AI in Health: How Technology Can Prevent Future Health Emergencies

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A. INTRODUCTION

After experiencing the COVID-19 pandemic, the world began to realise the importance of information and technology development to adapting to global pandemics. Marked with the transition from offline meetings to online meetings, all aspects of social interaction have changed significantly. Yet technology development is not only beneficial to facilitating social transitions, but also for accelerating global health emergency mitigation. Countries with pre-existing digital health technology adapted quicker towards data tracing and testing. Those with strong digital regulations also adapted better to health education and handling of misinformation. With technological advancement in all aspects of health, we are left to wonder whether technology could also aid us in future scenarios: predicting the probability of future health emergencies and quicker data-and-pathogen sharing.

On declaring that COVID-19 was no longer a global health emergency, Dr. Tedros Adhanom Ghebreyesus said: "The threat of another variant emerging that causes new surges of disease and death remains, and the threat of another pathogen emerging with even deadlier potential remains". In retrospect, the COVID-19 pandemic reminds us of the importance of the One Health agenda to preventing future health emergencies. Many infectious diseases (such as Anthrax, COVID-19, and MERS-CoV) can be transmitted through animals, and the One Health approach will allow multi-sectoral cooperation in humans, animals, and the environment in disease prevention. The World Health Organisation (WHO) has encouraged risk surveillance through the Health Emergency Preparedness, Response and Resilience (HEPR) framework. However, currently there is no platform that can objectively combine those inter-sectoral knowledge into corporeal preventative measures for infectious diseases.

Machine learning technology for predictive and generative purposes has been closely explored using *Artificial Intelligence (AI)*. AI has been used commercially, perhaps with the most famous example being ChatGPT. It has also been used extensively in other domains, from answering miscellaneous questions, to tailoring recommendations based on preferences. If AI can predict scenarios based on certain sets of data, then is it possible to implement a similar concept in the realm of global healthcare?

We value the scientific ability that can navigate the development of a disease and also its transmission. With the development of AI, we would like to measure its capability in early prediction of health threats before they manifest into emergencies that can take a toll on collective resources (financially, economically, socially). But the question is: Is it feasible? Can AI see patterns in infectious disease epidemiologic data and utilise them in dealing with other emerging diseases?

B. CURRENT IMPLEMENTATION OF AI IN HEALTHCARE

Artificial Intelligence (AI) is an umbrella term for a generic machine or a system that responds to data stimuli, and modifies its operation to maximise a performance index. Machine Learning (ML) is a branch of AI that utilises training a program with a set of data, and that conjures a certain desired output to its maximum performance coefficient.[1] ML has been implemented in pilot projects on several diseases, as summarised in Table 1. AI was designed to improve the accuracy of diagnosis, screening, therapy, and prognosis, as an effort to boost the quality of health services.

1. Kurt Benke and Geza Benke. 2018. Artificial Intelligence and Big Data in Public Health. International Journal of Environmental Research and Public Health 15, no. 12 (2018): 2796. (https://doi.org/10.3390/ijerph15122796).

Table 1. Overview of Current Implementation of AI in Healthcare.

Author, Year	Research Objectives	Outcome
Arun et al., 2018[2] Graham et al., 2019[3]	AI implementation on mental disorder diagnosis	High-accuracy AI has great potential in mental healthcare. A model using XGBoost has excellent accuracy (98 per cent), which makes it possible to determine a person's level of depression.
Grzybowski et al., 2020[4]	State-of-the-art Diabetic Retinopathy (DR) screening technologies	Comparing several deep learning Artificial Intelligence (AI) algorithms for diabetic retinopathy screening using funduscopy pictures, for it may be crucial in preventing diabetes-related blindness.
Wang, et al., 2021[5] Zoabi, et al., 2021[6]	AI on monitoring COVID-19 diagnostic and progression with clinical data	AI can monitor COVID-19 progression using serial CT images. Clinical and demographic data can also be used on COVID-19 testing.
Sahu et al., 2022[7]	Summarise AI potential in Drugs and Pharmaceuticals	AI may play a significant role in identifying target proteins, improving drug design success rates, reducing the health risks associated with preclinical trials, significantly lowering costs, data mining, and many other things.
Ranka et al., 2021[8]	Application of AI in cardiovascular medicine	This is where AI may be really helpful. It can analyse head CT scans for acute strokes, suspect acute coronary syndrome, interpret electrocardiograms, assist imaging decisions, and many other things.

2. Vanishri Arun et al., 2018. A Boosted Machine Learning Approach For Detection of Depression. In 2018 IEEE Symposium Series on Computational Intelligence (SSCI) (IEEE, 2018), pp. 41-47. (https://doi.org/10.1109/SSCI.2018.8628945).

3. Sarah Graham et al. 2019. Artificial Intelligence for Mental Health and Mental Illnesses: An Overview. Current Psychiatry Reports 21, no. 11 (28 July 2019): 116. (https://doi.org/10.1007/s11920-019-1094-0).

4. Andrzej Grzybowski et al. 2020. Artificial Intelligence for Diabetic Retinopathy Screening: A Review. Eye (London, England) 34, no. 3 (2020): 451–60. (https://doi.org/10.1038/s41433-019-0566-0).

5. Robin Wang et al. Artificial Intelligence for Prediction of COVID-19 Progression Using CT Imaging and Clinical Data. European Radiology, n.d., 1–8. (https://doi.org/https://doi.org/10.1007/s00330-021-08049-8).

6. Yazeed Zoabi, Shira Deri-Rozov, and Noam Shomron. 2021. Machine Learning Based Prediction of COVID-19 Diagnosis Based on Symptoms. NPJ Digital Medicine 3 (2021): 1–5.

7. Adarsh Sahu, Jyotika Mishra, and Namrata Kushwaha. 2022. Artificial Intelligence (AI) in Drugs and Pharmaceuticals. Combinatorial Chemistry & High Throughput Screening 25, no. 11 (August 1, 2022): 1818–37. (https://doi.org/10.2174/1386207325666211207153943).

8. Sagar Ranka, Madhu Reddy, and Amit Noheria. 2021. Artificial Intelligence in Cardiovascular Medicine. Current Opinion in Cardiology 36, no. 1 (August 1, 2021): 26–35. (https://doi.org/10.1097/HCO.0000000000000812).

Author, Year	Research Objectives	Outcome
Park et al., 2021[9]	Developing new ML algorithm to screen 39 diseases	Utilising Deep Neural Network (DNN) with LightGBM and XGBoost to aid disease diagnosis. ML shows promising results in connecting medical data to certain clinical diagnosis.

In general, these models are implemented as diagnostic tools for non-communicable diseases, but are not yet in the epidemiologic field. But regardless, these models set the foundation for medical determinants usability in machine-learning technology. Diagnostic models feed medical data (risk factors, biomarkers, medical images) into artificial neural network models and are trained to determine whether one individual is classified for a specific disease diagnostic or not. As parameters are fed into the deep learning models, the model will navigate patterns of functions which determine the end result.[10]

AI usage in disease analysis can have several advantages. Unlike human-navigated screening, AI does not experience fatigue. As a result, screening using AI algorithms can enable the consistent screening of thousands of sets of data without subjective skewing.[11] This quality will be valuable for analysing disease data, which has a preference for an accurate method that can screen a multitude of data in the shortest period of time.

Regarding the validity of data, deep machine learning is able to find patterns from various sources of data by repeating numerous trial-and-error series. This quality can help minimise potential issues, including data duplication, falsification, and incompletion. The Least Absolute Shrinkage and Selection Operator (LASSO) regression model can also be used to reduce a high variation of data coefficients (regularisation).[12]

9. Dong Jin Park et al. 2021. Development of Machine Learning Model for Diagnostic Disease Prediction Based on Laboratory Test. Scientific Reports 11, no. 7567 (2021): 1–11.

10. B. Acs, M. Rantalainen, and J. Hartman. 2020. Artificial Intelligence as the next Step towards Precision Pathology. Journal of Internal Medicine 288, no. 1 (July 28, 2020): 62–81. (https://doi.org/10.1111/joim.13030).

11. Grzybowski et al. 2020. Artificial Intelligence for Diabetic Retinopathy Screening: A Review.

12. Carmela Comito and Clara Pizzuti. 2022. Artificial Intelligence for Forecasting and Diagnosing COVID-19 Pandemic: A Focused Review. Artificial Intelligence in Medicine 128, no. 102286 (2022): 1–25.

AI can also learn complicated patterns that surpass human ability. AI in radiation therapy, for example, can learn subtle patterns consistently, as opposed to the high intra-operator variability of human appraisal.[13]

C. CHALLENGES DURING HEALTH EMERGENCIES

The World Health Organisation (WHO) launched One Health as an integrated strategy with the goal of promoting optimal health for people, animals, and the environment. In order to attain global health security, One Health can aid in achieving a deeper understanding of how to control illnesses using a wide range of strategies, including prevention, detection, preparation, reaction, and case management. But due to interdependence, all three factors cannot be isolated from one another and should be equally involved. To attain sustainability and to manage the many health challenges associated with these connections (including zoonotic illnesses, antibiotic resistance, food safety, and others), the One Health concept is unquestionably crucial.[14] For the purpose of pandemic prevention, preparedness, and response, a platform that can incorporate actions from all actors is highly desirable to increasing One Health cooperation.

During and after the COVID-19 pandemic, all countries realised that the current health system in the world is not sufficiently prepared to respond to a virulent disease. Diseases that are thought to be isolated in animals can be transmitted to humans (zoonotic diseases), with explanations that are currently still difficult to elaborate. Dividing human resources to studying both microbiology and disease prevention at the same time can be challenging. Healthcare flexibility to manage known diseases and to prepare for unknown diseases is desirable to creating global health security.

This challenge is certainly tough, particularly in this era of global mobility and international supply chains. A disease can be transmitted from one area to another, even during the latent phase, which can be activated by various variables. For

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13. Issam El Naqa and Martin J Murphy. What Is Machine Learning? In Machine Learning in Radiation Oncology: Theory and Application, n.d.; Lian Wang et al. Artificial Intelligence for COVID-19: A Systematic Review. Frontiers in Medicine 8 (n.d.): 1–15.

14. J. R. Sinclair. 2019. Importance of a One Health Approach in Advancing Global Health Security and the Sustainable Development Goals: -EN- -FR- Importance de l'approche Une Seule Santé Pour Améliorer La Sécurité Sanitaire Mondiale et Atteindre Les Objectifs de Développement Durable -ES- Importancia de La Noción de Una Sola Salud Para Promover La Seguridad Sanitaria Mundial y Los Objetivos de Desarrollo Sostenible. *Revue Scientifique et Technique de l'OIE* 38, no. 1 (1 August 2019): 145–54. (https://doi.org/10.20506/rst.38.1.2949).

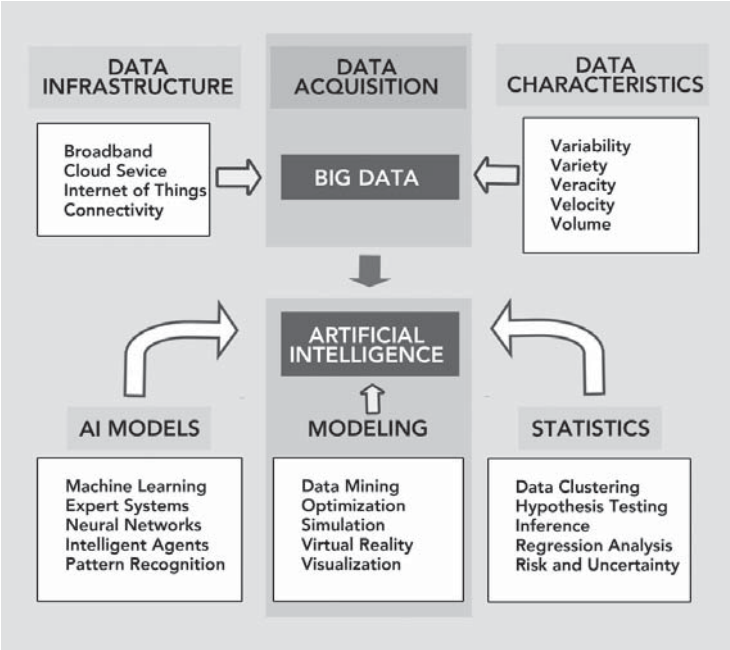
example, in the case of Tuberculosis (TB), latent TB screening has not been commonly practised to enable the detection of active TB cases. If a traveller comes to a TB endemic area, is exposed to TB, and then returns to their country of origin, they may cause the unpredicted emergence of tuberculosis in that area. The same risk can also apply to other infectious diseases. Therefore, preparation for an increase in cases and disease surveillance needs to be improved. The fact that an area is not endemic to certain diseases does not directly equate to disease immunity in that area. Many reports find an increase in the number of cases of a disease in areas that are not endemic, especially from patients that have a travel history to endemic areas. Hence, preparations for case spikes, such as recognising disease trends, what factors affect them, and how to determine the occurrence of significant cases, need to be closely monitored.

The aim of this hypothetical algorithm is to predict the possibilities of health emergencies based on clinical data. Although clinical knowledge can understand the progression of infectious diseases, it might be limited to predicting its trajectory in real-life dynamics. In theory, technology might be beneficial to translating empirical data into a framework, finding patterns of infectious diseases that might follow similar transmission patterns. Apart from that, mathematical modelling might give us a better understanding of pathogen heterogeneity, host variability, ecological dynamic, and other unknown factors.[15]

15. Anna Maria Niewiadomska et al. 2019. Population-Level Mathematical Modelling of Antimicrobial Resistance: A Systematic Review. BMC Medicine 17, no. 81 (2019): 1–20.

D. HYPOTHESIS OF DISEASE SURVEILLANCE USING AI

Figure 1. Artificial Intelligence (AI) and Data.[16]



Currently, we have survived several disease outbreaks in the Association of Southeast Asian Nations (ASEAN). Some known examples are explained in the table below. We are in possession of pre-outbreak data (demography, transmission route, virulence) and post-outbreak data (casualties, risk factors, management, time lapse). Retrospectively we now possess a better understanding of the transmission nature of some of these diseases, yet we are still not sure how the transmissions resulted in outbreaks.

16. Benke and Benke. Artificial Intelligence and Big Data in Public Health.

Table 2. Emerging Diseases in Southeast Asia, 2021.[17]

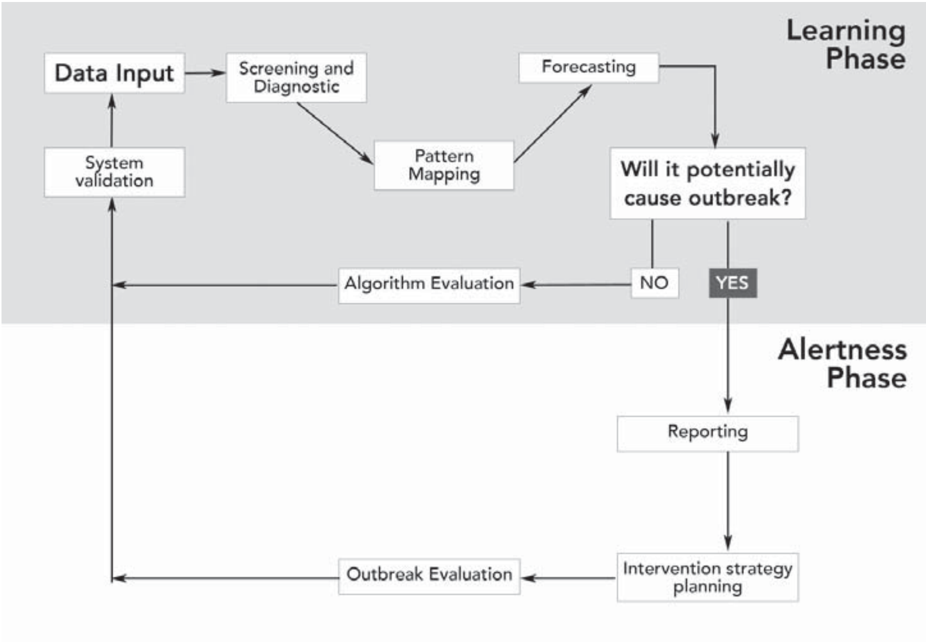
Disease Name	Description	Affected Countries
Highly Pathogenic Avian Influenza A (H5N1), 2014	First reported in Vietnam in 2003, affecting poultry and humans. ASEAN contributes 50 per cent of all cases	Thailand, Indonesia, Myanmar, Cambodia, Laos, Malaysia
Pandemic Influenza A (H1N1), 2009	Emerged from individuals with travel history to Mexico. Transmitted through human-to-human contact, found in 20 per cent of sampled pigs	Almost all Southeast Asian (SEA) countries
Coronavirus-19 Pandemic, 2019	Causing Severe Acute Respiratory Syndrome (SARS). Possibly involve animal reservoir but also transmit through human-to-human contact	All SEA countries
Tuberculosis	SEA was home to 43 per cent of all TB burden. Currently the global burden is also increased by drug-resistant TB, long TB, and co-infection	Indonesia, Thailand, Myanmar
Malaria	Spread through mosquitoes as vector. SEA holds the second highest burden of malaria globally. Thrives in tropical countries with access to water bodies	Indonesia, Thailand, Cambodia, Laos, Myanmar, Vietnam

There can be numerous factors that decide the infection rate, both intrinsic factors (age, lifestyle, genetic, nutrition) and extrinsic factors (prior infection, climate, occupation). To add to the challenge, some of the factors can be dynamic. Climate, for example, changed gradually in ASEAN due to global warming. Demographic composition can be influenced by birth rate, education, welfare, and other factors.

This hypothetical algorithm postulated the machine learning process to study the interdependence of each factor, and how it can contribute to disease outbreak. The idea is to compile medical data from these diseases, the outbreak timeline, and the end result of each outbreak. We then input the data into the system, and find the function that can yield the result that is most similar to the outbreak outcome. This process can take a lot of time, but it can give a better understanding of each disease. And in case of known similar factors within each disease, we can use the knowledge to test for new diseases, with the idea that infectious diseases may have similar influencing factors with one another. Hypothetically, we would need an ensemble of several algorithms to have a working outbreak alertness framework: screening algorithm, mapping algorithm, and forecasting algorithm.

17. ASEAN. 2021. ASEAN Strategy for Exotic, Emerging, and Re-Emerging Diseases and Animal Health Emergencies.

Figure 2. Hypothesised Screening Algorithm.



The screening and diagnostic algorithm is utilised to process medical data, then conclude whether someone can be diagnosed with a disease or not. This part of the ensemble is most likely to be successful, since a similar concept has been proven to be adaptable to various diseases. In this section, the inter-correlation of various data should be established, and used to validate a physician's diagnosis. Learning processes using XGBoost and LightGBM have been found to be the most accurate in several studies. However, each disease's algorithm might need to be developed separately, and similar factors can be concluded afterwards.

Positive data then needs to be inputted in the mapping algorithm. Each individual is marked on their respective domicile, and analysed for their transmission risk. Areas with high virulence risk (densely populated cities, transit cities, high mobilisation rates) should be marked with high risk. Once the number of cases approaches the normal threshold, monitoring should progress to predicting future cases.

A disease can be considered endemic if the number of cases at a certain given time surpasses the threshold of the common case number. So after achieving diagnostic data collection and mapping, we should forecast whether transmission of the respective infectious disease might increase in the future, and how fast it can progress. This phase has several benefits. First of all, it can detect unexpected disease outbreaks early, even before visible damage occurs, especially by eradicated or new diseases. Second, we can predict the magnitude of the disease and the estimated time to preventing that from occurring. Lastly, it can be used as a reference for assigning targets for intervention efforts.[18]

During the COVID-19 pandemic, numerous studies have tried to utilise the ML model to forecast case numbers. One of the commonly used models is the Autoregressive Integrated Moving Average Model (ARIMA). ARIMA is a univariate regression model that can produce averages per successive time frame. This model allows comparisons between specific time frames that can be valuable in determining disease outbreaks. This model is created with supervised learning mechanisms. Retrospective epidemiologic data are fed to the system, training them to make a fitting equation. Through trial and error, we pick the algorithms that match our desired outcome. And to evaluate the accuracy, a new retrospective dataset that has never been introduced before will be fed to the algorithm.[19] And now prospective data at any given time can be inputted into the algorithm to forecast whether it carries the risk of a disease outbreak.

A good ensemble should be cross-checked with health professionals and real-life situations to validate the system. The development and evaluation phase should be performed repeatedly to improve the predictive quality. Adapted from research by Park, et al., several parameters need to be considered during performance evaluation: predictive power, confusion matrix, SHAP method, F1-score, accuracy, precision and recalling.[20] The Shapley additive explanation (SHAP) method, in particular, can leverage each factor's predictive value to various diseases. Finding parallel factors between diseases will increase the algorithm's interoperability, which hopefully will also apply to new-emerging diseases. Predictive power or optimal accuracy can be objectively measured. Comparison with a physician is used to compare the system's prediction with the physician's diagnosis.

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18. Deepak Painuli et al. Forecast and Prediction of COVID-19 Using Machine Learning. In Data Science for COVID-19, 1st edition, vol. 1, n.d., pp. 381–97.

19. Painuli et al.; Said Agrebi and Anis Larbi. 2020. Use of Artificial Intelligence in Infectious Disease. In Artificial Intelligence in Health Care, 2020, pp. 415–38.

20. Park et al. Development of Machine Learning Model for Diagnostic Disease Prediction Based on Laboratory Test.

E. WAY FORWARD: REALISTIC STRATEGIES TO IMPLEMENT AI AS EPIDEMIOLOGIC GUIDE

ASEAN's commitment to regional health cooperation will play an important role in ensuring the success of this project's implementation. The region has already established the foundation for health cooperation, such as the ASEAN Portal for Public Health Emergencies, and ASEAN BioDiaspora. However, most discussions lean toward emergency responses, and have not extensively explored emergency prevention strategies. In line with the Health Emergency, Preparedness, Response, and Resilience (HEPR) architecture,[21] several considerations need to be discussed so as to improve ASEAN's health quality and prevent future endemics. Those considerations are as follows:

Although promising, AI in health should not be implemented unless supported with rigorous regulations. Our hypothesis to implement AI in epidemiological studies requires a huge amount of medical data (e.g., clinical records, outbreak history, mobility surveillance). A strong data safety regulation should be established first, to protect patients' privacy and assure researchers' ethical compliance. ASEAN member states have signed the ASEAN Strategic Framework for Public Health Emergencies for reporting and data sharing during health emergencies, in accordance with International Health Regulation (IHR) 2005 principles.[22] However, the corporeal strategies to implement the commitment should be discussed further in the ASEAN Health Ministers Meeting (AHMM).

Desirable regulations include but are not limited to: data safety, authorisation for dissemination, data privacy, digital consent, and data retaining.[23] Data anonymity can also be considered to protect privacy. As a reminder, citizens hold the rights to their medical data confidentiality, and policy makers are accountable should this right be violated. In addition, **the national health governing body should examine AI compatibility with national health practices, and legally determine the degree of acceptance in the medical field.** The ASEAN Guide on AI Governance and Ethics is at the developmental stage and is becoming the promising foundation of AI proliferation in the region.

There is a risk of insufficient or limited data eligibility for the analysis. Since not all ASEAN member states have fully implemented integrated digital health

21. Health Emergency, Preparedness, Response, and Resilience (HEPR) "Strengthening Health Emergency Prevention, Preparedness, Response and Resilience," 2023.

22. ASEAN Secretariat. 2020. ASEAN Strategic Framework for Public Health Emergencies.

23. Benke and Benke. Artificial Intelligence and Big Data in Public Health.

data, there are risks of incomplete data. Before input, all data should be screened for incompletion, duplication, or falsification. Indeed, AI can be trained separately to detect data duplication by teaching it examples of recurring phrase patterns. However, human vigilance to check individual data both as input and output is desirable for better reliability; not to mention that not all ASEAN member states have implemented Universal Health Coverage (UHC), raising risks of unrepresented cases, especially in the low-middle income communities. Therefore, regional transition towards better healthcare digitalisation and UHC will grant smoother integration of emergency risk surveillance with AI.

On the micro level, ensuring healthcare professionals' willingness to collaborate with novel technology is also important to ensuring its development. The majority of health workers are still apprehensive towards AI due to the fear of it competing with healthcare professionals. Although this scenario is very unlikely, it raises valid concerns for check-and-balance in ensuring that technology will operate only as an instrument for health workers. AI can indeed learn faster than humans, but humans still hold the executive advantage of empathy and reason. Health professionals are still very much needed to navigate data science, apply the results in communities, and observe the results. But in return, health workers should also willingly learn about AI. ASEAN should endorse capacity building regarding AI in health, encouraging its discourses in medical symposiums and medical curricula. Funded research will also increase data science attraction in health sectors.

Furthermore, introducing technology to healthcare also requires interprofessional collaboration with other sectors. Joint research between data scientists, clinical professionals, bioinformaticians, and epidemiologists should be encouraged. However, performing large-scale novel studies can be costly. Apart from professionals, these researches also require computational equipment, training programs, and technical and administrative assistants.[24] Funding schemes should be increased as a means to securing AI proliferation in health, especially in ASEAN. Funding opportunities from ASEAN partners (for example, HORIZON Europe or similar programmes) should also be considered to increase interest for AI development.

24. Grzybowski et al. Artificial Intelligence for Diabetic Retinopathy Screening: A Review.

F. CONCLUSION

The potential utilisation of AI to predict health emergencies should be considered to strengthen ASEAN's Health Emergency, Preparedness, Response, and Resilience (HEPR). A systematic ensemble that can forecast emergencies is vital, especially with the risk of climate-related health issues. Its implementation in ASEAN is not impossible. However, several aspects need to be solved in order to secure the safety and sustainability of this system. A regional commitment towards health emergency frameworks is needed to kick-start the implementation of AI in health for the betterment of ASEAN citizens.

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