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Learning and happiness during Covid-19 school closure in urban Malaysia

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ABSTRACT

COVID-19 school closure has disrupted education systems globally raising concerns over learning time loss. At the same time, social isolation at home has seen a decline in happiness level among young learners. Understanding the link between cognitive effort and emotional wellbeing is important for post-pandemic learning recovery interventions particularly if there is a feedback loop from happiness to learning. In this context, we use primary survey data collected during the first school closure in urban Malaysia to study the complex association between learning loss and student happiness. Machine learning methods are used to accommodate the multi-dimensional and interaction effects between the covariates that influence this association. Empirically, we find that the most important covariates are student gender, social economic status (SES) proxied by the number of books ownership, time spent on play and religious activity. Based on the results, we develop a conceptual framework of learning continuity by formalizing the importance of investment in emotional wellbeing.

1. Introduction

COVID-19 has impacted close to a billion students around the world with worldwide school closures to control the virus transmission process. By the end of January 2021, schools on average had been closed or partially closed for 5.5 months in 188 countries (UNESCO 2021).[1] In most countries, distance learning programs have been introduced to ensure learning continuity (Selvaraj et al., 2021; Toquero, 2021) using some form of technology-based delivery strategy with digitized learning content on TV and radio (see for e.g. Alvarez et al., 2020; Dreesen et al., 2020).

This disruption to school education is likely to worsen the existing learning crisis in the developing world (Betthäuser, Bach-Mortensen and Engzell, 2023). A burgeoning literature has documented potential and actual losses in cognitive skills with the associated rise in learning poverty (Asian Development Bank, 2021; Donnelly and Patrinos, 2021; Engzell et al., 2021; Hevia et al., 2022; McBurnie et al., 2020). Supporting studies document a loss of learning time (e.g. Asanov et al., 2021; Booth et al., 2021; Engzell et al., 2021). Even in high-income countries, learning loss from a reduction in normal schooling hours has been significant (Elliot Major et al., 2021).

Beyond direct effects, school closures had resulted in well-being consequences amongst children and adolescents. While home schooling and social isolation has minimized the risk of Covid infection, it has created an unintended consequence. The sudden disruption to the student's social environment has coincided with an increase in anxiety and other negative emotional feelings (Cuñado and de Gracia, F., 2011; Fegert et al., 2020). A recent systematic review of 36 countries from 11 countries[2] confirm that school closures and social lockdowns during the first COVID-19 wave were associated with adverse mental health symptoms such as distress and anxiety) and health behaviors (such as higher screen time and lower physical activity (Viner et al., 2022; Lee et al., 2020) documented that in the UK, a Young Minds survey with 83% of 2111 participants up to age 25 years with a mental illness history said the pandemic school closures had made their conditions worse. Moreover, there is evidence of growing use of antidepressant, among adults and adolescents, to cope with emotional change (Rossin-Slater et al., 2020; Singh et al., 2020; Rabeea et al., 2021; Pazzagli et al., 2022).

Understanding the link between cognitive effort and emotional wellbeing is important as there may be a potential feedback loop from

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[1] https://en.unesco.org/news/unesco-figures-show-two-thirds-academic-year-lost-average-worldwide-due-covid-19-school

[2] These countries are largely among developed countries – USA, Italy, Japan, UK, Canada, Spain with the exception of China, Turkey, Bangladesh and Brazil.

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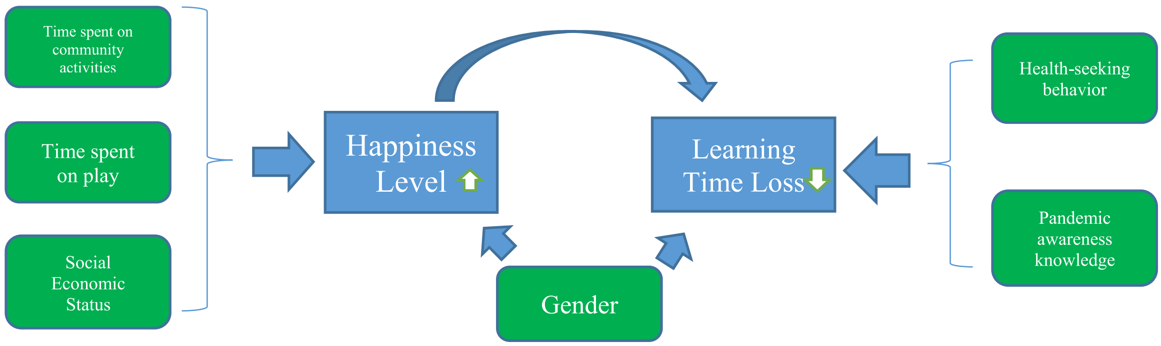

Fig. 1. ML-based Empirical Model of Learning Time Loss and Happiness Level: Visual Summary of the Key Findings.
Source: Authors.

happiness to learning. If so, this intersection between learning time and mental health offers an added justification for investment in mental health as a "catch-up policy" for successful post-pandemic return to school (Farquharson et al., 2021; Harmey and Moss, 2022). Evidence also confirms enough demand for such policy response - around a quarter of parents in UK surveyed prioritised greater access to mental health services (Farquharson et al., 2021). A UNICEF and WHO report on 122 countries (developing and developed) in 2022, including Malaysia, listed mitigating psychological health and wellbeing as a key action for a child to be ready to learn yet less than half the countries are implementing these "catch-up policy".[3]

In this context, this study uses a purposefully designed survey on secondary school students in urban Malaysia, a country with significant mental health related challenges among adolescents during the pandemic and yet limited academic research.[4] As per the government's National Strategic Plan for Mental Health 2020–2025, there is no school children specific mental health catch up policy during the pandemic. While the Ministry of Health has published a guideline titled "COVID-19 Mental Health Kit—In Hospital Setting and Quarantine Centre", it is exclusively for patients and health care workers (Samy et al., 2021). In general, there is a lack of availability of child- and adolescent-friendly multidisciplinary care for mental health conditions in Malaysia (UNICEF, National Institutes of Health Malaysia, Burnet Institute, 2022).

Mental health is well known to be multi-dimensional and complex to model (Lomas and Tyler, 2023). For this reason, we use ML methods to model the *students' happiness level*. ML is suited for nonlinear relationships and higher-order cross interactions[5] among the covariates and predictive variables that statistical analysis is unable to (Ryo et al., 2017; Goodfellow et al., 2016). We find that an increased happiness level is predicted by *gender, (more) time spent on play and religious activity, and (higher) social-economic status* (proxied by the number of book at home) in (evidenced in Heppt et al., 2022). For learning time loss, the key predictive covariates are *gender, (more) health-seeking behaviour and pandemic awareness knowledge* (e.g. proxied by data on how the disease spreads, and hygiene habits like hand washing, nail cutting and haircut frequencies).

In other words, gender is a common predictor impacting both happiness level and learning time loss, a finding that is also aligned with the emerging academic evidence (for studies on females more likely to have worse mental health and drop out of school during the pandemic, see (Borrescio-Higa and Valenzuela, 2021 and Flor et al., 2022 respectively). To the best of our knowledge, ours is one of the few to relate happiness level, or more broadly mental health, to learning time loss in the context of COVID-19 school closure. Interestingly, our ML model findings *exclude* sadness level as an important predictor of learning time loss. Our key empirical findings are abstracted in Fig. 1 that helps visualize the ML-based empirical model developed in the paper.

Based on these findings, we make multiple contributions to the literature. First, we add to the existing evidence on how home-schooling raises additional challenges for learners including an increased burden of domestic responsibilities, social isolation and inadequate parental support at home (Jones et al., 2021), particularly for female adolescents (Power, 2020). Second, we contribute to the literature on how pandemic awareness can have a socioeconomic impact and in this particular case the social impact of learning continuity (e.g. see Buesa et al., 2021). The societies that are more aware suffered a less intense impact of the COVID-19 pandemic, in terms of loss of lives and, to some extent, economic damage. We also relate hygiene-seeking behaviours to societal impact and social determinants of age and gender (e.g. see (Lee et al., 2020) and (Lee, 2020). Lastly, ours is one of the handful of studies on middle-income countries on happiness and learning during school closure (e.g. Asadullah, 2023; Xie et al., 2020; Hawrilenko et al., 2021). In contrast to past studies showing how *schooling* has a positive impact on mental health (e.g. Roeser and Eccles, 2000), we find the opposite: an increase in *happiness level* during school closure is associated with a reduction in learning time loss. This finding provides further justification for the growing emphasis in the policy literature on improved mental health provisions for post-pandemic learning recovery (e.g. see World Bank, the Bill and Melinda Gates Foundation, FCDO, UNESCO, UNICEF, and USAID, 2022).

The rest of the paper is organized as follows. Section 2 describes briefly the background of the MCO in Malaysia. Section 3 describes the data and its exploratory insights. Section 4 discusses the empirical results. Section 5 presents a conceptual framework summarizing the main findings. Section 6 concludes by additionally commenting on the policy implications of our analysis.

2. Background of study: Malaysian education during Covid-19

Following the outbreak of COVID-19, all educational institutions were closed down in Malaysia on March 18, 2020 in the first Movement Control Period (henceforth MCO). This affected 4.9 million students (Banoo, 2020). Malaysia introduced home-based learning on 18 March 2020 under the Pengajaran dan Pembelajaran di Rumah (PdPR) scheme

[3] https://www.worldbank.org/en/news/press-release/2022/03/30/less-than-half-of-countries-are-implementing-learning-recovery-strategies-at-scale-to-help-children-catch-up

[4] One exception is Muhammad Zaki et al. (2021) who use the Generalised Anxiety Disorder Questionnaire (GAD-7) data on 137 secondary students collected in early 2021 and confirm a positive association between psychological stress and pandemic exposure.

[5] For example, more complex ML pre-processes the X variables by cross-multiplying amongst themselves to achieve higher order interactions. This includes numerous terms like $x_1^{n1}x_2^{n2}x_3^{n3}\ldots$ where $n_1, n_2, n_3 \in Z$, a set of integers.

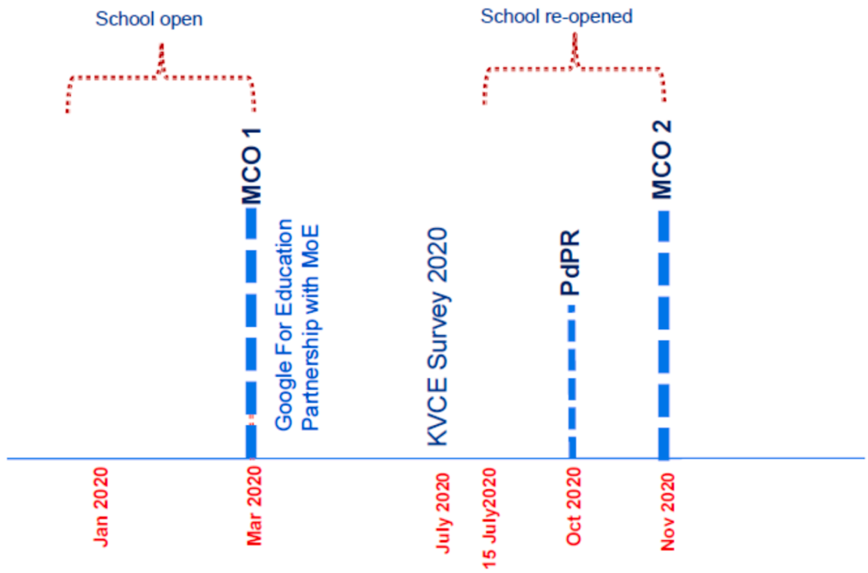

Fig. 2. Timeline of early school closure and re-opening in Malaysia, 2020.
Source: Authors.

Table 1
Summary Statistics.

	Before-MCO		During- MCO	
	Mean	Std. Dev.	Mean	Std. Dev.
Difference Variables				
Time use at home				
-Study more than 1 h per day	0.75	0.44	0.82	0.39
-Extra-curricular activities more than 1 h per day	0.66	0.47	0.47	0.50
-Religious activity more than 1 h per day	0.26	0.44	0.46	0.50
Emotional well-being				
-Feeling Happy	0.73	0.45	0.58	0.49
-Feeling Sad	0.06	0.23	0.18	0.39
Health and hygiene practice				
-Wash hands 7 times and above every day	0.04	0.20	0.40	0.49
-Cut nails once a week	0.53	0.50	0.79	0.41
-Cut hair once a month	0.17	0.38	0.04	0.20
Pandemic awareness knowledge				
-Aware that COVID-19 could be asymptomatic	0.40	-	0.96	-
-Aware that COVID-19 can spread by touching surfaces	0.61	-	0.97	-
Baseline characteristics				
Scout	0.54	0.49		
Female	0.53	0.50		
Enrolled in Junior school (age 13–15 years)	0.48	0.50		
Involvement in social community work	0.40	0.49		
Social Economic Status Proxy	0.11	0.31		
Number of books at home: 1–25				
Number of books at home: 26–50	0.25	0.43		
Number of books at home: 51–75	0.30	0.46		
Number of books at home: 76 +	0.14	0.35		
No of respondents	314			

Notes: (i) The base category for "Enrolled in Junior secondary school (age 13–15 years)" is Enrolled in Senior secondary school (age 16–17 years). (ii) Scout membership was captured by using two questions: "In this academic year, are you enrolled as a Scout member?" and "How long have you been a member of the Scouting movement?"

of the Ministry of Education, immediately after the first MCO.[6] While schools reopened in July 2020, many schools continued to offer online learning. A few months later, in October 2020, the government launched a formal guideline for PdPR. However, schools closed again in November 2021. Schools reopened again in October 2021. Fig. 2 summarizes the overall policy timeline.

Under the PdPR initiative, students utilise online resources to learn at their own pace, without attending daily online school lessons. Given the lack of supervision at home, learning continuity under the PdPR also hinges on learners' conditions at home as well as their mental health conditions. Although pandemic time official data on mental health is limited, adolescents in Malaysia faced significant mental health related challenges even before pandemic time school closure. As per national suicide registry data for the year 2009, 16.5% of the total number of suicide related deaths in Malaysia involve young adults aged 15–24 years (UNICEF, National Institutes of Health Malaysia, Burnet Institute, 2022). Appendix Table 1 reports more recent data on six indicators of prevalence of adolescent mental health problems in Malaysia: (i) conduct problems, (ii) emotional health problems, (iii) suicidal attempt one or more times in the past 12 months; (iv) loneliness most of the time or always in the past 12 months; (v) having been bullied on at least one day in the past month; and (vi) suicidal plan in the past 12 months. These also confirm emotional and mental health challenges across secondary school aged children in multiple dimensions.

The survey data was collected in July 2020 during the first wave of the COVID-19 pandemic, when a "Recovery Movement Control Order" (RMCO) was in place in Malaysia. Hence this study essentially examines the first year and initial experience of home-based learning. Effective implementation of home-based learning requires a supporting family environment and complementary educational infrastructure. Our survey data hence also includes parental involvement as a covariate proxied with parental presence at home during the MCO.

Lastly, although adolescents in rural Malaysia also face emotional and mental health related challenges (UNICEF, National Institutes of Health Malaysia, Burnet Institute, 2022), this is outside the scope of our study. We explain the justification for study location further in the next

[6] Karim, K. (2020, March 31). Edu Ministry introduces guidelines on online teaching, learning platforms: New Straits Times. https://www.nst.com.my/news/nation/2020/03/578945/edu-ministry-introduces-guidelines-online-teaching-learning-platforms

Table 2
ML Models for Learning Continuity.

	Non-ensemble Models		
	Decision Tree	Naïve Bayes.	Support Vector Machine (SVM)
Accuracy[1]	70.4%	69.7%	72.6%
Recall[2]	78.5%	87.8%	**94.1%**
Precision[3]	76.7%	72.2%	74.5%
Feature importance[4,5]	Health and hygiene practices ($x_{21,22}$): 0.21 ± 0.01 Gender (x_1): 0.17 ± 0.03 Health and hygiene practices ($x_{17,\ 18}$): 0.15 ± 0.03 Pandemic knowledge (x_{30_31}): 0.08 ± 0.02	Happiness during MCO (x_{12}): 0.04 ± 0.01 Health and hygiene practices ($x_{21,22}$): 0.03 ± 0.02 Health and hygiene practices ($x_{17,\ 18}$): 0.03 ± 0.02 Gender (x_1): 0.02 ± 0.01 Pre-Covid Happiness (x_{11}): 0.02 ± 0.01	Health and hygiene practices ($x_{21,22}$): 0.05 ± 0.01 Happiness during MCO (x_{12}): 0.03 ± 0.03 Gender (x_1): 0.03 ± 0.01 Health and hygiene practices ($x_{17,\ 18}$): 0.03 ± 0.02 Pandemic knowledge (x_{30_31}): 0.02 ± 0.02
		Ensemble Models	
	Bag of SVC	Gradient Boosting	Random Forest
Accuracy[1]	76.1%	74.8%	77.3%
Recall[2]	91.7%	85.6%	92.1%
Precision[3]	76.6%	78.0%	77.5%
Feature importance[4,5]	Health and hygiene practices ($x_{21,22}$): 0.04 ± 0.03 Health and hygiene practices ($x_{17,\ 18}$): 0.03 ± 0.02 Gender (x_1): 0.03 ± 0.02 Happiness during MCO (x_{12}): 0.03 ± 0.01 Current scout member (x_4): 0.02 ± 0.01	Gender (x_1): 0.08 ± 0.02 Health and hygiene practices ($x_{17,\ 18}$): 0.08 ± 0.03 Health and hygiene practices ($x_{21,22}$): 0.07 ± 0.03 Happiness during MCO (x_{12}): 0.04 ± 0.01 Number of Books at home (x_{15}): 0.03 ± 0.02	Health and hygiene practices ($x_{21,22}$): 0.08 ± 0.02 Health and hygiene practices ($x_{17,\ 18}$): 0.07 ± 0.01 Pandemic knowledge (x_{30_31}): 0.03 ± 0.003 Gender (x_1): 0.02 ± 0.01 Happiness during MCO (x_{12}): 0.02 ± 0.01

Notes: (1) The accuracy, recall and precision numbers are out of sample from 5-fold cross-validation. (2) The recall represents how good the model is picking up all the students with learning continuity. (3) The precision represents the percentage of students that actually display learning continuity after being picked out by the model. (4) The features importance for all the models are ranked in descending order of permutation importance. Only the top 5 covariates are shown. In contrast to the non-ML models, ML models do not have the concept of p-values. For a glossary of the variables used, refer to Appendix Table 2. (5) The key variables that appear across the different ML models are $\mathbf{x_1}$ (gender), x_{12} (happiness level during MCO), $\mathbf{x_{17\_18}}$ and $\mathbf{x_{21\_22}}$ (health and hygiene practices for hand washing and hair cutting respectively) and x_{30_31} (pandemic knowledge).

section.

3. Data and exploratory findings

Data used in this paper covers 12 secondary schools from 9 districts of the state of Selangor, Malaysia's main economic hub. In each district, we only selected sample schools from the principal town such as Kajang in Hulu Langat and Tanjong Karang in Kuala Selangor and Sungai Besar in Sabak Bernam. The data was collected online at the height of the pandemic when the country was subject to a movement control order. Hence the exclusive focus on urban Malaysia, and that too Klang Valley, economically the most prosperous part of the country. Sample respondents belong to adolescents aged 13–17 years who were enrolled in secondary schools at the time of the study.[7] There were 400 secondary school students invited for the online survey with 314 completions. 53% of the respondents are female (167 female and 147 male respondents), 52% enrolled in upper-secondary (164 upper-secondary students and 150 lower-secondary students) and 53% (169) were scouts.

The complete set of 38 covariates in the survey with their descriptions is in Appendix Table 2. The Table lists out omitted variables and their reasons for not including them in the study. These include the district (since they are close and contiguous geographically), the wearing and availability of masks which was made compulsory and the level of Scout activity with numerous missing rows.

The rest of the variables and their summary statistics are presented in Table 1. These variables are broadly classified into difference variables and baseline characteristics. The difference variables include the change in behaviour and mental states of the respondents before and during the MCO. This includes the difference in time use at home before and after MCO is implemented, the emotional states and health and hygiene practices, the pandemic awareness knowledge of COVID-19 and whether the respondents were involved in community work before the MCO. The baseline characteristics include unchanged characteristics during the MCO – for example gender, involvement in community activities before MCO and scout membership. The data for number of books at home as a proxy for Social Economic Status is also provided. These covariates are investigated for their potential societal impact mentioned in the introduction.

There are several important insights in our raw data. First, time spent at home study (at least 1 h) has increased during school closure (from 75% to 82%). Time spent in religious activities (i.e. a*t least* 1 h per day) has also increased (from 26% to 46%). On the other hand, *at least* 1 h per day spent in extra-curricular activities has decreased (from 66% to 47%). Emotional well-being has declined: 73% of adolescents reported being happy before the pandemic which declined to 58% during school closure. Further, those reporting feelings of sadness increased from 6% before school closure to 18%.

Among others, we find a sharp improvement in overall *health and hygiene practice and pandemic awareness knowledge. Before the pandemic school closure, only 4% of sample children reported* washing hands 7 times and above every day. This increased to 40% in post-pandemic months. Similarly, students reporting regular cutting of nails (once a week) increased from 53% to 79% while hair cutting (once a month) declined from 17% to 4%. There is also a sharp increase in the pandemic awareness knowledge during the MCO from 40% to 60–90% as campaigns to clarify the virus spread were implemented.

In contrast to emerging developing country evidence, there is a reverse gender gap in time use – boys spent significantly less time at study while the opposite was true for girls concerning playtime.

The above findings on emotional well-being are consistent with developing country research utilizing sample data on children and adolescents during the first year of the pandemic. For instance, China,

[7] In Malaysia, 13–15 years old are in junior secondary (form 1–3) while 16–17 in senior secondary (form 4–5).

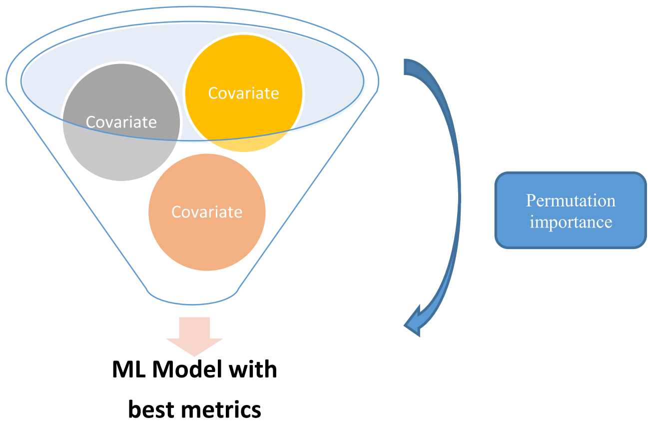

Fig. 3. Filtering of most important covariates in ML with Permutation Importance criterion.

(Jiao et al., 2020) report a sharp increase in stress, anxiety and depression among 3–18 year old children. Similar results are presented by (Saurabh and Ranjan, 2020) for children and adolescents aged 5–18 years in India. Research using Bangladeshi children also confirms the negative impact of COVID-19 on depression, anxiety, and sleeping disorder (Yeasmin et al., 2020). Moreover, the study finds children's mental disturbance to be positively linked to parental stress. Lastly, (Garcia de Avila et al., 2020) utilizing data on children aged 6–12 years for Brazil also confirm the negative impact of the pandemic on the mental health of children.

4. Empirical results

4.1. ML empirical results predicting learning time loss

Our key predictive variable (Y_1) is defined as the difference in the student's home study hours during the MCO (x_6)and before the MCO (x_5):

$$Y_1 = \begin{cases} 1 \;\; if \;\; x_6 - x_5 > 0 \;\; for \;\; increased \;\; home \;\; study \;\; hours \\ 0 \;\; if \;\; x_6 - x_5 \leq 0 \;\; for \;\; decreased \;\; home \;\; study \;\; hours \end{cases} \quad (1)$$

In our sample, 206 students (65.6% of the sample) unconditionally display low learning loss for $Y_1 = 1$, with lost school hours at least partially made up by increased home learning. Learning loss occurs for $Y_1 = 0$, where the number of home study hours actually decreased during MCO.

In our study, the covariates except the omitted variables are input into ML models with the most important covariates filtered based on their permutated importance. In statistics, this unrestricted use of covariates would have led to multi-collinearity and model endogeneity issues. However, ML methods are notoriously 'blackbox' in nature. For this reason, ExplainableAI in particular *permutation importance* (see Altmann et al., 2010 and Rai, 2019 for the background) is used to filter out the most important covariates for the prediction, as exhibited in Fig. 3. Permutation importance is particularly useful for tabular and structured data, and is robust to different model types. Permutation importance also provides for the estimate standard deviation typical in statistics through a randomisation process, which we report in our results. A more detailed explanation of how permutation works is in Appendix Fig. 1.

The out of sample results for accuracies, recall and precision of the ML methods from 5-fold cross-validation are in Table 2. The 5-fold cross validation method divides the data into 5 equal parts, with each part taking turn for out of sample testing, and the other 4 parts as in-sample.

Table 3
ML Models for *Happiness Level* during MCO.

		Non-ensemble Models	
	Decision Tree	Naïve Bayes.	Support Vector Machine (SVM)
Accuracy[1]	58.5%	60.5%	57.3%
Recall[2]	65.9%	74.5%	**85.7%**
Precision[3]	64.2%	63.7%	59.0%
Feature importance[4,5]	Increase in playtime (x_{7_8}): 0.23 ± 0.01 Number of Books at home (x_{15}):0.21 ± 0.05 Pre-Covid Happiness (x_{11}): 0.21 ± 0.04 Pandemic awareness knowledge (x_{30_31}):0.15 ± 0.03 Pandemic awareness knowledge (x_{28_29}): 0.14 ± 0.02	Pre-Covid Happiness (x_{11}): 0.09 ± 0.01 Increase in Religious time (x_{9_10}):0.03 ± 0.02 Increase in playtime (x_{7_8}): 0.03 ± 0.01 Current scout member (x_4) 0.02 ± 0.01 Community Activity involvement (x_{16}): 0.008 ± 0.02	Pre-Covid Happiness (x_{11}): 0.07 ± 0.02 Health and hygiene practices (x_{21_22}):0.04 ± 0.02 Increase in playtime (x_{7_8}):0.03 ± 0.03 Number of Books at home (x_{15}): 0.02 ± 0.02 Community Activity involvement (x_{16}): 0.02 ± 0.01
		Ensemble Models	
	Bag of SVC	Gradient Boosting	Random Forest
Accuracy[1]	61.4%	62.1%	60.1%
Recall[2]	79.1%	77.4%	67.7%
Precision[3]	63.3%	64.4%	65.2%
Feature importance[4,5]	Pre-Covid Happiness: (x_{11}):0.06 ± 0.02 Number of Books at home (x_{15}):0.04 ± 0.02 Current scout member (x_4): 0.03 ± 0.02 Health and hygiene practices (x_{21_22}):0.04 ± 0.02 Health and hygiene practices (x_{17_18}):0.03 ± 0.02	Pre-Covid Happiness: (x_{11}):0.08 ± 0.02 Current Scout member (x_4): 0.08 ± 0.03 Increase in Religious time (x_{9_10}): 0.07 ± 0.03 Number of Books at home (x_{15}): 0.04 ± 0.01 Gender (x_1): 0.03 ± 0.02	Pre-Covid Happiness: (x_{11}):0.16 ± 0.03 Community Activity involvement (x_{16}):0.1 ± 0.03 Current scout member (x_4): 0.1 ± 0.01 Pandemic awareness knowledge (x_{30_31}): 0.1 ± 0.02 Parental involvement (x_{26}): 0.1 ± 0.02

Notes: (1) The accuracy, recall and precision numbers are out of sample from 5-fold cross-validation. (2) The recall represents how good the model is picking up all students who are happy or very happy. (3) The precision represents the percentage of students who are actually happy or very happy after being picked out by the model. (4) The features importance for all the models is ranked in descending order of permutation importance. Only the top 5 covariates are shown. For a glossary of the variables used, refer to Appendix Table 2. (5) The key variables that appear across the 6 different ML models are $\mathbf{x_1}$ (gender), x_{11} (state of happiness during MCO), $\mathbf{x_{17\_18}}$ and $\mathbf{x_{21\_22}}$ (health and hygiene practices for hand washing and hair cutting respectively), $\mathbf{x_{9\_10}}$ (religious activity increased time spent) and x_{15} (number of books at home proxy for social economic status).

Table 4
ML Models for *Sadness Level* during MCO.

	Non-ensemble Models		
	Decision Tree	Naïve Bayes.	Support Vector Machine (SVM)
Accuracy[1]	77.3%	84.3%	82.8%
Recall[2]	52.1%	31.5%	7.1%
Precision[3]	41.3%	61.2%	70%
Feature importance[4,5]	Increase in playtime (x_{7_8}): 0.113 ± 0.01 Gender (x_1):0.09 ± 0.02 Number of Books at home (x_{15}): 0.09 ± 0.01 Community Activity involvement (x_{16}): 0.07 ± 0.01 Health and hygiene practices (x_{21_22}):0.07 ± 0.02	Pre-Covid sadness level (x_{13}): 0.04 ± 0.02 Health and hygiene practices (x_{17_18}): 0.02 ± 0.01 Parental involvement (x_{26}):0.01 ± 0.01 Gender (x_1): 0.01 ± 0.01 Increase in Religious time (x_{9_10}):0.01 ± 0.01	Pre-Covid sadness level (x_{13}): 0.04 ± 0.01 Community Activity involvement (x_{16}): 0.01 ± 0.01 Current scout member (x_4): 0.01 ± 0.01 Increase in Religious time (x_{9_10}):0.01 ± 0.01 Health and hygiene practices (x_{19_20}):0.01 ± 0.01
	Ensemble Models		
	Bag of SVC	Gradient Boosting	Random Forest
Accuracy[1]	84.1%	82.1%	85%
Recall[2]	14.5%	31.5%	31.3%
Precision[3]	90.0%	56.9%	71.4%
Feature importance[4,5]	Pre-Covid sadness level (x_{13}):0.04 ± 0.03 Community Activity involvement (x_{16}):0.03 ± 0.02 Increased Religious time (x_{9_10}): 0.02 ± 0.01 Parental involvement (x_{26}): 0.03 ± 0.01 Pre-Covid Happiness level (x_{11}): 0.02 ± 0.01	Pre-Covid sadness level (x_{13}): 0.04 ± 0.04 Health and hygiene practices (x_{19_20}): 0.02 ± 0.02 Health and hygiene practices (x_{17_18}): 0.01 ± 0.01 Health and hygiene practices (x_{21_22}): 0.01 ± 0.01 Increase in playtime (x_{7_8}): 0.01 ± 0.01	Age (x_2): 0.06 ± 0.01 Increase in playtime (x_{7_8}): 0.05 ± 0.01 Number of Books at home (x_{15}): 0.04 ± 0.03 Gender (x_1): 0.04 ± 0.004 Pre-Covid sadness level (x_{13}): 0.04 ± 0.01

Notes: (1) The accuracy, recall and precision numbers are out of sample from 5-fold cross-validation. (2) The recall represents how good the model is picking up all the students who are often or always sad. (3) The precision represents the percentage of students who are often or always sad after being picked out by the model. (4) The features importance for all the models is ranked in descending order of permutation importance. Only the top 5 features are shown. For a glossary of the variables used, refer to Appendix Table 2**.** The key variables that appear across the 6 different ML models are $\mathbf{x_1}$ (gender), x_{13} (sadness level during MCO), $\mathbf{x_{7\_8}}$ (time spent at home at play/ extra-curriculum activities), x_{16} (participation in community/ social work pre-MCO) and $\mathbf{x_{17\_18}}$, x_{19_20} and x_{21_22}(pandemic hygiene practices for handwashing, nail cutting and hair-cutting respectively). The x_{15}, number of books at home is used as a proxy for social economic status (SES).

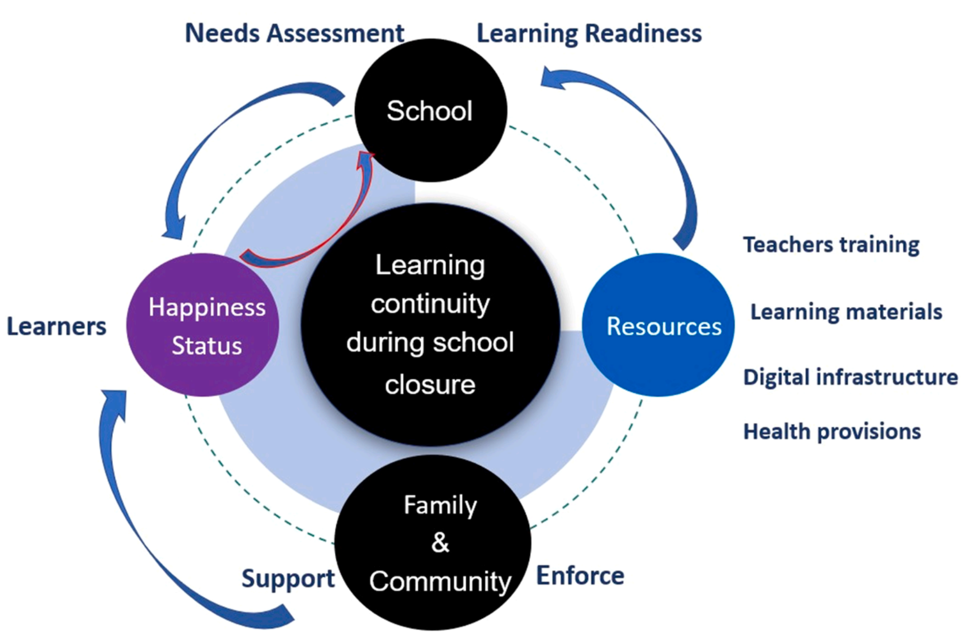

Fig. 4. Conceptual link between learning time loss and happiness level **Source**: Authors.

The average of the out of sample results is used. This prevents any possible training sample bias.

We use 3 first-generation ML models - Naïve Bayes classifier (see Geoffrey and Webb, 2010 for an introduction), tree-based classifiers, Support Vector machine(SVM) (see Noble, 2006 for an introduction) and 3 ensemble models (see Zhou, 2012 for an introduction) from gradient boosting (see Friedman, 2001 for an introduction), random forest (see Ho, 1995 for an introduction) and an ensemble of SVC. These are run using the sci-kit learn library in Python.[8] We fed 19 covariates into each of the ML model, and report the top 5 covariates by the absolute value of the permutation importance. This would not be possible with traditional statistics. The 6 ML models are used for robustness.

[8] A copy of the Jupyter notebook for the test results is in this link. (to be provided on request)

No	x_1	x_2	…	x_{10}
1	1	1	…	0
2	0	0	…	0
3	1	1		1
4	0	1		1
…				
n	1	1		0

Fig. A 1. Illustration of permutation importance. Notes: The figure shows the permutation importance algorithm, used in this study to show the individual contribution to the accuracy of each variable. Permutation importance is an ExplainableAI method. In this algorithm, suppose the x's (x_1, …,x_{10}) are covariates predicting y. To determine the importance of x_1 in predicting y, the rows in x_1 are interchanged randomly in multiple simulations. Each simulated interchange would of course result in a change in the value of y. The mean and standard deviation in the change in y is then recorded. This process is then repeated for the other x's. For consistency, the randomisation across the columns is done with the same seed.For x's with a greater predictive impact on y, there would be a greater change in the value of y, with greater confidence shown by the a smaller standard deviation.
Source: Adapted from Kaggle.com.

Table A1
Adolescent Mental Health in Malaysia: Selected Indicators.

Indicators	Estimate	Age group
Prevalence of conduct problems*	16.50	10–15
Prevalence of emotional health problems*	9.90	10–15
Prevalence of suicidal attempt one or more times in the past 12 months	6.90	13–17
Prevalence of loneliness most of the time or always in the past 12 months	9.30	13–17
Prevalence of having been bullied on at least one day in the past month	11.80	13–17
Prevalence of suicidal plan in the past 12 months	7.30	13–17

Source: Authors, based on NHMS – Adolescent Health 2017 and 2019 Survey data extracted from UNICEF, National Institutes of Health Malaysia, Burnet Institute (2022). All figures for 2017 except (*) which corresponds to 2019.

The random forest classifier has the highest predictive accuracy at 77.3%, more than 11% than the unconditional model. The ensemble SVM is the second highest at 76.1%. All the ensemble models perform better than non-ensemble models. Notice that the Naïve Bayes classifier, a benchmark classifier and the decision tree-based models offer a modest improvement over the unconditional value (65.2%) between 4.1% and 5.1%. The SVM has the highest recall measure at 94.1% while the gradient boosting classifier has the highest precision measure at 78%.

Four covariates stand out to predict learning loss. These are the x_1 (gender), x_{12} (happiness level during MCO), x_{17_18} (increase in health and hygiene practices pre and during MCO) and x_{30_31} (increase in pandemic awareness knowledge). These covariates are consistent across the different ML models. Generally, boys experience more learning loss as girls. (28.6% of boys to 17.9% of girls) Happier students are also less likely (71–56% from conditional probabilities) to show learning loss. A high recall rate (picking out students with no learning loss) is achieved using variables like adopting health and hygiene practices during the MCO and greater pandemic knowledge awareness.

The more complex ensemble ML models show improvement in accuracy of 4–6% than non-ensemble ML models. The authors attribute it to the individual variables (gender, mental health, hygiene and health practices and pandemic knowledge awareness) showing *small but significant cross interaction effects* driving learning continuity. As aforementioned, the more complex ML methods model higher-order cross interaction effects amongst the variables better.

4.2. ML Empirical Results predicting happiness level

The latter empirical results highlight the importance of happiness x_{12} in determining learning loss. Mental health is multi-faceted and includes the happiness and sadness levels For this reason, we explore the predictors for happiness and sadness levels during the MCO using the existing survey data with ML.

In the survey, the happiness level x_{12} is an ordinal output with very 'unhappy', 'unhappy', 'neutral', 'happy' and 'very unhappy'. Our primary objective is to identify factors that keep the students happy or very happy $Y_2 = 1$ and the at-risk students (often or always sad) for $Y_3 = 1$. The predictive variable Y_2 is:

$$Y_2 = \begin{cases} 0 \text{ if } & x_{12} \in \{Very\ \ unhappy, unhappy\ \ or\ \ neutral\} \\ 1 \text{ if } & x_{12} \in \{happy\ \ or\ \ very\ \ happy\} \end{cases} \quad (2)$$

In the case of sadness, the level x_{14} is an ordinal output with never, rarely, sometimes, often and always**.** Its predictive variable Y_3 is:

$$Y_3 = \begin{cases} 0 \text{ if } & x_{14} \in \{never, rarely, sometimes\} \\ 1 \text{ if } & x_{14} \in \{often\ \ or\ \ always\} \end{cases} \quad (3)$$

As for the distributions of Y_2 and Y_3, 57% of students (182/314) are 'happy' or 'very happy' during MCO. At the same time, 18% of students (57/314) are 'often' or 'always' sad during the MCO.[9] Note that the dataset for sadness for $Y_3 = 1$is imbalanced (i.e. with only 18% of the sample). This imbalance necessitates the use of the recall and precision aside from predictive accuracy to capture students 'at risk' of sadness.

Table 3 and Table 4 show the ML results for predicting the happiness level and sadness level during MCO respectively. Similar to the earlier analysis on learning loss, 15 covariates are fed into the ML models, and 6 ML models are used for robustness. Expectedly, both the mental states pre-MCO (happiness level x_{11} and sadness levels x_{13}) are dominant factors in determining happiness and sadness level during the MCO. An increase in religious time engagement pre and during MCO (x_{9_10}) and higher social status (proxied by x_{16} of more books at home) are also factors.

In addition, ML predicts the deterioration in children's happiness and sadness levels with recall and precision rates up to 85% and 90% respectively.

The factors that predict the sadness level are largely similar to happiness level but with some differences. The students who are more prone to sadness are those who spend less hours in religious activity (x_{9_10}), less play time (x_{7_8}) pre and during MCO. Interestingly, students who exhibit more health and hygiene practices (x_{17_18}) are associated with sad behaviour.

Interestingly, social economic status appears more important in predicting happiness than sadness level. In addition, it appears that gender x_1 - girls are more prone to sadness than happiness level.

5. Discussion and policy implications

For reasons related to stresses inherent in the infection itself as well as isolation caused by mass stay-at-home directives, the pandemic has implications for individual and collective health and emotional well-being. In Malaysian country context, even before covid-19, socioemotional health among secondary school age population was a significant

[9] The corresponding numbers *pre-MCO* are (229/314 or 73%) and (18/314 or 5%).

Table A2
Glossary of Predictor covariates.

Code	Description	Remarks
x_1	Gender	
x_2	Age	
x_3	School District	Not used.
x_4	Current scout member	
x_{5_6}	Increase in study hours at home before and during MCO period. (Learning continuity)	Y_1 variable
x_{7_8}	Increase in extra-curriculum hours spent at home before and during MCO period.	Extra-curriculum is regarded as 'play' activity.
x_{9_10}	Increase in religious activity hours spent at home before and during MCO period.	
x_{11}	Before MCO how happy did you feel in general? [Happiness Level]	
x_{12}	Yesterday how happy did you feel in general? [Happiness Level]	Y_2 variable
x_{13}	Before MCO how often did you feel sad? [How often sad]	
x_{14}	During MCO how often did you feel sad? [How often sad]	Y_3 variable
x_{15}	How many books do you have at home?	
x_{16}	Before MCO have you participated in any community service or social work activity	
x_{17_18}	Increase in hand washing frequency before and during MCO period.	
x_{19_20}	Increase in nail cutting frequency before and during MCO period	
x_{21_22}	Increase in hair cutting frequency before and during MCO period	
x_{23}	In the past 7 days have your FATHER worn a face mask every time when he left you	Redundant variable as mask wearing made mandatory
x_{24}	In the past 7 days have your MOTHER worn a face mask every time when she left you	Redundant variable as mask wearing made mandatory
x_{25_26}	In the past 7 days both parents go to work/ office with 1 indicating 'yes' and '0' otherwise.	
x_{27}	Awareness of COVID-19 during MCO through knowledge of the 3 most important symptoms of Covid-19	
x_{28_29}	Increased awareness of COVID-19 before and during MCO through knowledge that people who are asymptotic can be infectious	
x_{30}	Awareness of COVID-19 before MCO through that disease can be spread through touching contaminated surfaces	
x_{31}	Awareness of COVID-19 during MCO through that disease can be spread through touching contaminated surfaces	
x_{32}	Do you have a mask (even a homemade one or a face covering) to cover your mouth	Redundant variable as mask wearing made mandatory
x_{33}	If YES in the past 7 days have you worn it every time you left your house?	Redundant variable as mask wearing made mandatory
x_{34}	Years as a Scouts member	Not used.
x_{35}	BEFORE MCO how often do you meet for in-school Scouting activities?	Not used. Missing rows.
x_{36}	Please tick the Scout activities that you have ever participated in	Not used. Missing rows.
x_{37}	What is your highest level of achievement in Scouts?	Not used.
x_{38}	How important is Scouting activities to you? [Importance of Scouting activities]}	Not used.

The table is a glossary of all the data variables collected in the study. Some of the variables are omitted from the study due to theoretical considerations as irrelevant or spurious as commented in the table.

concern (see Appendix Table 1). According to adolescent data extracted from the 2017 National Health and Morbidity Survey (NHMS), 18.3% among school-going adolescents aged 13–17 years were depressed while another 10.0% had suicidal ideation and 6.9% had attempted suicide. Compared to the same survey conducted in 2012, this showed an increasing trend (Ministry of Health Malaysia, 2020a). The Malaysian government in its National Strategic Plan for Mental Health: 2020–2025 therefore has outlined a blueprint for inter-sectoral holistic approach (Ministry of Health Malaysia, 2020b). However, according to UNICEF, there is a lack of availability of child- and adolescent-friendly multidisciplinary care for mental health conditions (UNICEF, National Institutes of Health Malaysia, Burnet Institute, 2022). A coordinated whole-of-education approach to mental health promotion (including a national curriculum to support social and emotional learning) is also lacking. UNICEF further calls for "…a holistic and tiered approach to MHPSS that includes actions to: promote well-being; prevent poor mental health by addressing risks and enhancing protective factors; and ensure quality and accessible care for those with mental health conditions …and mobilization of all sectors – including health, education, social welfare and justice – as well as engagement with communities, schools, parents, service providers and children and adolescents themselves".

A recent international review of the psychological experience of quarantined people revealed persistent negative emotional development in multiple outcomes such as stress, depression, insomnia, anger and frustration (Brooks et al., 2020). The negative emotions prevailed even after the quarantine was lifted. However psychosocial assessment and monitoring of school children during Covid-19 has been lacking, particularly in developing countries. This is despite the fact that promoting social and emotional well-being in schools has long been acknowledged as important for children's educational development (Barry et al., 2017). Children can be in additional distress as educational activities shift from school to home-based online settings. In addition to a lack of facilities and unequal access to digital technology, learning at home can be undermined for various reasons. Exposures to infection at home, loss of a family member, and physical distancing can combine with economic distress (decline in family income, parental unemployment) and disruption to social networks to produce adverse psychosocial effects. This in turn may further undermine study efforts at home. Therefore documenting the mental state of children alongside time spent in learning activities during the school closure is critical for effective school reopening plans.

The pandemic has created new vulnerabilities for the youths and adolescents as the home environment for many does not offer a safe space (Cohen and Bosk, 2020). At the same time, international evidence indicates that the impact of school closures alone on deaths is rather modest, compared to other social distancing interventions (Viner et al., 2022). This has called for an emphasis on less-disruptive solutions including re-opening of schools in combination with social distancing measures.[10] Given this larger context, this section critically discusses our findings clarifying the main takeaways for post-pandemic school reopening efforts.

We find gender important for predicting learning continuity. In contrast to emerging developing country evidence, there is a revere gender gap in time use – boys spent significantly less time in study while the opposite was true for girls concerning playtime.[11] Similarly, we find social engagement to not matter. Youth-focused community-based programs in times of crisis can offer added mental protections. In our sample, a significant proportion of children are engaged in scouting programs.[12] However, exposure to scouting did not feature as an important factor for predicting learning continuity in our ML exercise. Resources at home (e.g. the availability of books) did not matter.

Instead, proxies of happiness or mental health emerged as the "common features". This is consistent with the psychology literature on learning motivation (see Dweck, 1986). Our results suggest that

10 For example, Singapore has adopted a hybrid home-based learning in both its tertiary and non-tertiary education.

11 Among developing country studies with no systematic boy-girl difference in mental health status, see (Mallik and Radwan 2021).

12 There is some evidence suggesting a positive association between scouting and health (Dibben et al., 2017) as well as scouting and education (i.e. why scouts can be better in science) (see Jarman, 2005 and Simac et al., 2019)

regardless of child gender, mental health matters for predicting learning continuity. Yet available research on and models of home schooling have been mostly focused on learning continuity. Our results therefore call for a re-evaluation of the policy framework to deal with future educational disruption.

Existing studies for Malaysia and other developing countries confirm the preference over a return to school instead of home-based education. On the other hand, existing studies already confirm the role of schools in protecting and nurturing the mental health of children (e.g. see Jones et al., 2012; Rasberry et al., 2015; Nordin et al., 2019; Caldwell et al., 2019). Recent reviews of the literature have identified several factors such as social isolation, insufficient physical activity and too much screen exposure (López-Bueno et al., 2021). Going by this evidence, bringing children back to school is expected to have the added benefit of improved mental wellbeing which leads to greater efforts in learning activities. At the same time, in the absence of a full return to school, ensuring mental well-being at home remains a key challenge for both health and education-related concerns. Beyond restoring networks with school friends, happiness among students also requires improving family life (Uusitalo-Malmivaara, 2012). Female caregivers in the household, particularly mothers, are critical for home learning. In Argentina, mothers supported children with their homework in 68% of households (in contrast to only 16% by both parents) (UNICEF, 2020). In the United Kingdom, 67% of women compared to 52% of men took charge of their children's education during the lockdown (Williams et al., 2020). Yet most parents have limited awareness and capability to provide counselling to young learners. This calls for new provisions.

We have summarized the above points in Fig. 4 acknowledging the feedback loop. The arrows highlight the dual importance of mental health – not just for learning continuity at home, but also for a successful return to school and catching up in terms of lessons in the post-lockdown period. The arrows also recognize both school and family as points of intervention for policymakers.

More specifically for Malaysia, Fig. 4 recognizes the inter-sectoral collaboration and a holistic approach emphasised in the government's National Strategic Plan for Mental Health (Ministry of Health Malaysia, 2020b). Resources should be allocated for preventive and promotive purposes instead of treatment. To this end, for families with vulnerable school enrolled children, improved access to community provisions is critical. At the primary care level, currently there are 1001 government health clinics offering mental health services (e.g. screening, intervention, and follow-up of stable mental patients), only 17 health clinics provide psychosocial rehabilitation services. In addition, following the recommendations of the Malaysian Mental Health Act 2001, Community Mental Health Centres (MENTARI) have been set up since 2012. But these are as few as 25 (Ministry of Health Malaysia, 2020). Equally, resources targeted at school should prioritize preventive and promotive measures such as (i) increasing awareness among teachers and students to minimize the burden of mental health related stigma, (ii) early detection of signs of depression and (iii) updating teachers training programs by including mental health as a component in the education and child psychology subjects (Ministry of Health Malaysia, 2020b).

Lastly, beyond serving as a reference framework for future school closure, the above conceptual model complements the RAPID framework developed by the World Bank and other development agencies that emphasizes a multi-dimensional approach for accelerating post-covid learning recovery, where one of the five focuses include developing psychosocial health and wellbeing of learners (World Bank, the Bill and Melinda Gates Foundation, FCDO, UNESCO, UNICEF, and USAID, 2022).

6. Conclusion

Given the growing global concern over learning loss owing to the sudden and unplanned school closure, this study has developed empirical models to accurately predict learning continuity for a developing country. In doing so, we have added to the existing literature on learning discontinuity (Asanov et al., 2021; Booth et al., 2021; Elliot Major et al., 2021; Goudeau et al., 2021; Hevia et al., 2022) by identifying factors that could boost study time at home while schools remain closed. More specifically, ours is the first that relates mental health directly to learning continuity in the context of COVID-19 school closure. We use a variety of ML methods to document and contrast its predictive accuracy for modelling learning continuity vis-à-vis traditional statistical methods.

Equally, while the effect of schooling on happiness is well-researched, the opposite link is not. Given the global decline in mental health during the COVID-19 pandemic, we have also examined the predictors of the mental state of learners. This paper is the first to link online learning continuity to emotional well-being. In doing so, we have also contributed to the literature on mental state during school closure (Ravens-Sieberer, 2021; Bahar Moni et al., 2021; Jones et al., 2021) as well as the interlinkage between happiness and schooling (Al-Yasin, 2001; Dursun and Cesur, 2016). Our analysis has shown the inter-connectedness between the health crisis and education crisis during the COVID-19 school closure. The main highlight is that proxies of mental states are systematically common as features of all ML models of learning continuity.

This therefore stresses the emotional development in schools for sustaining study effort at home during the school closure. At the same time, we find that mental health has declined sharply during school closure. These two patterns together hint at the complementary nature of children's health and educational status during school closure. School-based interventions that prevent anxiety and depression in children and young people can help protect educational human capital in times of crisis. However, crisis-induced prolonged school closure weakens this positive association as mental well-being itself declines during school closures. The policy implication is that developing country governments should rethink the role of schools beyond cognitive skills development, increasing the emphasis on promoting mental health and well-being. Since schools can safeguard the mental health of children, this is an additional policy payoff and yet another justification for the reopening of schools. In addition, while our study does not directly affect the design of educational computer systems, it does highlight the promise and potential for the use of computer systems (i.e. ML models) by educational authorities to develop an early warning system of identifying children who are vulnerable to learning discontinuity during school closure.

Lastly, our study has several limitations relating to potential sampling bias (owing to non-random selection of study schools), the use of subjective measures, and the cross-sectional design of the survey. While the current study is the first to investigate learning loss with a focus on mental health for a developing country, we did not include internationally established clinical instruments for measuring mental health problems, anxiety and depression. Second, our data is specific to urban peninsular Malaysia. Learning loss is likely to be much more severe in rural areas given poverty and poor internet connectivity. Therefore, our results provide a conservative assessment of learning discontinuity during school closure. Third, we have not tested whether the influence is direct or mediated by other common factors aside from gender. For example, mothers are key to effective monitoring and supervision of children for homeschooling. It could be that disruption to learning among distressed learners at home is simply capturing the effect of distressed mothers.[13] These issues are left out for future research.

[13] In our data, we do not have information on mental health of parents. Given the limited set of covariates in our study, we have left it to future researchers to unpack the causal link between happiness and learning continuity.

Conflict of interest statement

We have no conflict of interest to declare.

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Appendix

Fig. A1 and Tables A1 – A2.

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