Received 29 November 2021
Revised 6 June 2022
Accepted 22 August 2022

Effects of self-efficacy and learning environment on Hong Kong undergraduate students' academic performance in online learning

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Abstract

Purpose – This paper aims to illustrate the importance of the quality of Online Learning Physical Environment (OLPE) and Online Learning Self-efficacy (OLSE) in predicting academic performance in online learning, which was the primary mode of teaching during the outbreak of COVID-19 in Hong Kong. Policy recommendations were made based on the findings from a psychological perspective.

Design/methodology/approach – Responses from 104 Hong Kong undergraduate students were collected through a questionnaire survey. Data were analysed using multiple linear regression, simple linear regression, and Pearson correlation.

Findings – Despite the fact that OLSE showed no significant direct effect on academic performance in online learning, OLSE was positively correlated with and predictive of OLPE, while OLPE was positively correlated with and predictive of online learning performance. The findings indicated that undergraduate students from low-income families tended to have less superior academic performance, which was associated with poorer OLPE and OLSE.

Originality/value – The findings suggested that in order to alleviate learning inequality in online learning, policy makers may allocate funding to enhance OLPE and OLSE of undergraduate students from low-income families.

Keywords COVID-19, Online Learning Physical Environment (OLPE), Online Learning Self-efficacy (OLSE), Education, Hong Kong

Paper type Research paper

Introduction

It is a prevalent idea that students' academic performance and external resources are correlated. However, self-efficacy is also a crucial factor influencing one's academic performance. A vast number of studies have indicated the influence of self-efficacy on academic performance (Cheng and Chiou, 2010; Davis, 2009; Fang, 2014; Hannon, 2014; Jung, 2013; Obrentz, 2012). Despite this, few studies have investigated the association between Online Learning Physical Environment (OLPE) and Online Learning Self-Efficacy (OLSE). During COVID-19, the majority of face-to-face teaching has been replaced by online learning,

This paper forms part of a special section Teaching and Learning in Higher Education: Opportunities, Challenges, and Policy Implications, guest edited by Dr Stephanie Wing Lee.

Public Administration and Policy
Vol. 25 No. 3, 2022
pp. 250-263
Emerald Publishing Limited
1727-2645
DOI 10.1108/PAP-08-2022-0100

thus requiring a re-evaluation of the relationships that are known in the past by the traditional teaching context.

In this study, OLPE is defined as students' physical surroundings, such as lighting, air quality, noise level, and ambient temperature. Compared to academic performance, less attention has been placed on the physical environment. However, the quality of OLPE impacts on students' physiology, e.g., noise could impair students' attention span and encoding process which are critical for effective learning (Braat-Eggen *et al.*, 2017). Moreover, studies have indicated that lighting optimization plays a crucial role in the ideal study environment (Kudo *et al.*, 2019; Oselumese, 2016). All in all, self-efficacy has been suggested to be predictive of academic performance. It is plausible that OLPE impacts on OLSE as students' physical experience may affect the formation of OLSE mastery experience. Mastery experience refers to students' appraisal of their online learning experience, which could be positive or negative depending on the experience (Bandura, 1997). In addition, the physical disturbance may negatively affect students' online learning, which in turns undermines students' mastery experience and OLSE. Nowadays, online learning mostly takes place at students' home, which may vary to a large extent depending on students' economic status. Compared to other students, those from underprivileged families may be less satisfied with their online learning experience, hence negatively affecting OLSE and academic performance.

OLSE is defined as students' appraisal of their technological literacy in online learning rather than the level of technological literacy they achieved, e.g., how well the students consider themselves to operate online learning platforms and how efficient they communicate in a virtual environment subjectively.

Self-efficacy and academic performance in online learning

A plethora of studies have suggested that self-efficacy is positively correlated with academic performance (Cheng and Chiou, 2010; Davis, 2009; Fang, 2014; Hannon, 2014; Jung, 2013; Obrentz, 2012). Self-efficacy is a concept originated from social cognitive theory. It refers to one's belief in their ability to reach a particular level of performance on a specific task (Bandura, 1997). In learning, the self-efficacy mechanism assumes that students with higher academic self-efficacy are more motivated to learn. Therefore, they often attain higher academic achievement (Huang, 2012). Moreover, assuming all learners are equal in terms of knowledge, those who have higher academic self-efficacy tend to outperform those without, as they are motivated to actively engage in activities that would be conducive to the attainment of academic goals. Furthermore, a meta-analysis has shown that higher academic self-efficacy consistently fosters academic performance, which can be enhanced by various means (Talsma *et al.*, 2018). In this research, the idea of self-efficacy is adapted to the context of online learning, which refers to students' belief in their technological literacy, such as coping with technical issues, navigation, and communication. The adapted self-efficacy concept is known as Online Learning Self-Efficacy (OLSE). Aristovnik *et al.* (2020) suggested that students' lack of technological literacy prevented them excelling, illustrating the relationship between OLSE and academic performance in online learning.

Quality of online learning physical environment

By reviewing different aspects of physical environment in online learning, related knowledge may be applied to policy recommendations. Moreover, OLPE and OLSE influence the quality and appraisal of students' online learning experience which constitute their OLSE mastery experience. According to Realyvásquez-Vargas *et al.* (2020), online learning is a new teaching model that has subjected students to different levels of lighting, noise, ambient temperature, and air quality. The difference between such environmental elements may cause cognitive discomfort and distraction. On the other hand, those with favorable environmental conditions

may have an advantage over other students. Since these environmental factors have been shown to impact on academic performance, it is plausible that such impacts extend to students' OLSE. For instance, without proper lighting, students may suffer from shorter attention spans and worsened memory retention (Chellappa *et al.*, 2014), causing frustration. This in turn negatively affects mastery experience, which is one of the building blocks of self-efficacy.

Lighting

Tanner and Langford (2002) indicated that the quality of lighting improves productivity and performance in an online learning environment. Quality lighting enables students to see the surroundings clearly, which would improve their concentration (Sleegers *et al.*, 2012), thus resulting in better performance and class participation. Furthermore, quality lighting provides visual comfort and prevents other physiological discomfort, such as strained eyes and headaches which may impact on one's attention span. It is common for students to suffer from mental fatigue in an overly dim or bright environment (Smolders and de Kort, 2014). Moreover, learning is a taxing task which requires much cognitive processing including executive functions and memory retention (Chellappa *et al.*, 2014).

Noise

Noise could negatively influence learning effectiveness, as it affects students' ability to hear clearly. Research shows that noise induces disruption to listening comprehension and speech perception during classes. Such disruptions are harmful to students' performance on auditory tasks, such as listening in class as well as taking part in online verbal discussions (Klatte *et al.*, 2013). Irrelevant sound effect (ISE) refers to situations where the noise may not be loud, but the noise continuously varies in pitch, intensity, and frequency, which is characteristic of household noise. ISE negatively affects learning by impairing working memory and interfering with the encoding process during class. Nonauditory tasks such as revision or taking an exam are also affected, as such tasks taps into the cognitive domains of encoding, retrieval, and short-term memory (Monteiro *et al.*, 2018; Schlittmeier *et al.*, 2012).

Ambient temperature and air quality

Students' performance on cognitive tasks depends on their body temperature, which is influenced by the ambient temperature to a great extent. Uncomfortable temperatures alter physicochemical conditions and impair cognitive performance in students (Goodman *et al.*, 2018). Chang and Kajakaite (2019) investigated into the temperature range conducive to the enhancement of cognitive performance on tasks which evaluate logical reasoning, verbal ability, and executive functions, resembling those in classroom situations. Results showed that males and females performed better at lower temperatures and higher temperatures, respectively. Furthermore, Abbasi *et al.* (2019) found that with every 1 degree Celsius increase in temperature from 22 degrees Celsius, task accuracy decreased on varying levels depending on workload. Moreover, regarding air quality, Künn *et al.*, (2019) indicated that PM2.5 and CO2 concentrations were negatively associated with cognitive performance. With higher levels of PM2.5, brain oxygen level is decreased and hence impairs cognitive performance.

Existing policies supporting undergraduates in online learning context

In Hong Kong, two types of institutions offer undergraduate programmes: the University Grants Committee (UGC) funded universities and self-financing institutions. According to UGC (2020), in response to COVID-19, UGC allocated 50 million HKD to UGC-funded universities for enhancing student's support services. The funding encompassed a wide range of initiatives. For instance, holding activities over the internet such as psychological counselling and virtual career fairs. Also, the funding covered special arrangements and support for students with special

educational needs (SEN). Xiong *et al.* (2021) identified the top 5 online learning problems faced by university students. 60 percent of students found it difficult to self-discipline; 56 percent considered the learning atmosphere to be poor; 54 percent suffered from eye fatigue; and 50 percent complained about the unstable Internet connection. Such results imply that UGC's initiatives may not have effectively addressed the problems. Moreover, another limitation is that the funding only benefited students of UGC-funded universities, while no substantial financial assistance was allocated to any self-financing institutions.

Research gap

Despite extensive studies investigating the effects of environmental factors on physiology and self-efficacy respectively, the association between the effects of environmental factors and development of self-efficacy is seldom studied. Amid the COVID-19 pandemic, as most of the learning process takes place in a non-classroom environment which is vastly different from the traditional classroom setting, it would thus be meaningful to further investigate the relationship between self-efficacy and academic performance in an online learning environment. In addition, little is known about the correlational and predictive relationships among self-efficacy, academic performance, and environment in the context of OLPE model.

Research objectives

This study aimed to:

(1) Elucidate the relationships among online learning physical environment (OLPE), online learning self-efficacy (OLSE), and online learning academic performance;

(2) Evaluate OLPE and OLSE as predictors of online learning academic performance; and

(3) Suggest viable options for the Hong Kong government to improve OLPE and OLSE of students.

Hypotheses

(1) Hypothesis 1 (H1): Higher OLPE and OLSE are associated with better academic performance.

(2) Hypothesis 2 (H2): Higher OLSE predicts better academic performance.

(3) Hypothesis 3 (H3): Higher OLPE predicts higher OLSE.

Methodology

104 valid responses from participants fulfilling the following criteria were recruited: i) Online learning was the mode of teaching for at least 90 percent of classes during the past two semesters; ii) Participants attended online classes in the same environment at least 90 percent of the time; iii) Participants were current students from Higher Diploma (HD), Associate Degree (AD), or Bachelor's degree programmes in Hong Kong.

Measures

Online learning physical environment (OLPE). The Questionnaire of Effects from Online Classes (QEOC) (Realyvásquez-Vargas *et al.*, 2020) and two additional questions on the conditions of electronic device and network were used to measure OLPE. The scale consisted of

three dimensions of the online learning physical environment, including lighting, noise, and temperature, with 3 questions for each domain. Along with the two additional questions, a total of 11 items were measured using a 5-point Likert scale. OLPE has been shown to be satisfactory in terms of internal reliability (Cronbach's alpha = 0.821) and convergent validity (Average variance extracted measure for temperature: 0.795; Lighting: 0.691; Noise: 0.731).

Online learning self-efficacy (OLSE). The Online Learning Self-Efficacy Scale (OLSES) of Zimmerman and Kulikowich (2016) was adopted. It is a 21-item questionnaire with 5-point Likert scale, with questions on online learning experience of the students, students' appraisal of their OLSE related experience pertaining to three aspects of self-efficacy. OLSES has been demonstrated to have high internal reliability (Cronbach's alpha = 0.987).

Academic performance (AP). As a measure of academic performance, respondents are asked to provide their average GPA for the last two consecutive online semesters. Since the maximum attainable GPA scores varied from 4.0 to 4.3 for different institutions, scores were transformed into z-scores for standardization.

Data collection. The questionnaire consisted of the scales of OLPE and OLSE. Convenience sampling was employed by collecting responses via online forums.

Data analysis. Data were analyzed using multiple linear regression, simple linear regression, and correlation via Statistical Package for the Social Sciences (SPSS) version 28.

Findings

Correlation analysis of OLPE, OLSE and online academic performance

Descriptive statistics are shown in Table 1. Regarding correlation, two pairs of variables were found to be significantly and positively correlated. (1): OLE and OLSE ($r = 0.428, p = <.001$); (2): OLSE and standardized GPA (online learning academic performance) ($r = 0.282, p = .004$) (Table 2).

Table 1. Descriptive statistics of correlation

Descriptive Statistics	Mean	Std. Deviation	N
Standardized GPA	.0525	.86264	104
Online learning physical environment	3.8844	.68136	104
Online learning self-efficacy	3.8883	.52566	104

Table 2. Correlations table of OLPE, OLSE and online academic performance

Correlations		Standardized GPA	Online learning physical environment	Online learning self-efficacy
Standardized GPA	Pearson Correlation	1	.120	.282**
	Sig. (2-tailed)		.226	.004
	N	104	104	104
Online learning physical environment	Pearson Correlation	.120	1	.428**
	Sig. (2-tailed)	.226		.000
	N	104	104	104
Online learning self-efficacy	Pearson Correlation	.282**	.428**	1
	Sig. (2-tailed)	.004	.000	
	N	104	104	104

**. Correlation is significant at the 0.01 level (2-tailed).

Multiple linear regression with OLPE and OLSE as predictors of online academic performance

Multiple linear regression analysis was conducted to construct a model to predict online learning academic performance with OLPE and OLSE. A significant regression equation was found ($F(2, 101) = 4.368$, $p = .015$), with an R^2 of .08.

Only online learning self-efficacy was significantly predictive of academic performance ($\beta = 0.464$, $p = <.01$). However, the quality of the student's online learning physical environment was not significant ($p = .991$). Therefore, OLPE was excluded and a simple linear regression was conducted instead.

Therefore, H1 was rejected. OLPE was not associated with academic performance ($r = 0.120$, $p = 0.120$). OLPE and OLSE may not be jointly predictive of academic performance.

Simple linear regression with OLSE as predictor of online academic performance

With OLSE as the only predictor of online academic performance, a significant regression equation was found ($F(1, 102) = 8.822$, $p = .004$). OLSE was significantly predictive of AP ($\beta = 0.463$, $p = <.001$), also, the model had an R^2 of .08. The model accounted for 8 percent of the variation of AP. In other words, students' 8 percent change in academic performance could be attributed to OLSE (Tables 3 and 4).

As shown in Table 5, OLSE was significantly predictive of online academic performance ($\beta = 0.463$, $p = <.001$). *Standardized GPA* = -1.748+0.463**Online Learning self-efficacy*. Therefore, H2 was accepted.

To explore further, OLPE was chosen as the predictor of OLSE in another single linear regression analysis.

Simple linear regression with only OLPE as the predictor to OLSE

Regarding the regression model of OLPE as the predictor to OLSE, OLPE is significantly predictive to OLSE ($\beta = 2.605$, $p = <.001$). The model has an R^2 of .183 (Table 6). It implies that the model accounts for 18.3 percent of the variation of OLSE, which is a relatively high

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.282[a]	.080	.071	.83164	.080	8.822	1	102	.004	1.588

a. Predictors: (Constant), Online learning self-efficacy
b. Dependent Variable: Standardized GPA

Table 3. Model summary of simple linear regression (OLSE to predict online learning academic performance)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.102	1	6.102	8.822	.004[b]
	Residual	70.545	102	.692		
	Total	76.647	103			

a. Dependent Variable: Standardized GPA
b. Predictors: (Constant), Online learning self-efficacy

Table 4. Analysis of variance for simple linear regression (OLSE predicting online learning academic performance)

Table 5.
Coefficients table of simple linear regression

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	TOLPErance	VIF
1	(Constant)	-1.748	.612		-2.858	.005	-2.961	-.535					
	Online learning self-efficacy	.463	.156	.282	2.970	.004	.154	.772	.282	.282	.282	1.000	1.000

a. Dependent Variable: Standardized GPA

figure in social science research, also for a regression model with only one predictor (Itaoka, 2012). To further explain, 18.3 percent change in students OLSE can be attributed to OLPE.

With OLPE as the only predictor to OLSE. A significant regression equation was found ($F(1, 102) = 22.891$, $p = < .001$), also with an R2 of .183 (Tables 6 and 7).

As can be seen from Table 8, OLPE is significantly predictive to OLSE ($\beta = 2.605$, $p = <.001$)., the model is $OLSE = 2.605+0.350*OLPE$. Therefore, H3 is accepted.

Discussion

Relationship of OLSE and online learning academic performance

This study elucidated the relationships among OLPE, OLSE, and academic performance. Furthermore, OLPE and OLSE were identified as significant predictors of online academic performance (Figure 1 and Table 3). However, the regression model with OLPE and OLSE as independent variables had lower predictive power. One explanation is that there are other more influential independent variables not included in this study. According to Robbins *et al.* (2004), achievement motivation directs and energizes the student's behaviour for achievement. It has a multifactorial construct that is similar to self-efficacy, which consists of the students' values, objectives, motivational beliefs, and achievement motives (Wigfield *et al.*, 2016). It has been shown that achievement motivation explained 9 percent of variance of first-year GPA scores. Another potential variable is personality (Noftle and Robins, 2007), with a significantly positive correlation between Big Five conscientiousness domain and GPA.

OLSE is a rather novel concept which comprises three types of self-efficacy, including learning in the online environment, time management, and electronic literacy in the online learning context where studying becomes more self-directed (Zimmerman and Kulikowich, 2016). Self-efficacy of learning in the online environment facilitates academic performance with regard to the concept of mastery experience. OLSE consists of questions regarding students' satisfaction toward their online learning experience, such as whether they could navigate online courses efficiently and communicate effectively with teachers and students.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.428[a]	.183	.175	.47738	.183	22.891	1	102	.000	1.844

a. Predictors: (Constant), Online learning physical environment(
b. Dependent Variable: Online learning self-efficacy

Table 6. Model summary of simple linear regression (only OLPE as predictor to OLSE)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.217	1	5.217	22.891	.000[b]
	Residual	23.245	102	.228		
	Total	28.461	103			

a. Dependent Variable: Online learning self-efficacy
b. Predictors: (Constant), Online learning physical environment

Table 7. Analysis of variance of simple linear regression (only OLPE as predictor to OLSE)

Table 8.
Coefficients of simple linear regression (only OLPE as predictor to OLSE)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	TOLPErance	VIF
1	(Constant)	2.605	.272		9.571	.000	2.065	3.145					
	Online learning physical environment	.330	.069	.428	4.784	.000	.193	.467	.428	.428	.428	1.000	1.000

a. Dependent Variable: Online learning self-efficacy

Moreover, the relationship between AP and OLSE is mutually facilitating rather than one-way (Talsma *et al.*, 2018). It is clear that AP is associated with learning effort and OLSE. Therefore, a positive appraisal of AP reinforces students' mastery experience. Despite the fact that the potential causal relationship and its direction pertaining to OLSE and AP are still debatable (Pajares and Usher, 2008), it has been suggested that an upward spiral exists (Salanova *et al.*, 2006).

Relationship of OLPE and OLSE

OLPE and OLSE affect students' cognition that determines their online learning performance. As discussed in the literature review, lighting, noise, ambient temperature, and air quality of the OLPE, all impact on one's cognitive functions and online learning performance, which in turn affect mastery experience and facilitation of OLSE. To supplement, Al horr *et al.* (2016) discussed how lighting and window view could affect mood, stress, and ultimately task performance, suggesting that effective lighting results in positive mood and stress relief.

Policy recommendations

The need for quality OLPE

As discussed, the quality of OLPE affects formation of OLSE through altering cognitive performance for mastery experience, with OLSE correlated with academic performance. Hong Kong in 2018 was reported with an all-time high Gini coefficient of 0.539 (Oxfam Hong Kong, 2018), suggesting a serious wealth gap, with an average living space per person of 13.3 m2 (Transport and Housing Bureau of Hong Kong, 2019). Such figures imply that most of the undergraduates in Hong Kong may not have access to quality OLPE, suggesting a form of educational inequality, which is worsening amid COVID-19. According to Xiong *et al.* (2021), 58 percent of the survey respondents experienced a decrease in learning efficiency and academic performance under online learning settings. They found several environmental factors that are unfavorable to a quality OLPE which also impacted the academic performance. Students with less economic resources and limited living space are more susceptible to noise problems, which negatively affect concentration in class. This in turn negatively affects effective learning, i.e., resulting in failure to comprehend and encode class content, leading to impairment of OLSE.

Policy recommendation for improving OLPE and OLSE

This study proposes two alternatives to face-to-face teaching in response to the pandemic situation. The first alternative focuses on improving the OLPE and OLSE at home, while the second focuses on improving public online learning space.

Regarding visual health, the government may design a public education program to promote visual health care awareness for all students. At the beginning of the program, students should be briefed with visual health care knowledge then to introduce a set of exercises recommended by Sano *et al.* (2018), such as crunches, sit-ups, and squats. The design of Sano's exercise program yielded a significant decrease in the participants' dry eye

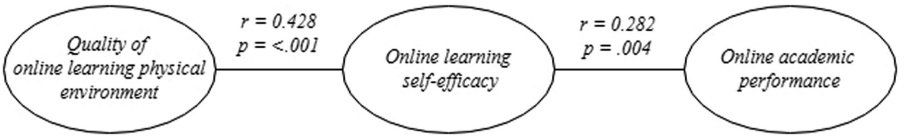

Figure 1.
The model of correlations

symptoms. To supplement the program, blue-light shield may be given to the students by the government. Furthermore, the government may advise on the recommended OLPE lighting, e.g., acceptable light intensity and color temperature. For air conditioning, a subsidy for electricity consumption could be arranged for the students on a means-tested principle during summer.

One of the constituting factors of OLSE is electronic literacy self-efficacy. Concerning the responses of OLSE scales, the students who scored high can utilize their electronic devices to fulfil learning objectives. However, a survey conducted by The Chinese University of Hong Kong (2020) found prevalent difficulties among undergraduates as 58 percent of the respondents reported technical issues. Moreover, 49 percent of the respondents complained about internet connection stability in another survey (Xiong *et al.*, 2021). According to the Office of the Communications Authority (OFCA) (2021), in Hong Kong, up to August 2021, near 300,000 registered residential dial-up access lines are equal to or greater than 1 Mbps and less than 100 Mbps. Such inferior bandwidth is commonly used by households with lower economic status as the optical fiber is inaccessible. Students who are using 8Mbps or lower bandwidth may be unable to enjoy smooth streaming for effective class participation. This in turn may negatively affect OLSE, rendering such students at a disadvantage compared to other students without such problems.

The government may provide financial support for the students to improve their internet bandwidth below 8 Mbps. If optical fiber installation is not possible for some cases, providing a 4G LTE router that can receive mobile signals for accessing the internet could be a viable option. To alleviate the hardware problem, the government may consider extending the "Bring Your Own Device" policy to UGC and Non-UGC undergraduate students or provide means-tested reimbursement. Finally, it is important to improve digital literacy of both students and teachers for effective online learning experience, with government financial assistance supporting such initiatives.

The second alternative would be to construct a public online learning space (POLS) with quality OLPE which promotes OLSE. The government may consider allocating spaces for the undergraduates to learn in a quality environment. For instance, according to the Research office of the Legislative Council Secretariat (2019), the vacancy rate of private flatted factories in 2018 was 6.3 percent, providing 16.4 million square meters of space that the government may utilize for developing quality OLPE and ensuring OLSE development of students. Moreover, the government may temporarily revamp Hong Kong's community halls for quality OLPE. Indoor public learning space could be subdivided into soundproof cubicles, fitted with tools for online learning such as noise-cancelling headphones, microphone, video camera, and high bandwidth Internet connection.

Conclusion

This study elucidated the relationships among OLPE, OLSE, and academic performance. Furthermore, OLPE and OLSE were identified as significant predictors of online academic performance. The findings suggested positive associations among OLPE, OLSE, and online academic performance. This study proposes ways to alleviate educational inequality which is further exacerbated by the pandemic.

This study has some limitations. First, the effect size of the regression models may be increased by including other relevant independent variables. Second, owing to the study design, casual interferences cannot be drawn. Lastly, the policy recommendations are based on data collected in the early stage of the pandemic, which may not be entirely applicable to current pandemic situation in Hong Kong.

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