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ORIGINAL RESEARCH

Widening Digital Divide: Family Investment, Digital Learning, and Educational Performance of Chinese High School Students During the COVID-19 Pandemic School Closures

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Abstract

The COVID-19 pandemic and school closures highlighted the need for research examining the effects of socio-economic status and digital learning on educational performance. Based on a panel dataset from a Chinese high school during school closures in 2020, our study explored whether the digital divide widened during the pandemic. The results showed that digital learning significantly mediates the association of socio-economic status with educational performance. In contrast, the indirect effects of digital learning were not significant before the outbreak of the COVID-19 pandemic. However, these effects immediately became significant during school closures and remote education instruction during the pandemic. After the schools reopened, the indirect effects of digital learning declined or even disappeared. Our findings provide new evidence for a widening digital divide during the COVID-19 pandemic school closures.

Keywords Digital learning · Educational performance · Family investment · COVID-19 · School closures

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Introduction

The COVID-19 pandemic tremendously changed the way we live our lives, inadvertently permitting digital learning, remote working, and online shopping to become substitutes for the traditional ways people study, work, and live, which profoundly influences future life (Natalia, 2022; Shek, 2021). Due to the disparities in access to digital devices and the internet, the digital divide possibly widened against this background, particularly the divide between affluent families and low-income families (Azubuike et al., 2020; González-Betancor et al., 2021; Jamil, 2021). Among all groups, the digital divide most dramatically affects the lives of children and adolescents.

During the school closures necessitated by the COVID-19 pandemic, students received differing quantities and qualities of digital learning. According to the United Nations (2020), schools in over 190 countries were shut down to control the spread of the virus, resulting in more than 1.6 billion learners being unable to attend school. Governments have introduced digital platforms to minimize learning losses and provide remote education during school closures. Thus, digital learning became the only choice for most students during COVID-19. However, the digital divide in learning may enlarge the existing gaps in educational performance between students from different families. It is suspected that students from lower socio-economic status (SES) families and communities with limited digital infrastructure may be particularly negatively impacted by the pandemic (United Nations, 2020). However, more evidence is necessary to test this argument.

As compared with studies in the literature focusing on the learning consequences of the COVID-19 pandemic school closures (Lee et al., 2020; Onyema, 2020; Zhang et al., 2022), the present study focussed on the impacts of SES and digital learning that account for the unequal educational performance of lower-SES students. Based on fieldwork in a Chinese high school during the school closures in 2020, this study investigated three research questions: (1) What are the effects of SES and digital learning on educational performance? (2) How does digital learning mediate the association between SES and educational performance? (3) Do school closures moderate the mediation of digital learning? The following section will present a critical review of the theory of family investment. Then we focus on the mediation of digital learning and the moderation of school closures. Finally, we present our marginal contributions and theoretical framework.

Literature Review

Family Investment and Digital Learning

We embedded the foundations of our research in the family investment model, which is perceived to be an essential mechanism linking SES and educational performance (Bradley & Corwyn, 2002; Conger & Donnellan, 2007). The early development of the family investment model put a particular focus on financial capital. For example, Becker and Tomes (1986) used the assumption of utility-maximizing behaviour as the basis for developing a specific model for transmitting financial capital from parents to children. However, the latest development of the family investment model has been quite flexible, involving several dimensions, including that the family (1) lives in an advantaged neighbourhood, (2) has adequate provisions of food, clothing, housing, and medical care, and (3) provides children with cognitive stimulation through tutoring or training (Conger et al., 2010). In other words, the family investment model focuses primarily on the benefits within families that accrue to the children's quality of life.

The family investment model has been supported by much empirical evidence (Conger et al., 2021; Zhang, 2021). For example, Fernald and Marchman (2012) found significant disparities in language development among infants from different families. During the preschool period, scholars have shown that kindergarten-age children from wealthier families achieve better cognitive and emotional development than those from poorer families (Christensen et al., 2014; Lurie et al., 2021; Zhang et al., 2019). Moreover, a body of research suggests that the disparities in academic achievement due to family background persist in primary school (von Stumm et al., 2020; Waters et al., 2021), secondary school (Van de Werfhotst, 2018; van Zwieten et al., 2021), high school (Barr, 2015; Reeves, 2012), and even university (Destin et al., 2019; Sulaiman et al., 2020). These results are consistent in developed countries (Daniele, 2021; von Stumm, 2017) and developing countries (Dolean et al., 2019; Iruka et al., 2014). Therefore, family investment is essential for children's quality of life, including educational performance.

Although the family investment model has been supported in many circumstances, only some studies have paid attention to its application in the digital context. With the rapid growth of information and communication technology, traditional learning is experiencing a revolution (Simon & Garcia-Belmar, 2016; Weisberg, 2011). It is believed that digital learning, which requires that students are equipped with computers and access to the internet, will be more and more prevalent in the future (Halamish & Elias, 2022). In the digital era, digital learning is regarded as a new type of family investment that provides supplementary information (Brand-Gruwel et al., 2005), offers engaging experiences (Bakar et al., 2006), compensates for the shortage of teachers (Pal et al., 2006), and helps develop higher-order thinking abilities (Claro et al., 2012). However, only some families can afford digital learning. According to Wang and Xing (2018), adolescents with a higher SES have better digital access. It is reported that during the pandemic, half of all learners did not have access to a household computer, and 43% had no internet available at home; moreover, the number is more significant in low-income countries (UNESCO, 2020). Due to the importance of digital learning, we suspect it could be an essential part of the family investment model.

Furthermore, the effect of digital learning on adolescents' well-being, especially educational outcomes, is still under debate. Some scholars believe that digital learning is beneficial. Empirical evidence in the United States, Chile, and Brazil suggests that digital learning can positively correlate with students' educational performance (Claro et al., 2012; Huang & Russell, 2006; Wainer et al., 2015; Mo et al., 2013) found that the math scores of children who owned a computer increased by a 0.17 standard deviation in China. Derksen et al. (2022) proved that the internet could improve English and biology scores, especially for low-achieving students. However, evidence from studies conducted in Israel, Germany, and Peru has shown that digital learning may not be related to test scores (Angrist & Lavy, 2002; Wittwer & Senkbeil, 2008). Furthermore, research in Brazil, Turkey, and the United States has found that educational performance can be negatively correlated with computers at home (Gumus & Atalmis, 2011; Vigdor & Ladd, 2014; Wainer et al., 2008). These results were thought to be due to students being distracted from effective learning by digital equipment at home (Fuchs & Wößmann, 2005). The increased "screen time" was at the expense of study time and other academic activities (Subrahmanyam et al., 2000). The most harmful consequences include the potential for students to be exposed to violent or pornographic material, which affects their mental health and social safety (Cristia et al., 2017; Wartella & Jennings, 2000). Therefore, the effects of digital learning still need to be studied in greater depth.

The controversial findings about digital learning may challenge the family investment model in the digital era. Nevertheless, only some studies have addressed the problem. Scholars usually agree that wealthy families are more likely to invest in digital learning by having computers and internet access at home (Azubuike et al., 2020; Song et al., 2020). Unfortunately, whether digital learning positively correlates with academic achievement remains to be determined. The COVID-19 pandemic's school closures provide a unique context for testing whether digital learning is a good family investment. We elaborate on our argument in the following section.

School Closures and the Digital Divide

In 2020, China experienced a sudden outbreak of COVID-19, during which all the schools closed beginning in late January (Lai et al., 2020). During the school closures, the Education Ministry launched an initiative called Ensuring Learning Is Undisrupted when Classes Are Disrupted, encouraging remote learning with traditional media, digital resources, and technological platforms. As a result, with the help of online technology, millions of students continued their studies via digital platforms. The school closures and online education lasted for about three months. However, thanks to the effective containment of the virus, students returned to school in late April and early May 2020.

The COVID-19 pandemic and school closures can be considered a quasi-experiment to evaluate digital learning. We designed three periods to assess our hypothesis according to the different phases of school closures during the pandemic. We conducted our fieldwork in a key-point high school (Zhongdian Gaozhong) in eastern China. The study period was divided into three phases according to the school closure. The first phase was before January 2020, when students took their final examinations in the 2019 fall semester, before the Wuhan outbreak. The second phase was from late January to late April 2020, when all students received online education at home. The final phase was from May to July 2020, about two months after the school reopened. We hypothesized that digital learning would have been an insignificant factor in the first phase because digital resources may have been needed to be more helpful at that time. However, digital learning was crucial during the second phase because online education was the only way to continue learning. In the third phase, we assumed that the effects of digital learning would have lasted, but its effects may have decreased.

Theoretical Framework

Figure 1 outlines our theoretical framework. Based on the family investment model, we assumed an association between SES and educational performance. Moreover, digital learning mediates the association between SES and educational performance. We further hypothesized that school closures moderated the mediation of digital learning. Specifically, we hypothesized that the impact of digital learning on academic achievement depends on the stage of school closure, which was divided into the stages of pre-closure, closure, and reopening.

We argue that our theoretical framework makes several marginal contributions to the literature:

1. We hope to add the dimension of digital learning to the family investment model. Although previous studies have focussed on similar issues, our research provides a more empirical basis for digital family investment.
2. We also show that the digital divide exists and tends to widen during school closures. This conclusion is of great value for understanding the digital divide during the epidemic.
3. Our data are exceptional because it is rare to collect data at the beginning of an outbreak.

Although there may be some problems with the representativeness of our data, the underlying educational inequality it reveals deserves our deep consideration and attention.

Methods

Data and Participants

We conducted our fieldwork at a key-point high school in eastern China in 2020. High school students were an excellent group to study regarding learning losses during the

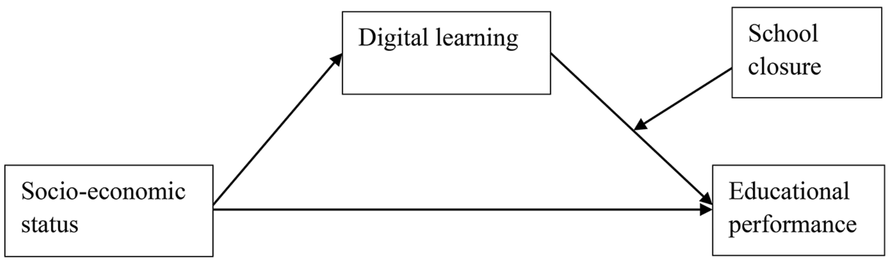

Fig. 1 The theoretical framework of the study

COVID-19 school closures because they took examinations regularly. Although there was no COVID-19 case in the county under study, the school was required to be closed after the pandemic outbreak in January 2020. In late April 2020, the schools reopened when the grade-three students were the first to return to school. The grade-one and grade-two students returned to school in early May 2020. Although our sampling strategy was non-representative due to the closure of schools, our school bore similarities to other key-point high schools across China (Liu et al., 2020). Every county has a key-point high school with the best teachers and equipment and the most talented students in the county.

We collected the panel data of the student's examination scores in 2020 in the months of January (before the closure), May (after the closure), and July (after the reopening). We also designed a survey to collect students' personal information. However, due to restrictions and school policy, the survey could only be conducted in August 2020, shortly after the level-three students finished their college entrance examination. There may be certain deficiencies in scientific standards due to the time elapsed before collecting the survey data. For example, concerning computer ownership, according to the International Data Group, annual computer sales in China increased by 20% in 2020. The pandemic affected families who did not have a computer but could afford one. Thus, we randomly selected participants from those who had a computer at home. After combining those with the homes that did not have a computer, we ran structural equation modelling (SEM) multiple times. Whether the selection share was 10%, 20%, 30%, or 40%, the indirect effect remained significant and more prominent in May than in January. Therefore, our result was robust, although our data had limitations.

The students completed the survey via online questionnaires. We received 1,982 responses and used 1,736 (88%) for the analysis following rigorous screening. The survey complied with the authors' universities' ethical standards, and the high school principal reviewed and approved the questionnaires. Every student was informed by their school that their participation was entirely voluntary. We merged the two datasets using students' IDs.

Measures

Students' results in Chinese, mathematics, English, and integrated curriculum were used to measure educational performance. The integrated curriculum represented students' choices from physics, chemistry, biology, history, politics, and geography. Because students may choose a different integrated curriculum, we used the total score (all subjects) and Chinese, mathematics, and English scores as our dependent variables.

SES was measured by family income, the father's education, and the mother's education. Students were asked to choose their family's economic conditions based on six levels (in RMB): below 10,000, 10,000–50,000, 50,000–100,000, 100,000–150,000, 150,000–200,000, and above 200,000. Parental education was assessed by the number of years of schooling: no schooling (0), primary (6), junior middle (9), senior middle (12), occupation-based college (15), research-based university (16), and postgraduate degree (18).

The presence of a computer and a study room was used to assess digital learning. The computer represented digital technology, while the study room represented the digital environment. Both indicators were dichotomized. Students were asked whether they had a computer or a laptop. Those who did not have a computer were coded as references. In addition, students were asked whether they had an independent study room. Those who did not have a study room were used as references. A study room is believed to provide a quiet and convenient environment for better acquisition of digital learning.

The control variables included gender, age, grade, *hukou*, and siblings. Age was measured by subtracting each student's birth year from 2020. Gender had boys and girls, with boys being the reference. The grade was calculated based on the three levels in China's high schools. *Hukou* is the identity of every citizen in China. According to the Household Registration System, each citizen was born with an agricultural or non-agricultural *hukou*. Non-agricultural *hukou* holders lived in urban areas, while agricultural *hukou* holders lived in rural areas. Working opportunities, social welfare, and other essential public services are not the same for individuals with different types of *hukou*. Although the *hukou* system has been reformed, it still affects people's lives today. In our analysis, the agricultural group is regarded as the reference. Finally, the numbers of sisters and brothers were added together for the total number of siblings.

Analytical Strategy

We employed SEM to analyse our data. First, we conducted the model using SEM in Stata software. Because we did not include the measurement analysis, the structure model entirely fit the data. Second, we conducted the group comparison in SEM after the mediating analysis. We wanted to evaluate whether the mediating effects of digital learning changed across the three-time points (January, May, and July). We used the standardized root mean squared residual (SRMR) and the coefficient of determination (CD) as the group-level fit statistics. If the fit were good, the SRMR would be close to 0, and the CD would be close to 1. Finally, we used different outcomes to check the robustness of our results.

Results

Descriptive Statistics

Table 1 shows the descriptive statistics for the main variables. In January, before the outbreak of COVID-19, the mean of students' total scores was 514. Specifically, the average scores were 94 for Chinese, 75 for mathematics, and 98 for English. After the COVID-19 school closures, all of the average scores declined, except for Chinese. The mean total score was only 470 in May, 44 points less than in January. Fortunately, the scores recovered to some extent in July after the schools reopened. Chinese and mathematics scores were higher in July than in January.

From January to July 2020, about 56% of the participants had computers at home, and about 47% had a study room. The average income was 2.710, meaning that most

Table 1 Descriptive statistics of the variables

Variable	Obs	Mean	Std.Dev	Min	Max
Total Score	5,081	495	135	0	911
Jan	1,706	514	145	184	911
May	1,719	470	126	0	874
July	1,656	501	130	0	899
Chinese Score	5,081	94	14	0	133
Jan	1,706	94	10	34	123
May	1,719	94	14	0	124
July	1,656	95	17	0	133
Mathematics Score	5,081	74	26	0	148
Jan	1,706	75	24	10	144
May	1,719	70	27	0	148
July	1,656	76	26	0	143
English Score	5,081	92	24	0	145
Jan	1,706	98	22	19	145
May	1,719	86	23	0	141
July	1,656	92	24	0	144
Computer	5,081	0.557	0.497	0	1
Study Room	5,081	0.469	0.499	0	1
Income	5,081	2.710	1.116	1	6
Father’s Education	5,081	9.875	3.207	0	18
Mother’s Education	4,872	8.522	3.492	0	18
Age	5,081	17.166	1.010	14	20
Gender	5,081	0.531	0.499	0	1
Hukou	5,081	0.271	0.445	0	1
Siblings	5,081	1.254	0.785	0	3
Grade	5,081	1.929	0.827	1	3

families earned 50,000–100,000 RMB per year. Fathers’ average years of schooling was 10 (high school), slightly higher than mothers’ education (9, middle school). Regarding socio-demographic variables, 53.1% of the participants were female, and the average age was about 17 years. About 27.1% of the students had urban *hukou*, while the remainder were from rural areas. The percentage of single children was small (14%); most had one or two brothers or sisters. This was likely because the State permits two children if the parents have agricultural *hukou*.

The Mediation of Digital Learning

Figure 2 shows the indirect effect of digital learning on the association of family income with the total score. The structural model indicated that family income significantly impacted computer ownership ($\beta = 0.070$) and the study room ($\beta = 0.067$). The computer affected the total score ($\beta = 16.862$), while the study room did not, indicating that computers were more effective than a study room during the school closures. Overall, the effect of family income on the score was 4.552, of which 26.96% was attributable to the indirect impact of digital learning. The bottom of Fig. 2 shows that the indirect effect of digital learning was 0.842 in January, accounting for 22.40% of the total effect. During the COVID-19 school closure and online education, the indirect effect increased to 1.497, accounting for 34.18% of the total effect in May.

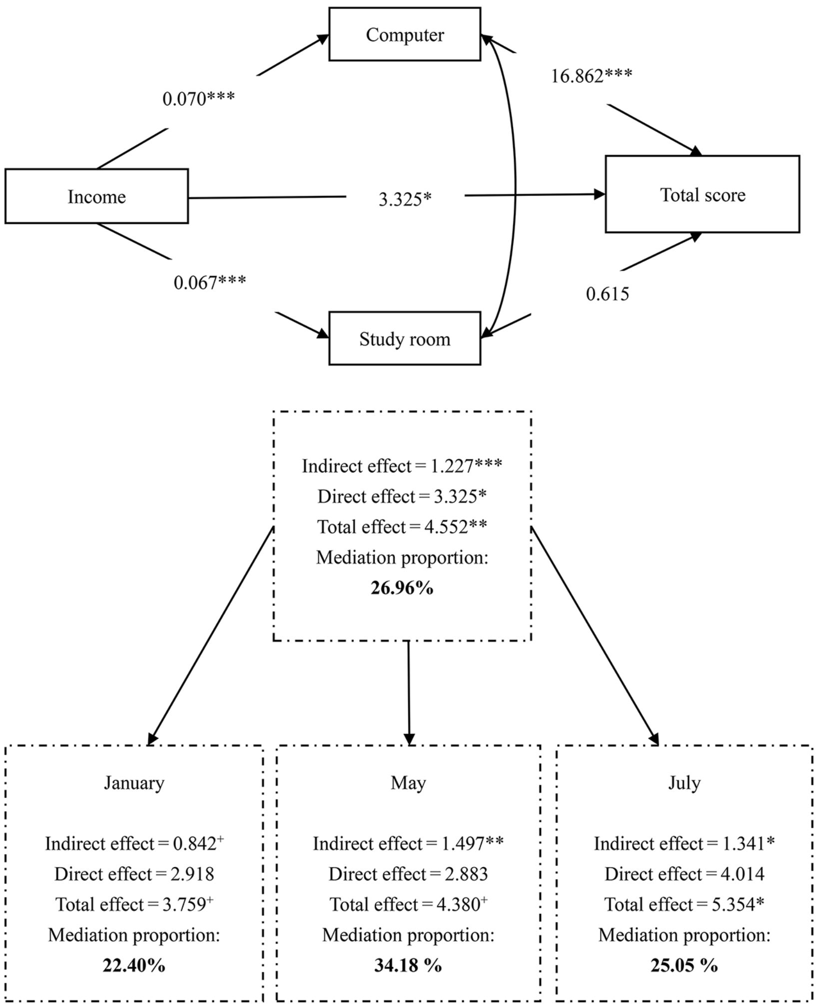

Fig. 2 The indirect, direct, and total effects of income on the total scores
Note: Coefficients are not standardized. $^{+}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

In July, when offline education began again, the indirect effect decreased slightly to 1.341, while the percentage changed to 25.05%.

The pattern was similar for the other SES variables. As shown in Table 2, the total effect of fathers' education on the total score was 2.596 in January. The indirect impact of digital learning was not significant. In May, however, the indirect effect was significantly greater (β = 0.439) than in January. The direct effect of fathers' education on the total score was insignificant during this period. The indirect effect was still substantial in July, but the effect size decreased slightly to 0.393. The indirect effect of digital learning on the association of the mother's educational level with the total score was nearly the same. The indirect effect was only 0.293 in January

Table 2 The indirect, direct, and total effects of variables on the total scores

Effects	January	May	July
Family Income			
Indirect effect	0.842+	1.497**	1.341*
Direct effect	2.918	2.883	4.014
Total effect	3.759+	4.380+	5.354*
Father's education			
Indirect effect	0.259	0.439*	0.393*
Direct effect	2.337*	1.757	1.760
Total effect	2.596*	2.196+	2.152+
Mother's education			
Indirect effect	0.293+	0.512**	0.426*
Direct effect	0.282	0.378	0.034
Total effect	0.575	0.890	0.459
Age			
Indirect effect	0.137	0.257	0.122
Direct effect	-11.774**	-15.282**	-15.648**
Total effect	-11.636**	-15.024**	-15.526**
Gender			
Indirect effect	0.031	-0.435	0.242
Direct effect	-16.614**	-16.558**	-19.501**
Total effect	-16.582**	-16.992**	-19.259**
Hukou			
Indirect effect	0.460	0.723	0.567
Direct effect	1.449	4.439	2.835
Total effect	1.908	5.162	3.402
Siblings			
Indirect effect	-0.115	-0.196	-0.153
Direct effect	-0.051	2.093	1.520
Total effect	-0.167	1.897	1.367
Grade			
Indirect effect	-0.045	-0.214	0.130
Direct effect	-114.747***	-61.575***	-54.576***
Total effect	-114.793***	-61.788***	-54.445***
Group-level fit statistics			
$SRMR_{(none)}$	0.009	0.009	0.010
$SRMR_{(coefficient)}$	0.039	0.026	0.034
$CD_{(none)}$	0.648	0.445	0.398
$CD_{(coefficient)}$	0.526	0.504	0.475

Note: +$p<0.1$, *$p<0.05$, **$p<0.01$, ***$p<0.001$

but grew significantly in May, increasing to 0.512. In July, the indirect effect slightly decreased ($\beta=0.426$) but was still substantial.

The indicators for group-level comparisons in Table 2 show that the coefficients across the three-time points could not be restrained to the same coefficient. In the baseline model, when all the coefficients and intercepts were free, SRMR(none) was 0.009 for the groups in January and May and 0.010 in July. Meanwhile, CD(none) was 0.648 in January, 0.445 in May, and 0.398 in July. When we constrained the coefficients of the three-time points to be equal, SRMR(coefficient) increased to 0.039 for January, 0.026 for May, and 0.034 for July. According to the standard, when SRMR was near zero, the model had a satisfactory fit to the data. Unfortunately, the constraints of the coefficients for the three-time points were not a good fit for the data. CD(coefficient) was decreased for the three-time points, indicating that the coefficients should not be constrained. Therefore, the impacts of both the father's and the mother's education on the total score were significantly different for January, May, and July, referring to the fact that the digital divide widened during the crisis.

Robustness Check Using Different Outcomes

Table 3 summarizes the analysis of the indirect effect of digital learning using performances in different subjects, such as with Chinese, mathematics, and English scores. The results were consistent. In terms of the Chinese score, the indirect effect of digital

Table 3 The indirect, direct, and total effects of socio-economic status on Chinese, mathematics, and English scores

Effect	Chinese Score			Mathematics Score			English Score		
	January	May	July	January	May	July	January	May	July
Family income									
Indirect effect	0.074	0.271***	0.123	0.172	0.314*	0.283*	0.552***	0.591***	0.632***
Direct effect	0.142	-0.022	0.282	0.552	0.931	1.122+	0.578	0.755	1.258*
Total effect	0.216	0.250	0.405	0.724	1.245*	1.405*	1.130*	1.347*	1.890**
Father's education									
Indirect effect	0.023	0.081**	0.036	0.053	0.092*	0.083+	0.168***	0.176***	0.188***
Direct effect	0.192+	0.023	0.091	0.567*	0.649*	0.421	0.330	0.253	0.234
Total effect	0.215*	0.104	0.127	0.620*	0.740**	0.504+	0.497*	0.428+	0.422
Mother's education									
Indirect effect	0.025	0.086***	0.038	0.065+	0.110*	0.089*	0.170***	0.195***	0.187***
Direct effect	0.138	0.140	0.138	0.063	-0.008	0.078	0.196	0.177	-0.053
Total effect	0.163+	0.226+	0.177	0.128	0.102	0.167	0.366+	0.372+	0.135
Group-level fit statistics									
SRMR (none)	0.009	0.009	0.010	0.009	0.009	0.010	0.009	0.009	0.010
SRMR (coefficient)	0.027	0.016	0.049	0.021	0.013	0.016	0.031	0.022	0.017
CD (none)	0.265	0.261	0.388	0.286	0.314	0.321	0.312	0.256	0.254
CD (coefficient)	0.295	0.269	0.262	0.306	0.298	0.300	0.260	0.258	0.257

Note: $+p<0.1$, $*p<0.05$, $**p<0.01$, $***p<0.001$

learning was not significant in January. However, it turned out to be significant in May, meaning that digital learning was significant during the school closures. For example, the indirect effect was 0.271 for family income to the Chinese score, 0.081 for the father's education to the Chinese score, and 0.086 for the mother's education to the Chinese score. After the school reopened, the indirect effect disappeared in July.

The indirect effect of digital learning on the association between students' SES and mathematics scores was not significant in January. However, it became significant in May, and the effect remained in July. Surprisingly, the indirect effects of digital learning on English scores were significant from January to July, and the effect size was the same. For example, the indirect impact of family income on English scores was 0.552 in January, 0.591 in May, and 0.632 in July. These findings suggest that digital learning is of immense importance for English in daily life. We will interpret these results in the discussion.

Discussion

The COVID-19 pandemic and school closures highlight the need for research to examine the effects of SES and digital learning on educational performance. Based on a panel dataset from a Chinese high school during the school closure in 2020, this study showed that digital learning significantly mediates the association between SES and educational performance. However, the indirect effect of digital learning was not significant before the outbreak of the COVID-19 pandemic. Nevertheless, it is of crucial importance during school closures and remote education. Furthermore, after the schools reopened, the indirect effect of digital learning declined or even disappeared. Our findings provide new evidence of the widening digital divide during the crisis. We interpret the results in the following.

First, the indirect effect of digital learning was primarily attributable to the computer's mediating effect. Previous studies have shown that families with a higher SES are more likely to invest in digital resources such as computers at home (Azubuike et al., 2020; Song et al., 2020). In addition, scholars have shown that digital resources at home positively correlate with students' education in the United States, Chile, and Brazil (Claro et al., 2012; Huang & Russell, 2006; Wainer et al., 2015). Our findings provide new evidence that digital learning positively impacts educational performance. While we can be only partially confident of the effects of digital learning, the results lead us to believe there is value in incorporating digital resources into family investment models. At the same time, study rooms did not significantly mediate such effects, although this may be due to the need for more accuracy in our measurements. In the future, we may need to look for more reliable variables to capture the family atmosphere in digital learning.

Second, our findings also showed that school closures moderated the indirect effect of digital learning. The mediation was insignificant before the outbreak of COVID-19. However, when schools were closed, and remote education started, the mediation became substantial. This vividly illustrates how the digital divide widened during the pandemic. The digital divide is an essential factor affecting the quality of life of children and adolescents (Shek, 2021). During the crisis, when digital learning was used as the sole means of communication, disadvantaged students were likely to be hit harder. With a computer, vulnerable students may be able to find valuable online resources to compensate for their learning gaps. Only when schools reopen and face-to-face teaching becomes the primary measure again will the digital divide gradually heal. Shek et al. (2022) found that the HyFlex mode, which integrated face-to-face and online instruction, used after school closures in Hong Kong, resulted in greater satisfaction among university students than the online-only mode. Therefore, in combination with our results, we must be vigilant about the purely online education mode.

Third, despite the compelling findings of the study, our analysis showed several surprising results. For example, the direct effect of SES on academic achievement was not significant in the analytical models. This may be due to our suspicion that digital learning can only partially mediate the association between SES and educational performance. According to the family investment model, other mediators may exist (Bradley & Corwyn, 2002; Conger & Donnellan, 2007). Another surprising finding was that digital learning mediation of English scores did not change during the school closures. We suspect that this was due to students' use of digital resources for English learning before the virus outbreak; as a result, they were not sensitive to distance education during school closures. We hope that future research can address these questions.

More importantly, our study emphasizes the widening divide in the digital era. With the fast development of technologies, people rely more on digital devices, such as computers. The computer is a medium through which people can learn, work, and communicate. In digital learning during COVID-19, having a computer at home was better than using a smartphone because of the screen size, convenience, and stability. However, only some families can afford a computer. As a result, the pandemic outbreak widened the digital divide (Shek, 2021), and the digital divide further increased economic and social inequality (Sánchez & Jiménez-Fernández, 2022). Our findings corroborate previous studies in the literature and indicate that the digital divide will enlarge the academic achievement gap. The academic achievement gap is one dimension of education inequality due to the uneven distribution of digital devices. Achieving education equality has long been the aim of public policy and social science. This paper reminds us of the necessity of considering the digital background when attempting to resolve education inequality.

Our study has several limitations. The first is that the data were collected from a high school. Although it was representative of key-point high schools in China, caution should be utilized when generalizing the findings beyond the context of this study. The second limitation is that the data cannot be used to analyse a causal inference. We had no control group because the COVID-19 school closures impacted all students. A better design would be one in which some students are affected by school closures while others are not. Moreover, the two groups of students should be randomly assigned. The third limitation is that the survey was conducted in August, right after the three examinations. In the first half of 2020, the behaviour of families owning computers might change, but our data could not reflect this change. For this reason, our results may be biased. We hope to have better data to solve the above problems in the future.

Despite these limitations, this may be one of the first papers to address the mediation of digital learning in the context of COVID-19. In addition, our findings have important policy implications. First, social welfare policies for children and families should consider the role of digital learning. Digital resources are expensive for lower-SES students, and the specific child allowance and family subsidies do not include the package of digital resources. Second, schools and teachers should collect information on whether their students can access digital learning. When digital learning is unavailable, other learning services should be considered to compensate for the learning losses of lower-SES students. Third, the construction of internet infrastructure is essential, as well. The development of internet infrastructure varies across regions and within provinces in China. The difference will reflect in students' educational performance, which may affect their lives. Therefore, reducing the divide and providing a better digital environment are necessary. Finally, parents at home can join their students in learning through remote education. Because the impact of digital learning may not be practical when students play games and engage in social chatting, it may be more beneficial for students if parents monitor their learning. With the collaboration of families, schools, and society, lower-SES students may have an equal opportunity to gain a satisfactory learning experience in the digital era.

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Declarations

Conflict of Interest The authors declare no conflict of interest.

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