrimental effect of shortages in qualified teachers (ShortTr X ShortIT, $\gamma = -4.40$, $p < .01$). The main and interactive effects of access to home and school IT resources accounted for a total of 0.23% and 5.83% of the levels 1 and 2 achievement variances, respectively, when compared to Model 2.[1]

Table 4. Fixed effects estimates (top) and variance-covariance estimates (bottom) for models of the predictors of mathematics achievement (for students with different levels of home academic resources).

Parameter	Low	High
	Fixed effects	
Intercept	488.12**(0.83)	514.94**(0.82)
Sex	−17.63**(0.67)	−17.83**(0.59)
Repeat	−27.99**(0.91)	−31.94**(0.95)
MoEdu	7.35**(0.37)	11.38**(0.39)
ClassSize	−3.04**(0.37)	−4.89**(0.41)
ShortTr	−7.18**(1.15)	−7.67**(1.15)
Home IT	6.32**(0.43)	0.68(0.55)
Home IT X MoEdu	1.27**(0.26)	−0.80(0.51)
ShortIT	−11.69**(0.92)	−8.61**(0.95)
ShortTr X ShortIT	−3.33**(1.23)	−3.06*(1.35)
	Random parameters	
Level 1 intercept	3844.37**(29.21)	4130.66**(25.75)
Level 2 intercept	2519.97**(63.10)	2683.71**(59.51)
% Level 1 variance	60.40	60.62
% Level 2 variance	39.60	39.38
% Reduction in level 1 variance when compared to model 2	0.19	0.03
% Reduction in level 2 variance when compared to model 2	6.70	1.39
−2 Restricted log likelihood	474,278.54	660,687.57

Note. Standard errors in parentheses.
**p* < .05; ***p* < .01.

Table 5. Fixed effects estimates (top) and variance-covariance estimates (bottom) for models of the predictors of mathematics achievement (for students with different levels of home cultural resources).

Parameter	Low	High
	Fixed effects	
Intercept	487.97**(0.88)	520.73**(0.92)
Sex	−19.00**(0.82)	−19.94**(0.73)
Repeat	−29.86**(1.05)	−27.50**(1.27)
MoEdu	7.14**(0.43)	12.08**(0.48)
ClassSize	−3.69**(0.40)	−5.94**(0.44)
ShortTr	−3.90**(1.21)	−10.04**(1.25)
Home IT	7.35**(0.56)	3.41**(0.60)
Home IT X MoEdu	1.15**(0.34)	−1.33**(0.51)
ShortIT	−10.25**(0.98)	−8.89**(1.03)
ShortTr X ShortIT	−4.22**(1.31)	−3.23*(1.43)
	Random parameters	
Level 1 intercept	3963.75**(36.34)	4016.75**(31.51)
Level 2 intercept	2525.12**(67.87)	2782.44**(68.72)
% Level 1 variance	61.09	59.08
% Level 2 variance	38.91	40.92
% Reduction in level 1 variance when compared to model 2	0.09	−0.04
% Reduction in level 2 variance when compared to model 2	6.54	2.92
−2 Restricted log likelihood	346,951.41	441,169.64

Note. Standard errors in parentheses.
**p* < .05; ***p* < .01.

Impact on students with different home resources

The results presented above underscored the substantive impact of access to IT resources on achievement. The ensuing analysis further examined the impact for students with different levels of home academic (HomeEdu, range 0 to 6) and cultural (HomeCul, range 0 to 3) resources. The distributions of students were first examined to divide them into groups with different resource levels. Results showed that 29% ($n = 41,886$), 30.7% ($n = 44,353$), and 40.3%

($n = 58{,}156$) of students had low (HomeEdu ≤ 4), average (HomeEdu = 5), and high (HomeEdu = 6) levels of home academic resources. HomeCul was more evenly distributed – 21.1% ($n = 30{,}467$), 29.2% ($n = 42{,}229$), 22.8% ($n = 32{,}907$), and 26.9% ($n = 38{,}792$) of students had no (HomeCul = 0), low (HomeCul = 1), average (HomeCul = 2), and high (HomeCul = 3) levels of home cultural resources, respectively. Models 1 to 6 were then estimated for students with low and high levels of these resources. For purposes of brevity, only the results for Model 6 for each category of students were presented.

HLM results (Tables 4 and 5) showed that among students with different levels of home academic and cultural resources, the results were generally similar to those obtained in the main analysis, except for the non-significance of Home IT (main and interactive effects) for students with high levels of home academic resources. However, the proportion of variance in achievement varied across the different groups of students. More specifically, access to home and school IT resources accounted for 0.19% and 6.70% of the within-student and between-school achievement variance respectively for students with least home academic resources, but only 0.03% and 1.39% of the variance respectively for students with the most academic resources (Table 4). Similarly, access to home and school IT resources accounted for more of the achievement variance for students with least (0.09% within-school and 6.54% between-school) than those with most home cultural resources (–0.04% and 2.92%, respectively)[2] (Table 5). These results indicated that access to IT resources had a larger impact on students from disadvantaged backgrounds than for students from advantaged families.

Discussion

The present study examines the effect of students' home and school IT access on their mathematics achievement, and differences in the impact of IT access for students of different SES backgrounds. The focus on IT as opposed to other more general resources takes cognisance of the increasingly important role of IT-enabled learning for students. Students' achievement in mathematics *vis-a-vis* other domains is examined in light of the importance of mathematical and scientific competencies in KBEs. The decision to focus on OECD economies as opposed to all the 68 economies (OECD and non-OECD) in PISA 2012 was informed by prior evidence of differential home and school influences on achievement in developed versus less-developed economies. To handle the nested data in PISA 2012, the present study employed HLM to take into account the possible correlation in achievement scores of students belonging to the same school and to partition achievement into within- and between-school variance. To minimise threats to validity, the HLM analysis also included control variables, namely students' gender and prior ability, mothers' education, class size, and schools' shortage of qualified teachers impeding instruction. The results showed that home and school IT access were positively related to students' achievement, and that these benefits were not evenly distributed among students from different familial backgrounds. These results are discussed in the ensuing discussion.

Home IT access

First, the results showed that students' access to home IT resources contributed to their achievement, controlling for the influence of mothers' education (an indicator of human capital and SES) and other variables. This indicates that home IT access is different from either

SES or human capital, thereby underscoring the separate contribution of technology on achievement. The results are consistent with those reported in previous studies on the effects of home IT access (e.g. Kim and Chang 2010), and particularly those by Attewell and Battle (1999) who controlled for familial income and capital in their study. However, the present study advanced our knowledge of the effects of home IT access by demonstrating the significant interaction effects between home IT access and mothers' education. This finding will be discussed in the section on equity implications later on.

School IT access

The results also showed that schools' IT resource shortages that compromised instruction negatively predicted achievement, controlling for the potential confounding variable of shortages of qualified teachers. This suggested that the challenges from IT resource shortages are distinct from those arising from shortages of qualified teachers in schools. The finding on the negative effect of schools' IT resource shortages is consistent with previous findings on the negative effects of schools' general resource shortages (Chiu 2010).

Despite the generally more resourced schools in developed economies, it is interesting to find that IT resource shortages remain a challenge to be addressed. However, there are different ways to mitigate the problem, including schools adopting cheaper computer systems, integrating IT into one or two subject areas at any one time, using laptops equipped with wireless connections instead of computer laboratories, locating computers in classrooms instead of centralised venues and rotating students in groups through small number of computers in classrooms (Johnson and Johnson 1992; Lowther, Ross, and Morrison 2003; Tearle 2004).

It is also noteworthy that the results showed that schools' IT resource shortages compounded challenges to achievement arising from shortages of qualified teachers. With regards to teachers' professional development, schools need to address two related issues: critically evaluate what constitutes quality professional development, and train teachers to integrate IT into teaching–learning in light of the hitherto weak empirical evidence on best practices (Lawless and Pellegrino 2007). To overcome the latter challenge particularly, schools can enhance teachers' professional development on IT knowledge and skills, IT-related classroom management skills and IT-supported pedagogical knowledge and skills (Hew and Brush 2007); let teachers learn by observation and experimentation; and align training with teachers' needs. The enhanced professional development would address Lawless and Pellegrino's (2007) clarion call to "separate and contrast professional development focused on the integration of technology into instruction with professional development focused on learning about technology … or professional development focused on learning how to use a particular piece of software …" (581–582).

Between-school variance

Interestingly, the impact of IT access explained more of the between- (5.83%) than within-school (0.23%) variance in achievement. It is not apparent why this is so, but the results may arise because there are more student-level control variables (i.e. gender, prior ability and mothers' education), all of which are incidentally powerful predictors of individual students' achievement, than school-level control variables (i.e., class size and shortage of qualified teachers) entered into the HLM models. These student-level control variables may have thus partialled out some of the student-level variance in the models.

The "compounding" of IT access effects at the school level contributes to the literature on school composite effects. According to Coleman and colleagues (1966), school composite effects reflecting the socio-economic composition of students are more highly predictive of student achievement, over and above the effect of students' individual SES backgrounds, than any other school-level variable. Higher SES schools benefit from the availability of parental support, students' peer pressure to succeed, qualified teachers with higher expectations of students, and a positive disciplinary and learning climate (Harker and Tymms 2004; Rumberger and Palardy 2005). In the context of the present study, students with similar levels of home IT access may belong to similar social classes, and attend schools with other similar students too. At the school level, shortages of IT resources impinging on instruction may vary according to the school's composite SES profile, with higher SES schools having less of these resource shortages and vice versa. Therefore, the between-school achievement variance explained by students' IT access suggests that the latter reflects yet another aspect of privilege that students in higher SES schools may enjoy to a greater extent than peers in lower SES schools.

Digital equity

The finding on the differential impact of home and school IT access for students from different SES backgrounds adds to the existing literature on digital equity. More specifically, a few prior studies have examined the cumulative effect of home and school IT access on achievement (Delen and Bulut 2011; Visser, Juan, and Feza 2015), but none has investigated the cumulative effect of this access for students with different familial backgrounds. Meta-analytic results generally showed that IT-integrated teaching benefitted all students similarly, regardless of their SES backgrounds (Li and Ma 2010; Cheung and Slavin 2013). However, a close examination of the results reported in Cheung and Slavin (2013) suggested that some higher SES students may benefit more than lower SES students as evidenced by the wider 95% confidence interval for higher (ES = 0.25; 95% CI = [0.03, 0.47]) *vis-a-vis* lower SES students (ES = 0.12; 95% CI = [0.08, 0.17]) reported.

Furthermore, measures of students' SES using traditional indicators such as parents' education, occupational status and income may be insufficient as there is burgeoning evidence that social stratification is also affected by the stock of familial capital (Savage et al. 2013). Therefore, the present study examines how access to home and school IT resources impacts students with different types of familial human, academic and cultural capital differently.

Results showed that first, students with more highly educated mothers benefited more from greater access to home IT resources. This result can be understood in light of the strategic purposes of IT consumption (e.g. facilitating new opportunities), more critical use of IT resources (e.g. comparing IT with non-IT media) and more confident use of IT by higher SES students. In contrast, lower SES students use IT for functional purposes, are less questioning of their IT experiences, and are less confident in IT usage (Korupp and Szydlik 2005; OECD 2010). However, the results also showed that students with least academic and cultural capital were most impacted by their access to home and school IT resources. For example, IT access explained the between-school variance in the achievement of students with least home academic (6.70%) and cultural (6.54%) capital substantively more so than that for students with more of these capital forms (1.39 and 2.92% respectively). These results are highly significant in practical terms, given that 2–4% of achievement variance explained in educational research is equivalent to the average learning gain in one school year (Baumert, Ludtke, and Trautwein 2006).

These two sets of results on digital equity are not necessarily contradictory when viewed from the complementary perspectives of digital access versus consumption (Korupp and Szydlik 2005; OECD 2010). More specifically, the results on students benefiting more from home IT access if they had highly educated mothers reflect their sophisticated use of home IT resources to support their learning, while the results on IT access (home and school) having a greater impact on disadvantaged students allude to their lack of basic access to IT-enabled learning. For these latter students, increasing their IT access may be the first step to enable them to at least have the opportunity to improve their learning.

Resource accessibility in human, academic and cultural familial capital therefore imposes structural limits, or what Klein and Kleinman (2002) termed "rules of play" (35), that influence how much different students can benefit from their access to IT resources at home and in school. Indeed, Kleinman (1998) cogently argued that these rules of play

> establish distinctive resource distributions, capacities, and incapacities and define specific constraints and opportunities for actors depending on their structural location. Power and its operation are then understood within this structural context. The rules of play that define structure gives certain actors advantages over others by endowing them with valued resources or indeed serving as resources themselves. (289)

In a related vein, the somewhat "varied" results of impact (i.e. students with more highly educated mothers benefitting more from access to more home IT resources versus students with less familial academic and cultural capital benefiting more from access to more home and school IT resources) affirm the value of differentiating students' socio-economic profile using familial capital in addition to the parental education variable. The more sophisticated measurement, in line with the evolving literature on social stratification, afford us with a more nuanced picture of the impact of IT access on students' achievement.

Conclusion

The present study, premised on the social construction of technology perspective (Klein and Kleinman 2002), addresses the issues of quality and equality in school achievement arising from the access to home and school IT resources. It makes a contribution to the extant literature by addressing various methodological limitations evident in previous studies. More specifically, it employed HLM to examine the mathematics achievement of a huge sample comprising 144,395 students from 7,308 schools in 22 OECD economies who participated in PISA 2012. The large international sample analysed addresses the problem of a lack of generalisability of findings that arise from the use of single-country samples in some studies. The use of HLM also took into account the nested structure of the data, thereby enabling us to analyse within- and between-school achievement variance explained by students' IT access. Lastly, the present study included various important control variables (students' gender and prior ability, mothers' education, class size, and shortages of qualified teachers impeding instruction) in the HLM analysis that are often not controlled in previous studies.

Results showed that after controlling for these variables, students' IT access positively predicted their mathematics achievement. More specifically, students with greater home IT access had higher achievement. At school, students whose schools had greater IT shortages had lower achievement. IT resource shortages also compounded the challenges arising from shortages of qualified teachers at school. The effects of IT access were more prominent at the school than individual student level. However, the results also showed that the benefits of IT access did not accrue to all students equally – students whose mothers were highly educated benefited additionally from home IT access, but students with least home academic and cultural resources were more impacted by IT access than those with more of these home resources. In summary, results of the present study affirm the contribution of IT access on achievement, but at the same time allude to significant equity implications particularly for students from disadvantaged families. These implications are noteworthy for educators and policymakers in light of STEM career opportunities predicated on students' mastery of mathematical and scientific literacies in KBEs.

The present study contributes to the literature on the impact of IT access on achievement in two ways. First, the analysis provides a more accurate picture of the impact of IT access by controlling for potential confounding variables such as mothers' education and schools' shortage of qualified teachers (among others), testing main and interactive effects of IT access (involving mothers' education and schools' shortage of qualified teachers) in the HLM, making an informed decision to increase statistical power (by including the large number of students and schools in the sample) and yet restricting the analysis to students in schools located in similar national contexts (i.e. OECD countries), and using multilevel modelling (HLM) to account for the nested nature of the data.

The present study also contributes to the burgeoning literature on digital equity. It employs Bourdieu's (1986) theory of social stratification to more accurately differentiate students according to their stock of familial capital, and then examines the differentiated impact of IT access on achievement. Indeed, the diverse pattern of results reported affirms the usefulness of this approach and enables us to have a more nuanced understanding of the role of technology in the discourse on digital divides.

Although the present study has provided a useful snapshot of the impact of IT access, it suffers from the common limitations associated with cross-sectional survey design. More specifically, the variables used comprise student- and principal-reported data, so the validity of these measures has to be assumed. Equally important, the significant relationships reported in the study should not be taken to be definitive evidence of causality between variables. Therefore, relevant theory (e.g. social construction of technology) was used to aid the interpretation of the relationships obtained. Additionally, the study has not examined how IT consumption may affect students' learning. Therefore, future studies can build on the present study by examining qualitatively how students use IT at home or how IT has been integrated in schools to benefit learning. The present study has also demonstrated the usefulness of using more refined conceptualisations of social stratification in studying digital equity. However, it has only included human, academic, and cultural capital variables. Future studies can examine the impact of IT access for students differing in levels of other types of familial capital (e.g. social capital). Additionally, future research can replicate the present study using samples in less developed economies and compare the results with those obtained in the present study, thereby contributing to the international research on the impact of technology on learning.

Notes

1. In HLM models with randomly varying slopes examined, the slope variance for Home IT (7.00, Wald $Z = 1.09$, one-tailed $p = .14$) and ShortIT (67.24, Wald $Z = 0.96$, one-tailed $p = .17$) were not significant. These results indicated that the effects of Home IT and ShortIT did not vary systematically across different schools, and therefore supported the examination of the achievement of the entire sample of students using fixed effect models. The collective analysis of data from different economies, as opposed to analysis of schools in individual economies, also addressed the potential problem of range restriction (Schleicher 2009).
2. The negative reduction in variance explained could be due to the more restricted range in predictor variables for students with high familial cultural capital (Heck, Thomas, and Tabata 2010).

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Notes on contributors

Cheng Yong Tan (PhD) is assistant professor of Learning, Development, and Diversity in the Faculty of Education, The University of Hong Kong. His research interests include socio-economic status, cultural and social capital, Asian and Western parenting, academic achievement, self-efficacy beliefs and school leadership.

Khe Foon Hew (PhD) is associate professor of Information Technology Studies in the Faculty of Education, The University of Hong Kong. His research interests include learning design and technology, computer-supported interaction, student engagement and knowledge sharing.

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