Review Article

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Safely opening schools: artificial intelligence techniques to control transmission of COVID-19

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ABSTRACT

Artificial intelligence techniques and similar digital technologies are promising applications for surveillance systems, contact tracing, and pandemic planning amid the COVID-19 pandemic. With no long-term effective treatment or vaccinations available, it is highly important to scale intelligence solutions to promote detection, school-level screening, monitoring, reducing burden of staff, and prediction potential COVID-19 outbreaks at schools. The objectives of this paper were to present the artificial intelligence for safely opening schools model, and build a solidifying analysis of current literature for applications of the system. The applications are imminent to promoting school health by maximizing the potential of AI technologies. While the AISOS model is not a silver bullet, the improvement in school transmission will be particularly useful as an emergent temporary, potentially permanent, measure of transmission control and monitoring.

Keywords: School health, Artificial intelligence, Machine learning, Disease transmission, COVID-19

INTRODUCTION

The coronavirus disease (COVID-2019) is caused by the novel severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2), and is a global pandemic. The virus has high transmissibility through air and physical contact, with no long-term effective treatment or vaccination methods so far. Despite various public health measures worldwide, digital technologies have not been widely adopted for surveillance systems, contact tracing, and pandemic planning.

Artificial intelligence and industry 4.0 applications may facilitate the safe opening of schools by surveilling the transmission of COVID-19. AI systems and machine

learning can play a critical role in the detection, school-level screening, monitoring, reducing burden of school staff, and predicting potential COVID-19 outbreaks on a scalable level. In this review, we synthesize AI techniques to control transmission of the virus among schools worldwide, and present the artificial intelligence for safely opening schools (AISOS) model, which if properly applied by countries, may facilitate safely opening schools.

AISOS MODEL

While the world continues to curb unprecedented challenges caused by the COVID-19 pandemic, AI systems have become invaluable assets in both predicting

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and detecting pandemics. AI incorporates machine learning algorithms to spot patterns in large scale data sets. For school transmission dynamics, the AISOS model will facilitate surveillance, detection, screening, and continued COVID-19 monitoring (Figure 1). The applications of the AISOS model are noted as; COVID-19 surveillance, namely contact tracing, thermal imaging,

remote monitoring, wearable sensors, school response including health planning and preparing, utilizing surveillance technology, and employing automated service systems and child recovery comprising of calculating risk in exposed child, tracking contagion in real-time, and managing the quarantined child (Figure 2).

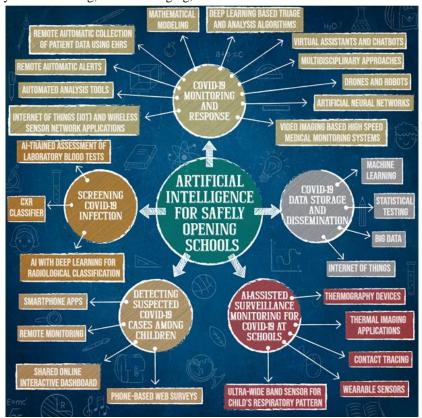


Figure 1: Artificial intelligence for safely opening schools model.

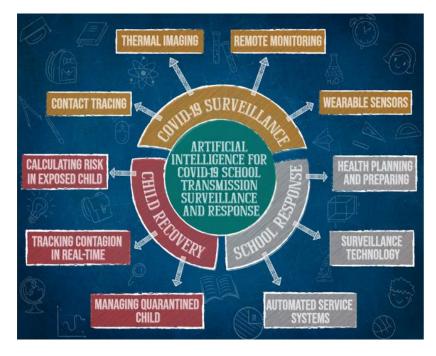


Figure 2: Applying the AISOS model; COVID-19 surveillance, school response, and child recovery.

CASE FOR ARTIFICIAL INTELLIGENCE AND INDUSTRY 4.0 TECHNOLOGIES

AI has proved a promising digital technology in the early prediction of spread of infectious outbreaks. Notably, a Canadian health monitoring platform named BlueDot algorithm, using AI driven algorithms and machine learning, informed the world of the outbreak on 31 December, 2019. BlueDot has also made accurate predictions in the past about the 2009 H1N1 influenza pandemic, 2014 Ebola outbreak, and 2016 Zika virus outbreak. Another company, Metabiota using AI, machine learning and natural language processing algorithms early on warned East Asian countries of the spread of COVID-19 outbreak.² Artificial intelligence methods are driven by data and provide tools for tracking and estimating severity, spread and duration of disease outbreaks. An example is the use of trained modified auto-encoders (MAEs) to predict future confirmed cases of COVID-19 with high accuracy across different provinces in China. These models can make predictions about the impact of interventions on the trajectory of COVID-19.3 Combining the digital technology with data from text messages, social media and the internet can help make predictions about the spread of the disease and help in taking appropriate measures.

Artificial Intelligence solutions and cloud computing may be used as an efficient and cost effective tool to organize and analyze this enormous amount of data for further processing. Artificial Intelligence may also be used to reduce misinformation by managing the overabundant information about the pandemic. Other uses that have proven to be effective in reducing transmission include non-contact systems for large scale screening. Examples include infrared thermal cameras and RGB cameras to detect individuals with fever and abnormal respiratory patterns respectively. RGB cameras can conduct and analyze respiratory measurements of suspected individuals with the use of AI detection algorithms.⁴⁻⁶ Similar applications were used in China which provided data on individual movement and diagnosis to a central database analyzed by an AI algorithm which issued a color code to guide movement restrictions.⁷

Thousands of schools across the world remain closed due to ongoing threat of COVID-19 transmission among students. A private K-12 Meadows school in Las Vegas, United States has planned to use an artificial intelligence powered thermal screening system to ensure students' and return to classrooms. The system scans for signs of elevated temperatures upon entering the school premises. If students are flagged, they are to be asked to remain seated separately for around 10 minutes, and a re-reading of their temperature is conducted. If the temperature is normal, they are cleared, and if not, they are sent home. Surveillance product manufacturers are adjusting their technology to the COVID-19 pandemic with a variety of computer programs detecting whether a student is wearing a mask. The program employs AI technology to

measure how well students and employees are social distancing. The counterargument to using thermal imaging to screen for temperatures is the lack of fever during different phases of COVID-19 infection in some individuals. Overall, there may still be value in collecting a wide array of data at the school level amid the pandemic.

ROLE OF SCHOOLS OPENING

Although information on transmission of SARS-CoV-2 virus in young children is still scarce, as of 28 September, 2020, the centre of disease control and prevention (CDC) reports that children between younger than 17 years of age represent 8.5% of all COVID-19 cases in the United States.^{8,9} Large case series have shown a lower infection rate in this group when compared to older age groups; however, the afore mentioned could be due to the increased severity of symptoms within the older age group, part of social distancing measures, and the insufficient tests performed on children due to the majority of cases having an asymptomatic or mild presentation. A retrospective study of 105 children between the ages of 1-16 years infected with COVID-19 in Wuhan, China reported only 8 (7.6%) critically ill patients. 10,11 The infection rate in children seems to be more similar (0.8% difference) to those in other population groups.¹² Even though few reports have suggested trace levels of virus transmission in children under 10 years old, there is an upward rate of child-adult transmission being reported. An example among various others is an account of an ill 3-month-old infant whose parents presented with symptoms consistent with COVID-19 seven days after giving her care without precautionary measures. 10

For the above, the importance of promptly elucidating primary routes of transmission will lead to the modification of respective measures related to social contact behaviour without putting household contacts at risk. The Epi Trax surveillance system was used to elucidate three COVID-19 outbreaks in childcare facilities. It was confirmed that 184 persons had a link with at least one of these institutions, 31 positive cases were found, of which 42% were presumed to be children. The same data displayed that 12 children became ill at these facilities and a transmission of 26% of household non-facility contacts involved positive SARS-CoV-2 facility infected children. From these three institutions, it could be shown that the now universal measures of respiratory droplet care, frequent disinfection, daily symptom monitoring, and temperature taking could require a more complex scheme in school settings.¹³

There has been a lack of sufficient public health attention towards adolescents and young adults (AYA), which includes individuals between the ages of 10 and 24 years. Evidence suggests presymptomatic and asymptomatic transmissions, which are suggested as main factors in SARS-CoV-2 transmission, may play a significant role in

this age group. There is a need for more focus on efforts at testing, reducing transmission, and prevention around AYA especially youths from ethnic and racial minorities. There is also a need for more research about the potential effects of SARS-CoV-2 associated immune response on their developing brains, which could include impairment in decision making process. Numerous neuropsychiatric symptoms have been identified in patients with COVID-19 and possibility of long-term neuroinvasive effects in AYA has been described in literature.

This population is more likely to have no, mild, or atypical symptoms which leads to a high risk of forward transmission because of delayed diagnosis and isolation measures. 13,14 This also makes COVID-19 case data less reliable as symptomatic and severe cases are more likely to be tested. Social distancing measures like educational institute closures and lockdowns could also explain the lowercase rate in AYA. AYA may also be more likely to transmit SARS-CoV-2 because of behavioural factors. This could be due to lack of motivation to follow practices of social distancing, hand washing etc. Another contributing factor could also be the fact that AYA are more likely to have household close contacts in the form of family members. 14

A study of 23 COVID-19 clusters of families with children was conducted in Greece. It included 109 family members of which 43 were children. Children including five infants and one adolescent were the index cases in six family clusters. They found no evidence of transmission from a child to child or child to adult. Infected children were also more likely to be asymptomatic and have low viral loads. 15 Another cluster of COVID-19 was investigated in Europe. One index case was linked to 12 cases after 16 individuals stayed together in a chalet for four days in the Swiss Alps. One case was a nine year old child who developed mild symptoms. He attended three different schools and a ski class during his symptomatic period. The child was also tested positive for picornavirus and influenza virus confection in addition to SARS-CoV-2. After the schools were informed, two shut down for two weeks and a third school shut down for a week. The classmates and teachers of the child were considered to be high risk and isolated.

All of the contacts tested negative for SARS-CoV-2 but a significant percentage tested positive for picornavirus and influenza virus. This indicated that picornavirus and influenza virus are more easily transmitted than SARS-CoV-2. This also suggested that children are less likely to be infected, as his two siblings did not test positive for SARS-CoV-2 after staying at the chalet. It also suggested that children develop mild disease and are less likely to transmit the virus.¹⁶

More epidemiological studies are needed to assess transmission dynamics in children. This should include different study designs namely longitudinal cohort studies in schools and daycares, RCTs and household studies. Mathematical models can be used to expand on the results of epidemiological studies. Study samples should be representative of the population to minimize bias. The ideal specimen for diagnosis in children could also be different from adults. The results of epidemiological studies should be combined with laboratory data in context of biologic, behavioral and social factors to better understand transmission dynamics in children.¹⁷

Modelled projections and considerations of COVID-19

Creating models, whether based on markov decision susceptible-infected-recovered approaches, bavesian tools, survival-convolution methods, a generalized linear mixed effects models (GLMM), or multivariate linear analyses are tools to create the best outlook for the future based on a current scenario utilizing present data. A recently proposed model on github incorporated the costs of COVID-19 morbidity and the economic costs of mitigation measures using a markov decision process in a susceptible-infected-recovered (SIR) model assessing the effect of different public health interventions on mitigating COVID-19 and their cost. This model's code includes a herd immunity threshold as well as mitigation measures that consider healthcare system capacity, vaccine release dates, and illness severity, as well as an overcapacity fatality rate. 18 A model from Columbia University forecasts the effects of utilizing mitigation strategies in China, South Korea, Italy, and the United States using a survival-convolution method accounting for the incubation period and utilizing a variable rate of transmission based on permutation to account for uncertainty. They predict more than 6.5 million cases if mitigation measures against COVID-19 are mollified.¹⁹

However, in contrast to these models we must address other variables comprehensively, including modelling the effect of opening elementary, middle and high schools partially, entirely with or without university openings. A thorough analysis of the cost benefit analysis of online schooling and its economic sequelae is necessary by utilizing python nodes or gradient descent to find the global minimum by minimizing the theta in a cost function J of theta through identifying the location where the rate of change of cost is zero, specifically where theta n is equal to n-alpha multiplied by derivative of J (theta) with respect to theta n, where alpha is the learning rate. This is important for each approach taken to COVID mitigation so as to identify the minimum total national cost and not to rule out the combination of continuing student education with the alleviating benefit of decreased transmission risk off campus. 2d KD trees could be utilized from multiple angles in this regard, for instance, immune vs. infected or for a more complex 2d tree such as societal cost of increased tuition and initial economic benefit from coupling student enrolment with greater morbidity expenses of the healthcare system versus decreased student enrolment with societal benefit of decreased COVID-19 transmission alongside greater testing.

Accounting for local economics which change variable distributions outside of normal distributions may be better addressed with generalized linear mixed effects models (GLMM). This approach has been taken with 80% of American counties; however, further work can be done to precisely include more variables in the model and specify the said angles.²⁰ Testing is one such variable that is often not included in models and is a major factor: Comprehensive testing as early as 31 December, 2019, in Vietnam and South Korea along with quarantine laws, flight bans and limited proximity on flights have suppressed their COVID-19 spread by providing more targeted treatment, despite raising detected cases and prevalence. Bayesian analysis utilizing total testing variability as an impacting factor on the total increases in prevalence showed that there was a decrease in infectivity in Orange County following a stay at home order.21 Models must also include increases in flights and changes in airline guidelines on seating proximity, which has a RR of 7.3 as shown in a Vietnamese study.22 The Korean CDC implemented a smart quarantine system that responds in real-time with a risk assessment of COVID-19 to foreign outbreaks as per the fifth article of the quarantine law.23 Multivariate linear analyses on data from Johns Hopkins was assessed by Accenture, identifying increased mortality of COVID-19 with a lack of insurance, overcrowding and the period elapsed since regional viral prevalence; however, perhaps surprisingly, classical cardiovascular risk factors were not positively correlated with COVID-19 mortality.^{24,25}

This is a simplistic approach and accounting for the vast number of variables in the type and date of school opening, considering local economic abilities of counties to install advocated measures as well as accounting for compliance and enforcement of such measures, perhaps the better method would be using artificial intelligence as a progressive operational perceptron rather than a multilayer perceptron, a deep learning method. 26,27 Along with artificial intelligence, as mentioned above, nonlinear fractional differential equations have a significant role due to the vast number of variables that can be accounted for in correctly modelling COVID-19 transmission as well. Parameters as specific as the retail purchase rate of the hosts in the market have been accounted for through the use of fractional derivatives, Laplace transforms and the Adams Bashforth method.²⁸ Based on Italian data, chaos theory applications were utilized by Atangana of South Africa and Taiwan to create a mathematical model indicating that non-locality can be represented by fractalfractional differential operators using the Mittag-Leffler function.²⁹ This model has been further modified from fractional differential and integral operators to assess COVID-19 transmission through Chebyshev polynomial indicated by:

$$(\varphi 2, \psi 2) = (2(t + 2t2)\pi, 2(t + 2t2)\pi)$$

Where ϕ is the sum of those infected those in incubation i.e. spreading phase. Data shows different solutions for

 $(\phi 1, \psi 1)$ for Europe, China, Russia, Brazil, and the United States. Furthermore, connection coefficients are variable with time.³⁰

Fundamentally, due to earlier transmission rates of SARS-CoV-2 in the incubation phase compared to other coronavirus infections, our simulation strategies chosen to assess the need for testing, lockdowns, contact tracing, social distancing, and the balance of economic benefits of opening K-12 schools versus universities early or later with healthcare burden and capacity, partially or fully will ultimately dictate the most reasonable policy measures. 31,32

Hao et al used a model to reconstruct the full transmission dynamics of SARS-CoV-2 in Wuhan across five time periods based on key events and interventions. They generated a SAPHIRE model by extending the SEIR (susceptible-exposed-infectious-recovered) include three more components, unascertained cases, presymptomatic infectiousness, and case isolation in the hospital. They identified high infectivity and high rate of asymptomatic or latent infections as two key features of the outbreak. They used effective reproduction number (Re) as a measure of transmission. They observed a significant drop in Re with interventions like face masks, social distancing, and quarantine away from close contacts. They estimated 87% of infected individuals to be ascertained before 8 March and a basic Re of 3.54; which dropped to 0.28 (95% CI, 0.23-0.33). The ascertainment rate during the early Wuhan outbreak was estimated to be 0.23 (95% confidence interval 0.14-0.42). It rose to only 0.16 even with door-to-door screening across the city from February 17-19, 2020. They also looked at the probability of resurgence of infections following lifting of control measures after two weeks of no ascertained infections; assuming 87% unascertained cases, they estimated the probability to be 0.32. Zu et al collected data from the National health commission of China and developed an eight compartment SEIPQR model of SARS-CoV-2 transmission. Strict interventions imposed by the Chinese government, such as lockdown, widely done contact tracing, and monitoring of infected persons coming in the country proved effective. The effective reproduction number (Re) dropped from 2.620 in January 2020 to less than 1.0 in February 2020. The confirmed cases reduced by 99.85% by May 2, 2020.

IMPLICATIONS FOR PUBLIC HEALTH

Public health officials have been put to the test of their careers amidst the ever rising numbers of individuals diagnosed with COVID-19 worldwide. In a study done by Mizumoto and Chowell that was published in February 2020, they calculated the virus' reproduction number, known as R-naught.³³ R-naught serves as a numerical representation for how infectious a virus is; the number is an estimation of how many individuals will become subsequently infected for each newly diagnosed case. Their study analyzed the passengers of the now infamous

Diamond Princess cruise ship, which had 454 infected passengers at the time of data collection.³³ This study was one of the preliminary studies that solidified the highly infectious nature of SARS-CoV-2 and documented the evidence that necessitated the austere lockdown and shelter in place orders that would follow for nearly every country on Earth.33 The authors showed that in the confined setting of the cruise ship, the virus reached Rnaught values as high as 11. In comparison, the numbers at the time as evidenced by epidemiological data from Singapore and China suggested an R-naught value varying from 1.1-7.0.33 Following the implication of quarantine measures, the R-naught value quickly dwindled below 1.0, the cut-off for classification as a causative agent of a pandemic.33 This data was some of the first to demonstrate the validity of quarantine measures.

Public health requires adherence to the rules from the entire population to be effective, however, it can be undermined by the uncontrolled actions of a small minority. Contact tracing has been a highly contentious subject and has received pushback for a multitude of reasons despite repeated confirmation of its importance from officials such as Dr. Anthony Fauci, director of the National institute of allergy and infectious disease (NIAID). This has led to a high number of studies aimed at establishing the efficacy of contact tracing for preventing the transmission of SARS-CoV-2. In a study done by Cheng et al published in May 2020, 100 patients were enrolled after testing positive for SARS-CoV-2 by time polymerase chain reaction (RT-PCR) nasopharyngeal swab. The 100 patients had a total of 2761 close contacts following their diagnoses, which led to the subsequent diagnoses of 22 additional cases, for a 0.7% overall attack rate (95% CI, 0.4%-1.0%).34 To further stratify the data, the additional cases were separated into two groups. The first group was exposed within 5 days of symptom onset (n=1818) and the second group was exposed after 5 days following the onset of symptoms (n=852). All cases of disease spread involved contacts that were exposed within 5 days of symptom onset. Interestingly, 299 contacts were exposed prior to the onset of symptoms and they were proven to be at risk with an established attack rate of 0.7% (95% CI, 0.2%-2.4%), matching the overall attack rate.³⁴ The study concluded that transmission is highest in the time period before and immediately after onset of symptoms. Therefore contact tracing alone is insufficient to contain the transmission and other methods for transmission control, such as social distancing, are required.³⁴

Song and Karako penned an editorial for the journal Bioscience trends and pointed out the critical importance of making information rapidly available and disseminated to the public and researchers alike. The article states that sharing all that is known about the virus as it is discovered is pivotal for the treatment plans established by healthcare workers and the guidelines set forth by public health officials for how the public should respond

and what changes need to be made to daily life.³⁵ Additionally, the interagency coordination and collaboration led to the world health organization (WHO) declaring the novel coronavirus to be a public health emergency of international concern (PHEIC), only the sixth time they have done so.³⁵ Aside from what is published in academic journals, the coronavirus has prompted the use of more age appropriate methods of dissemination of information including websites such as the NEJM coronavirus page, the Lancet COVID-19 resource center, and the cell press coronavirus resource hub.³⁵

CONCLUSION

As the pandemic continues to severely impact young individuals, communities and school workers, it is imperative that non-profit and political leaders respond adequately and timely. The AISOS model can help improve response at the school level and among states and countries that are impacted by the pandemic, albeit an equity-fluent and long-term view is necessary. A multistake and multi-disciplinary cooperation and data exchange action plan is required nationally and internationally. The AI community, policy makers, developers ought to formulate the problem of safely opening schools, identifying relevant data, and utilize open datasets. While the AISOS model is not a silver bullet, the improvement in school transmission will be particularly useful as an emergent temporary, potentially permanent, measure of transmission control and monitoring.

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