Jurnal Ekonomi Malaysia 55(3) 2021 103 - 112
http://dx.doi.org/10.17576/JEM-2021-5503-07

Digital Divide in Education during COVID-19 Pandemic

(Jurang Digital dalam Pendidikan semasa Pandemik COVID-19)

Sarimah Surianshah
Universiti Malaysia Sabah

ABSTRACT

This study aims to examine the impact of digital divide on student outcomes using primary data. We used a sample of 233 secondary school students in the rural area of Sabah, Malaysia, during the COVID-19 pandemic from October to November 2020, about six months into student mandatory online learning. A random sampling method was employed in data collection using online questionnaire. This study adopted the two-step least squares method. We specifically measured students' outcomes based on their perspectives of online class effectiveness and student financial constraints to attend these classes. The findings proved the existence of digital divide among students in rural areas. Specifically, the students' low level of online learning attendance produced positive and statistically significant effect on their perspective of the effectiveness of online learning. In addition, the availability of digital devices at home significantly influenced student decision to take part-time jobs in order to help them purchase these devices to enable them attend classes. The findings suggest that there exist digital access barriers among students in rural areas during the pandemic. The study implies that the government or policymakers need to effect strategic intervention such as digital endowment to ensure that the digitally disadvantaged students are not left behind their peers.

Keywords: COVID-19; digital divide; student outcomes; rural area; government intervention
JEL: I2, I3, C3

ABSTRAK

Kajian ini bertujuan untuk mengkaji kesan jurang digital terhadap kemenjadian pelajar menggunakan data primer. Kami menggunakan sampel sebanyak 233 pelajar sekolah menengah di luar bandar Sabah, Malaysia, semasa pandemik COVID-19 dari Oktober hingga November 2020, lebih kurang enam bulan pelajar wajib menjalani pembelajaran dalam talian. Kaedah persampelan secara rawak telah dilakukan dalam pengumpulan data menggunakan soal selidik secara dalam talian. Kajian ini menggunakan kaedah kuasa dua terkecil dua langkah. Secara khususnya, kami mengukur kemenjadian pelajar berdasarkan perspektif pelajar terhadap keberkesanan pembelajaran dalam talian dan kekangan kewangan pelajar untuk mengikuti kelas. Hasil kajian membuktikan wujud jurang digital di kalangan pelajar di luar bandar. Secara khusus, tahap kehadiran pelajar yang rendah dalam pembelajaran dalam talian menghasilkan kesan positif dan signifikan secara statistik terhadap perspektif mereka akan keberkesanan pembelajaran dalam talian. Di samping itu, ketersediaan peranti digital di rumah sangat mempengaruhi keputusan pelajar untuk mendapatkan kerja secara sambilan untuk membantu mereka membeli peranti ini bagi membolehkan mereka menghadiri kelas. Dapatan ini mencadangkan bahawa terdapat halangan akses digital di kalangan pelajar di luar bandar semasa pandemik tersebut. Kajian ini menunjukkan bahawa pihak kerajaan dan pembuat dasar perlu melakukan campur tangan yang strategik seperti pembahagian dana digital untuk memastikan pelajar yang tidak mempunyai kelebihan dalam digital tidak ketinggalan berbanding rakan sebayanya.

Kata kunci: COVID-19; jurang digital; kemenjadian pelajar; kawasan luar bandar; campur tangan kerajaan

Received 12 April 2021; Revised 24 September 2021; Accepted 29 September 2021; Available online 04 October 2021

INTRODUCTION

On 19th February 2021, the Malaysian Prime Minister launched the Malaysia Digital Economy Blueprint (MyDigital) which is in line with the 12th Malaysia Plan (12MP) and the Shared Prosperity Vision 2030. It aims for every Malaysian to be involved in digitalisation and thus drive Malaysia towards a Digital Economy nation (Economic Planning Unit 2021). One of the challenges outlined in the MyDigital blueprint is to achieve digital accessibility for students in rural areas. The Department of Statistics Malaysia (DOSM) reported that internet access by individuals in Malaysia has increased by 5 percentage points to 91.7 per cent in 2020 as compared to 87.0 per cent in 2018. However, it also reported that a disparity still exists in internet accessibility between urban and rural population by about 15.0 percentage points. Thus, a strategic intervention needs be conducted to ensure that no individuals, especially students in rural areas, are left behind in the digitalisation process.

This study examines the impact of a digital divide on student outcomes in a rural area of Tawau, Sabah. According to the Department of Statistics Malaysia general report in 2021, the Tawau region has a mean household income of less than half the national average at RM7,901. The residence are thus expected to experience a pronounced digital divide as compared to other regions. Some studies in developed and developing countries have shown that the digital divide is a challenge for those who are in need, especially in the current situation of the COVID-19 pandemic (Dimaggio et al. 2012; KewalRamani et al. 2018) when digital literacy is of crucial importance. Thus, this study was conducted to provide some policy recommendations to mitigate the digital divide among rural students so that they are not left too far behind their advantaged peers.

The Movement Control Order declared the closure of all schools, and with it the beginning of fully online learning for students throughout Malaysia. Exceptions were however made to allow students to take the national examination on 24th June 2020 and for exams at all levels on 15th July 2020. Following these all schools were closed starting from the second week of December 2020 until early of March 2021. Several interventions have since been implemented to improve students' digital access particularly those in rural areas. Among these are upgrading the internet facilities in the remote rural areas and the relaunching of the DidikTV KPM programme, formally known as TV Pendidikan- Educational TV, introduced in 1972 but has long remained dormant. However, accessibility constraints may limit the impact of these interventions.

The lack of digital devices and problem of access can affect students' attendance in online classes. Chaudhuri et al. (2005) and Lieberman (2020) showed that the geographical factor is a significant determinant in influencing individual decision on whether to pay or otherwise to get internet access for attending online classes. In addition, James (2010) and Whitacre and Mills (2007) indicated that network externalities is another significant factor necessary to bridge the digital gaps. However, their studies did not examine aspects of distance involved in getting internet access that might affect student attendance in online learning. Hence, this study shall incorporate the factor of distance in the model estimates that may indirectly affect student outcomes.

To sum up, this study fills the gap in the literature as related to the perspective of Malaysian secondary students on their educational outcomes, in particular in the use of digital learning, in rural areas. This study also aims to examine potential endogeneity bias in the model estimates. I expect a reverse causality effect to exist in the baseline model where students' perceptions of online learning effectiveness might affect their attendance in school. This argument is in line with the theory of planned behaviour by Ajzen (2020). A two-step least squares method is used to address the problem and students' travel distance to secure internet access and their mode of transportation used as instruments.

The remainder of this paper is organised as follows: The next section presents an overview of student outcomes and a related theory to support the empirical concerns of this study. It follows with a methodology section, results and discussions section and ends with a conclusion section that includes policy recommendations related to the economics of education.

LITERATURE REVIEW

The planned behaviour theory (PBT) by Ajzen (1991) suggests that there exist a relationship between i) attitudes; ii) subjective norms; and iii) perceived behavioural control, and the i) salient behavioural; ii) normative; and iii) control beliefs related to behaviour. In a recent study, he highlights through a few empirical works that the PBT model provides a conceptual framework for researchers to examine additional factors that may affect individual behaviour (Ajzen 2020). The PBT theory may explain the expectation in this study on the existence of a reverse causality problem in the model estimates. This study expects that students' attitudes on online learning effectiveness will affect their behaviours in attending online classes. This study will provide a further empirical test to PBT theory by determining factors of students' behaviours that indirectly affect their attitudes.

Past studies have shown a mixed impact of online learning on student outcomes through using several methods and proxies. Using quasi-experimental research, Lin et al. (2017) established a positive and significant effect of online learning on student outcomes and motivations. A meta-analysis on online learning by Means et al. (2009) in the US showed that, on average, students attending online learning perform better than their counterparts who attended face-to-face learning. Similarly, an experimental study on science students by Terrell and Dringus (2000) and Halasa et al. (2020) found that an interactive environment in online learning may boost student performance. However, a survey by Aucejo et al. (2020) revealed a significant negative impact of COVID-19 on student outcomes in terms of experience and expectation. The negative effects of COVID-19 on student outcomes such as students' learning motivation, student attendance, and student attainment were also observed by Chen et al. (2020), Sintema (2020), and Tan (2020). Recent studies, by Hart et al. (2018, 2019) and Kuhfeld et al. (2020) for example, also demonstrated adverse effects of COVID-19 on student outcomes. These results were robust based on different circumstances. For example, Kuhfeld et al. (2020) showed that using some additional out-of-school time due to the pandemic, could make students more likely to be better in reading than in maths tests. Hart et al. (2019) demonstrated that first taker students for downstream courses such as English 1, Geometry and World History followed via a virtual platform, were more likely to pass these courses compared to their credit recovery peers who were taking contemporaneous ones.

One of the determinants of student outcomes is student attendance rates. This issue is less examined in the Malaysian context. In other places such as a large urban school district in California, Lin et al. (2017) recorded a pronounced student absenteeism rate. Using extensive observation from K-12 schools, Kurtz (2020) showed that students from low-income families were more likely to miss online learning than their peers from high-income ones. In the same context, Lieberman (2020) reported that double absenteeism cases recorded during the COVID-19 pandemic with high schoolers are slightly more likely to play truancy than their middle and elementary peers. Similarly, Santibanez and Guarino, (2020) and Southall et al. (2021)the virus that causes COVID-19 infection, in the UK in early 2020, resulted in the introduction of several control policies to reduce disease spread. As part of these restrictions, schools were closed to all pupils in March (except for vulnerable and key worker children found that absenteeism in middle and high schools is higher than in primary schools in the UK and the US.

Due to the COVID-19 pandemic, a few countries or institutions have drafted interventions or policies to combat the impacts of the virus on student attendance rates in online learning (Duquesne University, 2021; Hollands et al., 2020). Conceptually, interventions can be classified into direct and indirect ones. Direct interventions can be proxied by allocating school-aids incentives to students and giving extra time for them to do schoolwork (Galiani & Perez-Truglia 2011; Kurtz 2020). Indirect interventions by comparison will take into account the involvement of communities or others in the institutions. Many studies have shown the importance of indirect interventions on student attendance. For example, close monitoring of students within their environments will help to reduce absenteeism (Guerrero et al. 2013; Suryahadi & Sambodho 2013). In addition, improvement in instructors' capability to adopt interesting multimedia approaches in teaching would give a positive impact on student attendance (Kebritchi et al. 2017; Lin et al. 2017). Lastly, social-emotional support will help to boost students' motivation to attend online classes (Santibanez & Guarino 2020).

Lastly, family socioeconomic factors such as parental education level and home resources are another potential explanation for student outcomes in online learning that should be highlighted. Chen et al. (2021) and Sackey (2007) showed that in the presence of adequate household resources and highly educated parents, children attendance in school improved. In addition, parents' long-term capital endowment proved important for their children's long-term human capital endowment compared to short-term attributes such as student attendance rate (Sackey 2007).

METHODOLOGY

DATA AND DESCRIPTIVE STATISTICS

A total sample of 233 students participated in the study survey. The students were from a secondary school located about 40 km from Tawau, Sabah, Malaysia. There was no community hall facility in the area as well as internet access.

TABLE 1. Descriptive statistics analysis

Variable	Mean	n
Online learning effectiveness (high=1)	0.069	16
Online class attendance (low=1)	0.408	95
Computer usage at home (base: very often)		
Seldom (=1)	0.240	56
Often (=1)	0.674	157
Financial constraint (high=1)	0.163	38
Demographic characteristics		
Male (=1)	0.326	76
Age	15.773	233
Number of siblings	1.180	233
Home resources availability (1=Yes)		
Internet (=1)	0.820	191
Own computer (=1)	0.326	76
Shared computer (=1)	0.416	97
Own mobile phone (=1)	0.876	204
Shared mobile phone (=1)	0.167	39
Mother's education (base: No or primary)		
Secondary (=1)	0.446	104
Tertiary (=1)	0.112	26
Child don't know (=1)	0.253	59
Father's education (base: No or primary)		
Secondary (=1)	0.446	104
Tertiary (=1)	0.146	34
Child don't know (=1)	0.253	59

The random sampling method was used to collect survey data using online questionnaire method, over a period from October to November 2020, about six months after the students commenced online learning.

The questionnaire comprised three parts. Part A and Part B were from a modified questionnaire adopted from the Trends in International Mathematics and Science Study (TIMSS). Part C, which concerned student perspective questions was constructed after Hussiin (2020). This study used a 5-point Likert scale to score a series of student perspectives, from score 1 (strongly disagree) to 5 (strongly agree). Table 1 shows descriptive statistics from the sample including respondents' demographic characteristics.

Table 1 shows that 7 percent of the students have positive perceptions of online learning compared to traditional learning. Approximately 60 percent of students attended online classes and reported that they had a moderate level of 60 percent computer usage at home. Approximately 80 percent of students reported that they have internet and own mobile phones either with or without internet subscriptions. However, it was noted that almost half of them needed to attend online classes and perform their online assessments using shared computers.

The demographic characteristics revealed that the majority of students were female (67%), aged 15 years old and have at least two siblings. They came from rural areas and have at least one parent with a secondary-level education.

EMPIRICAL MODEL

To measure the impact of digital divide on student outcomes, two approaches were employed in the study. First, the probit model of education production function was used. For each observation of student *i* the model can be written as follows:

$$\Pr\left(Y = 1|X_j\right) = F\left(X_j^{'}\alpha_j\right) \tag{1}$$

where $\Pr\left(Y = 1|X_j\right)$ is the probability of Y that is the student outcomes: i) whether student *i* has agreed that online learning is better than traditional or face-to-face (F2F) learning given X_j, and ii) whether student *i* has chosen to have a part-time job so as to afford an extra internet pass to attend online classes given X_j. X_j for j = 1, …, p are the vector of factors influencing Y such as online class attendance and digital devices at home. α_j is the coefficient estimates from the probit regression that maximize the log-likelihood of the cumulative distribution function of the standard normal distribution, $F\left(X_j^{'}\alpha_j\right)$. This study presents the results in terms of marginal effects that will explain the change in the probability that students agree that online learning is more effective than traditional learning in response to a one-unit change in the explanatory variable of Equation (1), holding other explanatory variables at their means.

In short, this study examines the marginal product of the input factors of educational production model as follows:

$$\text{MPS} = \Delta Q/\Delta S \tag{2}$$

where MPS is the marginal product of student outcomes, ΔQ is the change in the level of student perspectives, and ΔS is the change in the quantity or level of student attendance.

Next, this study employs an identification strategy to address the potential endogeneity problem in Equation (1) using a two-step least squares method. This study expects that there is a reverse causality problem between student attendance in online learning and students' perceptions of online learning following the PBT theory. Hence, to address this issue, I use instruments such as distance for students to commute to get internet access and modes of transportation. Indirect interventions in both digital accessibility aspects are expected to increase students' attendance in online learning. The instruments are employed in the two-step least squares model, and it can be written as follows:

$$Y = \alpha_0 + \alpha_1 X + \alpha_2 \hat{X} + \ldots + \alpha_j X \mu \tag{3}$$

where X is endogenous variables, namely student online attendance level and computer usage at home, and $\hat{X}$ is the predicted results from the following first-stage estimate of Equation (4). Following the PBT theory, this study also expects that students' attitudes on online learning effectiveness will affect their behaviours in using the computer at home and in attending online classes.

$$\hat{X} = \delta_0 + \rho_k Z_k + \delta_1 X + \gamma_j D_j + \varepsilon \tag{4}$$

where Z_k for $k = 1,\ldots,q$ are the q instruments for the endogenous variables; that is the distance and mode of student transportation to travel to get internet access.

To check the validity of the two-stage least squares method, this study examines the significance of the Wu-Hausman F-statistics (Hausman 1978; Wu 1974), the F-statistics of first-stage regression of Equation (4), and the Sargan's (1958) X^2 statistics. The Wu-Hausman F-statistics shows the validity of the causal variable of interest, whether it is endogenous or not, and hence ensure whether the baseline model of Equation (1) yields biased estimates or otherwise. Both the F-statistics of the first-stage regression and the X^2 statistics indicate the strength of the instruments. A strong instrument is one that is highly correlated with the endogenous variable or satisfies Stock et al.'s (2002) suggestion of an F-statistics that should exceed ten to be reliable when there is one endogenous regressor. For an analysis with more than one instrument, I check on the overidentifying restrictions test of Sargan X^2 statistics. This test will check whether the instruments are uncorrelated with the structural error term in Equation (1). It also identifies whether our IV model is mis-specified and if one or more of the excluded exogenous variables should, in fact, be included in the structural equation.

Overall, the key assumptions of the two-step least squares estimates are: i) the instruments are highly correlated with the endogenous variables and ii) the instruments are uncorrelated with other determinants of the dependent variable of the baseline model. The term uncorrelated with other determinants of the dependent variables is equivalent to saying $Cov(\varepsilon, Z_k) = 0$, is the exclusion restriction of the two-step least squares model (Angrist & Pischke 2009).

RESULTS AND DISCUSSIONS

Table 2 summarizes the results for the marginal effects of the probit model and the two-step least squares model, also known as the instrumental variable (IV) model. The post-estimation results of the IV model indicate that there is evidence of an endogeneity problem in the baseline estimates in column (1). This finding indicates the existence of a reverse causality effect between students' attendance and perception of online learning. The evidence is supported by statistically significant results of the endogeneity test, thus upholding the null hypothesis of the test, namely that student attendance and computer usage at home are exogenous. The instruments employed, such as student travel distance to internet sources and their transportations mode, also showed strong results with the test of overidentifying restrictions statistically significant. Overall, the significant results of the IV post-estimation indicate that the exclusion restriction of the method is assured.

The first-stage estimates of the IV model in Table 3, explain in detail the significant results of the instruments on the endogenous variables. We can see that students who have to travel at least 400 meters from internet sources are frequently absent from their online classes. Conversely, the effects on students' frequency of computer usage at home are pronounced if their homes are located no further than 100 meters from internet sources. The contrast in student response as function to digital accessibility shows the existence of significant digital gaps in education.

Both probit and IV models show that students who are less likely to attend online learning do agree that online learning is more effective than face-to-face learning. The positive impact is more than ten times once the endogeneity problem, relating online class attendance with student outcomes, has been addressed. The results are inconsistent with the study by Halasa et al. (2020) who found a positive effect of online learning on student outcomes. However, it is in line with Tan (2020) and Chen et al. (2020) who revealed that online learning disadvantages were attributed to several challenges. In addition, Figure 1 illustrates the difference in terms of effect on students who are likely to be absent from school and who prefer to say that online learning is better than face-to-face learning.

TABLE 2. Student educational outcomes estimates

Dependent variable: Online learning effectiveness (high=1)	(1) Marginal effects	(2) IV model
Online class attendance (low=1)	0.015**	0.206**
	(0.006)	(0.089)
Computer usage at home (base: very often)		
Seldom (=1)	-0.004	-0.048
	(0.006)	(0.184)
Often (=1)	-0.006	0.068
	(0.005)	(0.168)
Male (=1)	-0.001	-0.022
	(0.003)	(0.055)
Home resources availability (1=Yes)		
Internet (=1)	0.010	0.133**
	(0.007)	(0.052)
Own computer (=1)	0.000	0.009
	(0.003)	(0.054)
Shared computer (=1)	0.003	0.007
	(0.004)	(0.056)
Own mobile phone (=1)	0.005	0.126
	(0.007)	(0.111)
Shared mobile phone (=1)	0.001	0.051
	(0.006)	(0.097)
Mother's education (base: No or primary)		
Secondary (=1)	0.050*	0.033
	(0.027)	(0.043)
Tertiary (=1)	0.055**	0.142
	(0.027)	(0.096)
Child don't know (=1)	0.052*	0.047
	(0.028)	(0.060)
Father's education (base: No or primary)		
Secondary (=1)	-0.000	0.029
	(0.006)	(0.053)
Tertiary (=1)	0.000	0.000
	(0.000)	(0.000)
Child don't know (=1)	0.004	0.104
	(0.006)	(0.073)
Observations	199	162
Wu-Hausmann F-statistics (p-value)		0.025
Sargan chi-squared statistics (p-value)		0.988
Minimum eigenvalue statistic		0.964

Notes: Standard errors in parentheses. Significance levels: * $p < .1$, ** $p < .05$, *** $p < .01$

TABLE 3. First-stage estimates of IV model of student educational outcomes

Dependent variables:	Online class attendance (low=1)	Computer usage at home (seldom=1)	Computer usage at home (often=1)
Distance to travel (in meters) x transportation:			
50 x school bus	1.093**	-0.105	0.031
	(0.458)	(0.425)	(0.515)
100 x school bus	1.369*	1.435**	-1.362*
	(0.842)	(0.652)	(0.785)
100 x car or motorcycle	0.508	0.918*	-0.770
	(0.728)	(0.575)	(0.683)
150 x school bus	0.122	0.657	-0.659
	(0.870)	(0.874)	(0.974)
200 x school bus	0.722	1.424**	-1.204 a
	(0.919)	(0.639)	(0.786)
200 x car or motorcycle	0.104	1.032*	-0.654
	(0.911)	(0.566)	(0.685)
300 x school bus	1.151a	1.230*	-1.211 a
	(0.915)	(0.724)	(0.881)
300 x car or motorcycle	0.227	0.574	-0.114
	(0.789)	(0.628)	(0.763)
400 x school bus	2.285***	1.207*	-0.521
	(0.851)	(0.648)	(0.902)
400 x car or motorcycle	1.467*	1.084*	0.272
	(0.799)	(0.594)	(0.720)
500 x school bus	1.151a	1.352*	-1.337 a
	(0.914)	(0.743)	(0.876)
500 x car or motorcycle	0.233	1.087*	-0.912
	(0.853)	(0.676)	(0.779)
1000 x school bus	2.545***	1.024 a	-0.973
	(0.901)	(0.841)	(0.939)
1000 x car or motorcycle	1.224 a	0.808	-0.667
	(0.816)	(0.777)	(0.856)
1500 x school bus	0.870*	0.548*	-0.567 a
	(0.550)	(0.330)	(0.413)
Medium of online learning (1= Google)	0.003	-0.064	0.089
	(0.129)	(0.097)	(0.116)

Notes: Standard errors in parentheses. Significance levels: * $p < .1$, ** $p < .05$, *** $p < .01$, a $p < .2$. Other control variables as in Table 1 are included in the estimation but omitted here for simplicity.

This group is however relatively small compared to its counterparts. It is supported with more than double of the effect size of the relationship between highly not attend students and face-to-face learning.

Among potential explanations for the results is that students might lose motivation and chose to study at their own pace or adopt asynchronous methods without rushing to travel to get internet access (Tan 2020). In addition, their remote location may also play an important role that might indirectly influence them to demand for extra money to attend online learning (Chen et al. 2021). To address inequitable learning access, asynchronous learning is preferable as compared to a synchronous type of learning where students have assured access to learning contents (Hollands et al. 2020). Also, Lin et al. (2017) suggest that teaching effectiveness may help to attract students' attention in online learning. It could be in the form of providing better digital facilities for

TABLE 4. Student educational outcomes based on financial status estimates

Dependent variable: Financial constraint (high=1)	(1) All sample	(2) Students travel more than 400 meters =1	(3) Students travel more than 400 meters =0	(4) Male	(5) Female
Online class attendance (low=1)	0.034	0.025	0.098	0.071	0.023
	(0.048)	(0.064)	(0.060)	(0.061)	(0.053)
Computer usage at home (base: very often)					
Seldom (=1)	0.154	0.857***	-0.029	0.936***	-0.003
	(0.108)	(0.185)	(0.124)	(0.282)	(0.098)
Often (=1)	0.173*	0.910***	-0.068	1.031***	0.012
	(0.101)	(0.189)	(0.108)	(0.304)	(0.093)
Male (=1)	0.088**	-0.004	0.143**		
	(0.045)	(0.052)	(0.059)		
Home resources availability (1=Yes)					
Internet (=1)	-0.053	-0.078	-0.014	-0.113*	0.037
	(0.054)	(0.059)	(0.073)	(0.062)	(0.066)
Own computer (=1)	-0.047	-0.047	0.000	-0.094	-0.114*
	(0.047)	(0.058)	(0.058)	(0.084)	(0.059)
Shared computer (=1)	-0.027	-0.085	0.064	0.098*	-0.099*
	(0.048)	(0.055)	(0.064)	(0.058)	(0.055)
Own mobile phone (=1)	-0.046	-0.051	-0.019	-0.112	-0.074
	(0.077)	(0.079)	(0.095)	(0.084)	(0.080)
Shared mobile phone (=1)	0.038	0.075	0.018	0.187*	-0.095
	(0.063)	(0.073)	(0.090)	(0.100)	(0.062)
Mother's education (base: No or primary)					
Secondary (=1)	-0.046	-0.068	-0.067	0.056	-0.021
	(0.068)	(0.073)	(0.104)	(0.110)	(0.066)
Tertiary (=1)	-0.047	0.005	0.000	0.199*	0.000
	(0.093)	(0.093)	(0.000)	(0.118)	(0.000)
Child don't know (=1)	0.056	0.106	-0.091	0.357***	-0.044
	(0.080)	(0.096)	(0.100)	(0.139)	(0.100)
Father's education (base: No or primary)					
Secondary (=1)	0.095	0.097	0.158	-0.079	0.155*
	(0.070)	(0.080)	(0.113)	(0.096)	(0.085)
Tertiary (=1)	-0.020	0.045	0.000	-0.286**	0.092
	(0.096)	(0.097)	(0.000)	(0.112)	(0.124)
Child don't know (=1)	0.071	0.068	0.182	-0.201*	0.206**
	(0.087)	(0.104)	(0.118)	(0.112)	(0.103)
Observations	233	109	104	76	145

Notes: Standard errors in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

teachers and periodic training on teaching information technology. Column (2) of Table 2 shows the positive and significant impact of internet availability on student outcomes which support the crucial importance of reducing inequitable learning access for students.

Lastly, the main results in Table 2 indicate that parental involvement in their children education may have intrinsic influence on student outcomes. It posits that mothers' education plays a more crucial role compared to the fathers' in influencing children education. The positive maternal education factors are consistent with those reported in extensive studies by Surianshah (2019) who showed the existence of intergenerational socioeconomic effects between mothers and daughters. The result may also be explained by a common close relationship naturally forged from

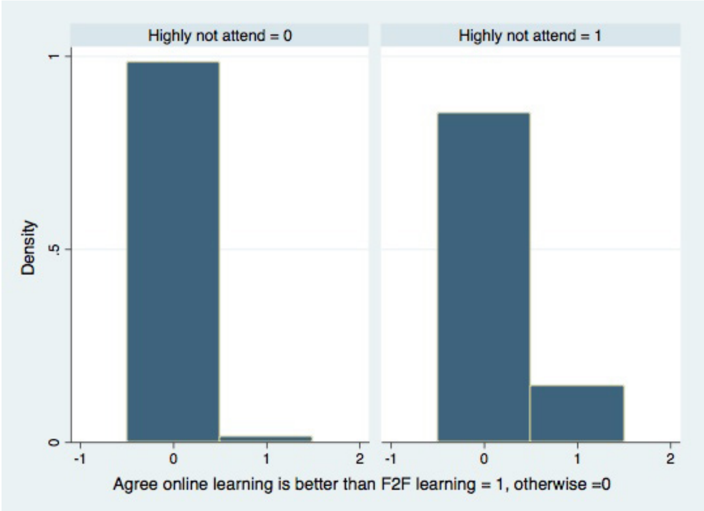

FIGURE 1. Student perspective on online learning versus student attendance in online learning

early childhood between mothers and their children. Mothers by nature are more intimately involved in their children development and upbringing and thus naturally serve as role models for them (Ceka & Murati 2016; Lee 2020).

Table 4 shows the effect of interest variable, from student perspective on online learning, whether poorer students are motivated enough to work in order to afford extra internet passes for attending classes. This study found no evidence that class attendance was affected by their financial status. However, ready availability and usage of digital devices, such as frequency of computer usage at home, showed positive and significant impact of student financial status on class attendance. This suggests that there is an increasing demand for computers within households by students, particularly males, during the pandemic. They were motivated enough to earn money, such as taking part-time jobs, in order to pay for extra internet passes. This may explain our previous finding that demand for online learning increases with low class attendance.

On aspects of gender, Table 4 shows that male students with high educated fathers tend to have lower financial constraints to attend online classes compared to female students. This finding reveals that family socioeconomic status plays a vital role on students' online learning, but there still exist inequitable gender-based socioeconomic benefits. In terms of other socioeconomic status, students with increasing financial constraint during the pandemic is similar to those who shared computer and mobile phone at home, due to limited or no subscription to internet service. This finding showed that the government's previous intervention in allocating free netbooks to qualified students, especially those from the low-income families, is less effective. However, after six months of mandatory online learning at all education levels, the government has strengthened the free netbook project, namely the "A student A Laptop", to facilitate students in online learning particularly those from B40 family income group. According to Musu (2018), this initiative should be regularly conducted to reduce the digital accessibility gap between low and high-income families in Malaysia.

CONCLUSION

This study established that the low level attendance of student online learning exerts positive and statistically significant effect on their perspective regarding effectiveness of online learning. Primary data of secondary school students in a rural area of Sabah, Malaysia were used in the analysis. It should be highlighted that the pronounced effect on student perspective persisted even after the reverse causality effect, following the PBT theory, between online learning attendance and online learning has been addressed. However, the effect of low level online attendance on students' perceptions is marginal. This study also found that the meagre availability of digital devices at home significantly motivates decision by the student to take part-time jobs in order to attend online classes. These findings to some extent reveal that there still exist pronounced digital access barriers for students in rural areas.

Based on the findings of this study the following policy recommendations are proposed: i) Reduction in digital barrier – the distance for students to travel to use internet access is crucial to future considerations on digital endowment intervention. For instance, installation of network externalities should be located at least within 400 meters from most of their homes; ii) teachers' accountability for student social-emotional wellbeing particularly in this COVID-19 situation.

This can be assured through making frequent contacts with delinquent students and implementing interesting teaching methods, as suggested by Kebritchi et al. (2017) and Kurtz (2020). They also recommended that digital divide that exist among instructors themselves is another challenge that should be addressed; iii) strategic interventions in digital endowment allocation. This may assist in increasing student educational outcomes and reduce digital divide between disadvantaged and advantaged students.

ACKNOWLEDGEMENT

The author would like to thank Universiti Malaysia Sabah (UMS) for providing the fund under the Skim Geran Acculturation (SGA) under grant number SGA0043-2019. The author also would like to thank the Ministry of Education Malaysia (MOE) and the school's Parents and Teachers Association.

REFERENCES

Ajzen, I. 1991. The theory of planned behaviour. *Organizational Behavior and Human Decision Processes* 50: 179–211.

Ajzen, I. 2020. The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies* 2: 314–324.

Angrist, J.D. & Pischke, J.S. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. New Jersey: Princeton University Press.

Aucejo, E.M., French, J., Paola, M., Araya, U. & Zafar, B. 2020. The impact of COVID-19 on student experiences and expectations: evidence from a survey. *Journal of Public Economics* 191: 104271.

Ceka, A. & Murati, R. 2016. The role of parents in the education of children. *Journal of Education and Practice* 7: 61–64.

Chaudhuri, A., Flamm, K.S. & Horrigan, J. 2005. An analysis of the determinants of internet access. *Telecommunications Policy* 29: 731–755.

Chen, C.Y., Byrne, E. & Vélez, T. 2021. Impact of the 2020 pandemic of COVID-19 on families with school-aged children in the United States: roles of income level and race. *Journal of Family Issues* 00: 1–22.

Chen, E., Kaczmarek, K. & Ohyama, H. 2020. Student perceptions of distance learning strategies during COVID-19. *Journal of Dental Education* July: 1–2.

Dimaggio, P., Harittai, E., Celeste, C. & Shafer, S. 2012. Digital inequality: from unequal access to differentiated use. *In Studies in the Inequality in the United States: A Reader* edited by J. Brueggemann. Oxfordshire: Routledge.

Duquesne University. 2021. COVID-19 class attendance policy. Duquesne University. https://www.duq.edu/academics/schools/natural-and-environmental-sciences/covid-19-class-attendance-policy (accessed 17 July 2021).

Economic Planning Unit. 2021. Malaysia digital economy blueprint. https://www.epu.gov.my/sites/default/files/2021-02/malaysia-digital-economy-blueprint.pdf (accessed at 20 February 2021).

Galiani, S. & Perez-Truglia, R. 2011. School management in developing countries. *In Studies in the Education Policy in Developing Countries* edited by P. Glewwe. Chicago: University of Chicago Press.

Guerrero, G., Leon, J., Zapata, M. & Cueto, S. 2013. Getting teachers back to the classroom. A systematic review on what works to improve teacher attendance in developing countries. *Journal of Development Effectiveness* 5: 466–488.

Halasa, S., Abusalim, N., Rayyan, M., Constantino, R.E., Nassar, O., Amre, H., Sharab, M. & Qadri, I. 2020. Comparing student achievement in traditional learning with a combination of blended and flipped learning. *Nursing Open* 7: 1129–1138.

Hart, C.M.D., Berger, D., Jacob, B., Loeb, S. & Hill, M. 2019. Online learning, offline outcomes: online course taking and high school student performance. *AERA Open* 5: 1–17.

Hart, C.M.D., Friedmann, E. & Hill, M. 2018. Online course-taking and student outcomes in California community colleges. *Education Finance and Policy* 13: 42–71.

Hausman, J.A. 1978. Specification tests in econometrics. *Econometrica* 46: 1251–1271.

Hollands, F., Brodziak, L., Pratt-Williams, J., Shand, R.D., Drummond, K. & Artzi, L. 2020. *Measuring Attendance during COVID-19: Considerations for Synchronous and Asynchronous Learning Environments*. Institute of Education Sciences. https://ies.ed.gov/blogs/research/post/measuring-attendance-during-covid-19-considerations-for-synchronous-and-asynchronous-learning-environments (accessed 17 July 2021).

Hussiin, H. 2020. Kesan Covid-19 Kepada Pelajar UMP: Satu Kajian Ringkas. *UMP News*. https://news.ump.edu.my/experts/kesan-covid-19-kepada-pelajar-ump-satu-kajian-ringkas (accessed 20 October 202).

James, J. 2010. Mechanisms of access to the Internet in rural areas of developing countries. *Telematics and Informatics* 27: 370–376.

Kebritchi, M., Lipschuetz, A. & Santiague, L. 2017. Issues and challenges for teaching successful online courses in higher education. *Journal of Educational Technology Systems* 46: 4–29.

KewalRamani, A., Zhang, J., Wang, X., Rathbun, A., Corcoran, L., Diliberti, M. & Zhang, J. 2018. Student Access to Digital Learning Resources Outside of the Classroom. https://files.eric.ed.gov/fulltext/ED581891.pdf (accessed 18 July 2021).

Kuhfeld, M., Soland, J., Tarasawa, B., Johnson, A., Ruzek, E. & Liu, J. 2020. Projecting the potential impact of COVID-19 school closures on academic achievement. *Educational Researcher* 49: 549–565.

Kurtz, H. 2020. *National Survey Tracks Impact of Coronavirus on Schools: 10 Key Findings*. EducationWeek.

Lee, C.M. 2020. *A Mother's role in early childhood development*. SBCC Child Development. https://www.healthwaymedical.com/a-mothers-role-in-early-childhood-development/ (accessed 17 July 2021).

Lieberman, M. 2020. *5 Things You Need to Know About Student Absences During COVID-19*. EducationWeek.

Lin, M., Chen, H. & Liu, K.S. 2017. A Study of the effects of digital learning on learning motivation and learning outcome. *Eurasia Journal of Mathematics Science & Technology Education* 13: 3553–3564.

Means, B., Toyama, Y., Murphy, R., Bakia, M. & Jones, K. 2009. Evaluation of evidence-based practices in online learning: a meta-analysis and review of online learning studies. In *U.S. Department of Education, Office of Planning, Evaluation, and Policy Development*. www.ed.gov/about/offices/list/opepd/ppss/reports.html

Musu, L. 2018. *The Digital Divide: Differences in Home Internet Access*. National Center for Education, Institute of Education Sciences. United States Department of Education Statistics. https://nces.ed.gov/blogs/nces/post/the-digital-divide-differences-in-home-internet-access (accessed 18 July 2021).

Sackey, H.A. 2007. The determinants of school attendance and attainment in Ghana: a gender perspective. *AERC Research Paper*. https://www.issuelab.org/resources/21818/21818.pdf

Santibanez, L. & Guarino, C. 2020. The effects of absenteeism on cognitive and social-emotional outcomes: lessons for COVID-19. In *Annenberg Institute for School Reform at Brown University* (Issue 20).

Sargan, J.D. 1958. The estimation of economic relationships using instrumental variables. *Econometrica* 26: 393–415.

Sintema, E.J. 2020. Effect of COVID-19 on the performance of grade 12 students: implications for STEM education. *Eurasia Journal of Mathematics, Science and Technology Education* 16: 1–6.

Southall, E., Holmes, A., Hill, E.M., Atkins, B.D., Leng, T., Thompson, R.N., Dyson, L., Keeling, M.J. & Tildesley, M.J. 2021. An analysis of school absences in England during the COVID-19 pandemic. *BMC Medicine* 19: 1–14.

Stock, J.H., Wright, J.H. & Yogo, M. 2002. A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics* 20: 518–529.

Surianshah, S. 2019. Household education expenditure, school effects, and teacher absenteeism in Malaysia. Unpublished PhD. Diss., University of Nottingham, United Kingdom.

Suryahadi, A. & Sambodho, P. 2013. Assessment of public policies to improve teacher quality and reduce teacher absenteeism. SMERU Working Paper December 2013.

Tan, C. 2020. The impact of COVID-19 on student motivation, community of inquiry and learning performance. *Asian Education and Development Studies* 10: 308–321.

Terrell, S.R. & Dringus, L. 2000. An investigation of the effect of learning style on student success in an online learning environment. *Journal of Educational Technology System* 28: 231-238.

Whitacre, B.E. & Mills, B.F. 2007. Infrastructure and the rural-urban divide in high-speed residential internet access. *International Regional Science Review* 30: 249–273.

Wu, D.M. 1974. Alternative tests of independence between stochastic regressors and disturbances: finite sample results. *Econometrica* 42: 529–546.

Sarimah Surianshah*
Faculty of Science and Natural Resources
Universiti Malaysia Sabah
Jalan UMS, 88400 Kota Kinabalu, Sabah
MALAYSIA.
E-mail: sarimah.surianshah@ums.edu.my

*Corresponding author