# Technology and Student Motivation in Online Learning Based on Socioeconomic Background

Sarimah Surianshah(✉), Suriani Hassan, and Nurul Atika Sazana Jamin

Faculty of Science and Natural Resources, Universiti Malaysia Sabah, Jalan UMS, 88400 Kota Kinabalu, Sabah, Malaysia
sarimah.surianshah@ums.edu.my

**Abstract.** This study examines the effects of technology commonly used by students on student motivation in online learning in Mathematics and Science based on socioeconomic status. We used a sample of 360 secondary students in both urban and rural areas of Sabah, Malaysia. A random sampling method was employed in data collection. This study used the two-stage least squares approach. Analysis of the student motivation model revealed significant differences between students from urban and rural schools. Also, with the availability of technology, students from low social backgrounds are more likely to have low motivation in digital learning, with the effects become pronounced when the endogeneity problem is addressed using intergenerational household socio-economic background variables. Findings from this study perhaps may provide policymakers with insight into a better technology or ICT applications that can increase student motivation levels and ultimately engagement in digital learning in Mathematics and Science, especially in the current Covid-19 crisis. Also, it may provide guidelines to households to provide better technology for better educational outcomes of their children.

**Keywords:** Technology · Student Motivation · Online Learning · Socioeconomic Backgrounds · Endogeneity

## 1 Introduction

This study attempts to examine the effect of technology on student motivations in online learning. According to [1], technology can be defined in both views of "how humans use technology" and "how technology is used". The evolvement of technology has changed the education system in all parts of the world. Recently, the emergence of the Coronavirus which is also known as Covid-19 had a great impact on every individual's learning regardless of social and economic status. In Malaysia, the B40 (bottom 40%) income status households with an income threshold of RM4,849 in the year 2019 are the most affected group. However, the upper-middle and high-income households also facing the same issue [2]. Their load of work becomes increasing due to the instruction to work from home, while they opt-in organizing better online learning environment for their children.


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There are many advantages of online learning such as an option form of learning due to the pandemic, feasible, interactive, and convenient [3–5]. But, one prominent disadvantage of online learning is that it is a costly type of education especially for those with limited technology availability. [6] in their study found that even students at higher education level also face these challenges in online learning. Technology availability for online learning can be in the form of internet access, computer, and smartphone. [7] show the importance to facilitate institutions and students with these devices to foster their positive perceptions towards online learning. [8] and [9] have found a positive and significant effect of the availability of new tools and software for online learning on student outcomes. While [10] found inequality in household adaptation to online learning especially during the pandemic Covid-19. [11] had shown the significant effect of managing home resources for better impact on student academic attainment. Hence, in this study, we aim to examine the effects of technology that is how students use technology on student motivation in online learning based on their socioeconomic background. This study focuses on different challenges that may be faced by students in learning subjects of Mathematics and Science. The practical nature of both subjects may influence students' motivation in online learning. [12] found weaker effects of technology literacy based on students' socioeconomic background in educational domains, such as mathematics and reading. They suggest using different domains in future studies.

This study fills the gap in literature of Malaysian secondary students' educational production model based on school-level socioeconomic background. Differ from other studies, we also consider potential endogeneity effects in the educational production model. Unobserved factors in the baseline model will be considered to provide suitable inferences for the model estimates. Finally, addressing the endogeneity effects may help to formulate suitable policy actions to improve student outcomes in online learning. Eventually, it may help the Ministry of Education to achieve its current education blueprint and Sustainable Development Goals (SDG)-4's – quality education aspiration.

## 2 Methodology

A total of 360 random samples of students from selected secondary schools located in urban and rural areas in Tawau, Sabah, Malaysia had participated in the online survey. The survey consists of three parts which are student characteristics, home technology facilities, and student perception including motivation in online learning during the Covid-19 pandemic. We used the 5-point Likert scale to measure student perceptions that anchored from 1 (strongly disagree) to 5 (strongly agree). The online survey's questions were accumulated from previous studies such as by [13, 14], and [15] that related to this study's main interests. The reliability for each variable was analyzed by the Cronbach Alpha test, and the test's objective was fulfilled. It followed [16] suggestion that the Cronbach alpha values which is greater than 0.6 are acceptable. The demographic of the dataset is as described in Table 1.

Table 1 shows that females are major in respondents with the majority of the respondents having a high level of motivation in online learning than face-to-face learning (78%). The majority of the students (90%) have their own smartphone and only

**Table 1.** Demographics

| | Standard deviation/n | Mean |
|---|---|---|
| High student's motivation in online learning (= 1) | 283 | 0.786 |
| Technology own possessions | | |
| Smartphone availability (1 = yes) | 324 | 0.900 |
| Computer availability (1 = yes) | 96 | 0.267 |
| Internet availability (1 = yes) | 149 | 0.414 |
| Non-technology own possessions | | |
| Study desk (1 = yes) | 211 | 0.586 |
| Own room (1 = yes) | 213 | 0.592 |
| *Gender* | | |
| Male | 159 | 0.442 |
| Home location (base = rural) | | |
| Urban | 155 | 0.431 |
| Household income level[a] | 0.372 | 1.188 |
| Mother education attainment level[a] | 0.823 | 2.786 |
| Father education attainment level[a] | 0.794 | 2.888 |
| Number of observations | 360 | |

Notes: [a]: scale from 1–4, from lowest to the highest level. n indicates number of samples

about 30% and 40% of the respondents respectively possess own computer and internet at home. For non-technology devices possessions, own study desk and room are respectively in moderate level (60%).

## 3 Empirical Strategy

In examining the effect of technology on student motivation in online learning, this study had employed two approaches. First, we apply the probit method as a baseline model. Then, we conduct a standard two-step least squares (2SLS) method by introducing a few instruments to address potential endogeneity bias in the baseline model.

There are many sources of endogeneity such as reverse causality effects, measurement error, and so on. Here, we expect that our endogeneity problem sources from a measurement error where there are unobserved factors that significantly affect our interest variables, smartphone availability. [17] and [18] among others had shown the significant effect of family socioeconomic background on their children's outcomes. Specifically, in this study, we expect that parental effects such as education level is closely attributable to children possession of smartphone.

In assumption that smartphone availability is a necessity good for children nowadays, we regard that having high educated parents may affect the availability of the goods. However, some high educated parents may restrict their children's activities, for instance, owning smartphone, in order to maintain their children's focus and motivation on studying [19]. Hence, in this study, we aim to describe these relationship effects or known as intergenerational effects from parents to children, with children's socioeconomic background is proxied by technology devices ownership.

The first model of this study is the probit model. The probit model of the education production model can be written as follows:

$$S_i = \alpha + X_i\beta_i + D_{ij}\gamma_j + \mu_i \tag{1}$$

where $S_i$ is the measure of student $i$'s motivation in online learning, $X_i$ is the vector of technology possession availability level, $D_i$ is the vector of $j$ control variables such as student characteristics and home location, and $\mu_i$ is an error term.

Equation (1) also has been disaggregated based on school-level socioeconomic background to extensively examine the socioeconomic effects. [20] has highlighted various aspects of socioeconomic background in her review study on student outcomes that had been used by previous social sciences researchers.

The second model in this study is the two-stage least square model (2SLS) or known as the instrumental variable method (IV). The 2SLS model can be written as follows:

$$S_i = \alpha + X_i\beta_i + X_i\widehat{\beta}_i + D_{ij}\gamma_j + \mu_i \tag{2}$$

where $Y_{ik}$ for $k = 1, \ldots, q$ are the $q$ instruments for the student technology possession availability level, that is parents' education attainment level and household income level which are proxy for intergenerational socioeconomic background.

To check the validity of the 2SLS method, we look at the significance of the Wu-Hausman F-statistics [21, 22], the F-statistics of first-stage regression of Eq. (3), and the [23]'s $X^2$ statistics. The Wu-Hausman F-statistics shows the validity of the causal variable of interest, whether it is endogenous or not, and hence ensures whether the baseline model of Eq. (1) yields biased estimates or not. Both the F-statistic of the first-stage regression and the $X^2$ statistics indicate the strength of the instruments. A not weak instrument is the instrument that is highly correlated with the endogenous variable or satisfies [24]'s suggestion of an F-statistic that should exceed ten to be reliable when there is one endogenous regressor. For an analysis with more than one instrument, we check on the overidentifying restrictions test of Wooldridge's robust score test. This tests whether the instruments are uncorrelated with the structural error term in Eq. (1).

## 4 Results and Discussion

Table 2 summarizes the results for the marginal effects of probit model-column (1) and instrumental variable (IV) model-column (2). The post-estimation results of the IV model indicate that there is evidence of an endogeneity problem in the baseline model (see bottom section of Table 2). The evidence is supported by statistically significant results of the endogeneity test of Wu-Hausmann test. This finding means that there are measurement errors in the education production model of student motivation in online learning. Following [18] this problem arises may be due to socioeconomic mobility

**Table 2.** Estimates student motivation in online learning - All sample

| Dependent variable: | (1) | (2) |
|---|---|---|
| Student's motivation in online learning (1 = high) | Marginal effects | IV model |
| Smartphone availability (1 = yes) | 0.064 | 0.786* |
| | (0.070) | (0.593) |
| Computer availability (1 = yes) | −0.085* | −0.131** |
| | (0.050) | (0.065) |
| Internet availability (1 = yes) | 0.023 | 0.037 |
| | (0.047) | (0.052) |
| Study desk availability (1 = yes) | 0.025 | −0.006 |
| | (0.047) | (0.056) |
| Own room availability (1 = yes) | 0.039 | −0.030 |
| | (0.047) | (0.080) |
| Male (= 1) | −0.006 | 0.010 |
| | (0.045) | (0.053) |
| Home location (base: rural) | | |
| Urban | −0.104** | −0.042 |
| | (0.044) | (0.069) |
| Constant | | 0.134 |
| | | (0.511) |
| Observations | 360 | 360 |
| Wu-Hausmann F-statistics (p-value) | | 0.167 |
| Sargan chi-squared statistics (p-value) | | 0.353 |
| Minimum eigenvalue statistic | | 2.027 |

Notes: Standard errors in parentheses. Significance levels: $^{*}p < .2$, $^{**}p < .05$, $^{***}p < .01$.

factors in the households. Hence, to solve this problem we include socioeconomic intergenerational factors in the model estimation and analyze the following model using the instrumental variable method (see column 2 of Table 2).

Table 3 shows the first-stage estimation of the instrumental variable method. The results show that the instruments employed have shown significant results. The overidentifying restriction (see Sargan chi-square value in Table 2) also shows statistically significant results which indicate that the instruments are uncorrelated with the error term and we had correctly specified the structural equation. Findings from Table 3 suggest that students who had higher mothers' education attainment level and household income tend to have their own smartphone to attend online classes. It means that students with high parental socioeconomic status tend to produce children with a high socioeconomic background, an indication of the presence of positive socioeconomic mobility.

**Table 3.** First-stage estimates of Table 2

| Dependent variable: Smartphone availability (1 = yes) | Coefficients |
|---|---|
| Household income level[a] | 0.055* |
| | (0.031) |
| Mother education attainment level[a] | 0.025* |
| | (0.018) |
| Father education attainment level[a] | 0.014 |
| | (0.021) |

Notes: Standard errors in parentheses. Significance levels: $^{*}p < .2$, $^{**}p < .05$, $^{***}p < .01$. [a]: scale from 1–4, from lowest to the highest level. Other explanatory variables as in Table 2 are included in the estimation but omitted here for simplicity.

After controlling for the endogeneity problem, the results of Table 2 shows that students who own smartphones approximately ten times significantly had a high motivation in online learning. A potential explanation for this is that students might have the freedom to attend and arrange their online classes with own possession of smartphone, without sharing with other siblings. These positive attitudes and behaviour effects towards technology are consistent with the theory of the Technology Acceptance Model by [25] and the Theory of Planned Behaviour by [26]. In addition, students also may be convenient to use their smartphones to attend strategic learning methods from instructors such as asynchronous and synchronous as highlighted by [27] and [28].

However, it appears that the presence of other technology devices such as computers or the internet at home does not improve students' motivation in online learning. Computer possession is statistically decreasing student motivation in learning. This result might be due to low literacy in information technology (IT) among students, especially in the low socioeconomic background. Low literacy in IT might reflect a low acceptance of technology among the users. [25] shows the significant effects of users' acceptance of technology to the system usages for development. The low effect of computer availability is statistically significant for students who attend schools located in rural areas (see Table 4). This is probably due to low knowledge and experience to use ICT among the communities [29]. Besides, a low internet connection to adopt the device may weaker the effects of the technology.

Investigating the model further, Table 5 shows the estimates of student motivation in online learning disaggregated by students' class level. To the best of our knowledge, there is limited study for Malaysia that examines the effects of student motivation on digital learning by school social background. Here, we regard that class ranking level is a proxy of a student's school social background. Hence, in this study we test whether students' class or social backgrounds influenced their outcomes. Columns 1 and 2 in

**Table 4.** Estimates student perception on online learning based on school location

| Dependent variable: Student's motivation in online learning (1 = high) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Marginal effects | | IV models | |
| | Urban | Rural | Urban | Rural |
| Smartphone availability (1 = yes) | 0.074 | 0.058 | 1.232 | 0.687 |
| | (0.126) | (0.087) | (1.110) | (0.795) |
| Computer availability (1 = yes) | −0.094 | −0.083* | −0.210 | −0.118* |
| | (0.115) | (0.055) | (0.169) | (0.073) |
| Internet availability (1 = yes) | −0.001 | 0.031 | −0.056 | 0.057 |
| | (0.099) | (0.053) | (0.138) | (0.064) |
| Observations | 90 | 270 | 90 | 270 |
| Wu-Hausmann F-statistics (p-value) | | | 0.160 | 0.391 |
| Sargan chi-squared statistics (p-value) | | | 0.901 | 1.224 |
| Minimum eigenvalue statistic | | | 0.482 | 0.480 |

Notes: Standard errors in parentheses. Significance levels: $^{*}p < .2$, $^{**}p < .05$, $^{***}p < .01$. Other explanatory variables and the first-stage estimations as in Tables 2 and 3 respectively are included in the estimation but omitted here for simplicity.

Table 5 show the baseline models while other columns show the instrumental variable models. Differ from the all-sample model in Table 2, the findings show that there is no or less endogeneity bias problem in the baseline model with only the low-class level model has shown a significant result of endogeneity test.

Similar to Tables 2 and 4 findings, Table 5 also shows positive effects of smartphones availability on student motivation in online learning especially for students from high-class levels. Here, the computer variable also shows a negative effect on student learning especially for students at the low-class levels or having low educational attainments. Computer, as well as internet, are both technology devices that are not becoming main devices needed at home for students from the school-socioeconomic level. They possibly have limited knowledge to use the devices or low acceptance of the devices as compared to their peers from the high-class level or high attainment. These findings demonstrate the government's urgency to support institutions that have a large proportion of low-achieving students with better knowledge and experience in how to use technology rather than adding those IT devices. Increasing number of computer or IT related classes may be a good strategy in achieving the goal of IT literacy, as stated in the Malaysian Education Blueprint, particularly among the low-achieving students [11].

**Table 5.** Estimates student perception on online learning based on class level

| Dependent variable: Student's motivation in online learning (1 = high) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Marginal effects | | IV models | |
| | Low-class level | High-class level | Low-class level | High-class level |
| Smartphone availability (1 = yes) | 0.067 | 0.095$^{*}$ | 2.256 | −0.056 |
| | (0.128) | (0.070) | (1.953) | (0.455) |
| Computer availability (1 = yes) | −0.168$^{**}$ | −0.103$^{*}$ | −0.334$^{**}$ | −0.092$^{*}$ |
| | (0.084) | (0.056) | (0.163) | (0.065) |
| Internet availability (1 = yes) | −0.022 | 0.001 | −0.007 | 0.007 |
| | (0.076) | (0.055) | (0.124) | (0.060) |
| Observations | 187 | 173 | 187 | 173 |
| Wu-Hausmann F-statistics (p-value) | | | 0.083 | 0.685 |
| Sargan chi-squared statistics (p-value) | | | 0.652 | 0.079 |
| Minimum eigenvalue statistic | | | 0.529 | 1.347 |

Notes: Standard errors in parentheses. Significance levels: $^{*}p < .2$, $^{**}p < .05$, $^{***}p < .01$. Other explanatory variables and the first-stage estimations as in Tables 2 and 3 respectively are included in the estimation but omitted here for simplicity.

## 5 Conclusion

The Covid-19 pandemic has changed Malaysia's education learning system to online learning. This has created great challenges for students' motivation in learning. However, the advancement of technology may facilitate students' learning outcomes. Hence, in this study, we examine the effects of technology commonly used by students on student motivations in online learning. We take into account potential unobserved factors in the baseline model such as intergenerational mobility effects to provide appropriate policy responses for the education sector in particular.

After addressing the potential endogeneity problem in the education production model, the findings of this study indicate that only students with higher educational attainment tend to utilize a positive effect of smartphones on their studying motivation during online learning. Also, this study found a negative effect of technology devices such as a computer on students' motivation in online learning. This effect is pronounced for students from low school-level socioeconomic backgrounds, that is schools located in rural areas and low educational attainment classes.

Findings from this study suggest for the government or policymakers to proactively equip institutions with technology literacy human capital in order to achieve, among others, the current Malaysia Education Blueprint goal-shift 7: ICT leverage to scale up quality learning by 2030, regardless of socioeconomic background.

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