**Review Article**

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# Emergency preparedness for public health threats, surveillance, modelling & forecasting

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**In the interconnected world, safeguarding global health security is vital for maintaining public health and economic upliftment of any nation. Emergency preparedness is considered as the key to control the emerging public health challenges at both national as well as international levels. Further, the predictive information systems based on routine surveillance, disease modelling and forecasting play a pivotal role in both policy building and community participation to detect, prevent and respond to potential health threats. Therefore, reliable and timely forecasts of these untoward events could mobilize swift and effective public health responses and mitigation efforts. The present review focuses on the various aspects of emergency preparedness with special emphasis on public health surveillance, epidemiological modelling and capacity building approaches. Global coordination and capacity building, funding and commitment at the national and international levels, under the One Health framework, are crucial in combating global public health threats in a holistic manner.**

**Key words** Capacity building - epidemiological modelling - health threats - One Health - preparedness - public health - surveillance

One health approach is integral in enhancing the preparedness for ongoing and upcoming potential public health threats such as emergence of infectious diseases, antimicrobial resistance, environmental pollution, climate change, non-communicable diseases, natural disasters, and bioterrorism[1,2]. A proactive, coordinated, interdisciplinary and cross-sectoral approach across human, animal and environmental sectors remain the core pillar of One Health framework to mitigate the public health challenges[3]. The need for early response to emerging zoonoses before these spill over into human population has been underscored by the gravity of life losses caused by the ongoing COVID-19 pandemic, which has been classified as an 'emerging disease of probable animal origin'[4,5]. A better understanding and early prediction of how an animal pathogen might have crossed species barriers to infect humans and then to an epidemic or pandemic potential can productively prevent many emerging diseases[6]. Therefore, the holistic One Health programmes are important for the elucidation of various zoonotic pathogen transmission pathways and for conceptualizing policies to prevent the outbreaks at the source of origin[3].

In the globalized era, with rapid population and trade mobility, any infectious disease can spread across the world within a span of 36 hours[7]. The epidemic intelligence-based analysis of the drivers of the emerging infectious diseases in Europe during 2008–2013, categorized 'travel and tourism' as the most prominent and frequent disease driver[8]. With the increasing number of air travel of around 3.6 billion people/year[9], the national and international boundaries have become more porous to facilitate the introduction of infectious agents into new regions within a time frame even shorter than the incubation period of most pathogens. The severe acute respiratory syndrome (SARS) pandemic with its epidemic origin in Guangdong, China had flourished into a pandemic affecting "5 countries within 24 hours and to more than 30 countries on 6 continents within 6 months" with 8096 cases and 774 deaths[10]. Other recent emergence and spread of infectious diseases of global health significance facilitated by air travel include the initiation of the chikungunya epidemic in Europe in 2007 from a single infectious traveler from India[11], the pandemic influenza in Mexico[12], the spread of New Delhi metallo-beta-lactamase-1 (NDM-1) gene from India to Sweden and to multiple other countries[13], the Middle East respiratory syndrome (MERS) epidemic in South Korea, which is the largest epidemic outside Saudi Arabia, from a single infectious traveler returning from Saudi Arabia[14], the 2014-2016 West African Ebola virus outbreak costing 11,325 lives, with imported cases in seven countries[15], and the 2015-2016 Zika outbreak spread from Brazil to 87 countries and territories[16] and more recently the COVID-19 pandemic[17]. A study on H1N1 pandemic influenza strain highlighted the fact that despite the presence of high-efficiency particulate air (HEPA) filters in aircrafts, the attack rate in a 9-hour flight was estimated as high as 4.3 per cent[18]. Therefore, in the interconnected world, public health preparedness is the key to avoid devastating losses from such emerging threats[1].

The pillars of emergency preparedness for public health threats rely on the integrity of surveillance and forecasting models which aids in mobilizing resources and timely responses[19]. Public health surveillance is crucial in recognizing new cases of any emerging infections as well as in estimating the present health status of the populations. The epidemiological models support the preparedness and decision making of stakeholders by simulating the probable scenario such as transmission pathways, disease dynamics, along with the evaluation of various alternative intervention strategies[20]. The predictive information systems based on routine surveillance, modelling and forecasting affect the organizational decisions and public awareness of health-related events. The temporal and spatial risk for many infectious diseases, especially in case of vector-borne diseases, predicted through advanced surveillance and disease models incorporating the environmental data has enhanced the epidemic prevention and control capabilities[21].

The emergency preparedness measures should work closely in frame of an integrated global network with national and international relevant stakeholders[20]. The successes of such global efforts were illustrated to control SARS, the first pandemic of 21st century which depended on a combination of open collaboration and the rapid and accurate communication of surveillance data within and among the countries[10]. The role of effective risk communication, involvement and coordination among the individuals, healthcare providers, policy makers, community, international organizations and stakeholders is vital for prompt response to emergencies at all stages of the risk prioritization, preparedness and planning[22]. The operationalization of One Health framework is essential to avoid fragmented planning and implementation of swift and effective response by mobilizing sufficient resources in appropriate time[23].

## Public health preparedness: An overview

The core realm of global health security is public health preparedness based on the pillars of prevention, early detection and response[24]. The emergence of COVID-19 pandemic has evoked worldwide concerns across the public health administrators to strengthen the preparedness capabilities[25]. These measures can help in the improvement of hazard-specific capacity of the countries through the effective priority setting and mobilization of key resources including information, funds, equipment, drugs and response teams, based on their availability and perceived effectiveness[22,26]. The essential components of public health preparedness comprises of robust surveillance system, risk assessment and management, capacity building and maintenance, intersectoral collaboration and international coordination[27].

The emergency preparedness to address foreseeable public health problems should be enriched with the information from epidemiological models with valid assumptions, quantitative predictions, and policy needs[28]. Modelling and simulations are key resources to tackle the unprecedented emergencies effectively by assisting in decision making upon time-pressured situations to interlink theory, policy and practice[28]. These modelling and simulation exercises need to be combined with participatory surveillance to establish early warning systems for increasing the resilience to combat public health emergencies[29]. The analytical capability of forecasting has been demonstrated in recent outbreaks of influenza, dengue, Zika, and Ebola in assisting management at policy level for the real-time outbreak response[30-36]. Furthermore, the scaling up of organizational public health workforce is essential for instigating a rapid effective response in case of an emergency. The capacity building of the workforce for adequate and rapid intervention and response should be regularly strengthened by regular training, use of modern epidemiological and molecular tools, technical assistance, periodic assessment and feedback, peer networking, and relevant incentives[37]. The outline of various components of public health preparedness has been highlighted in Fig. 1.

The ongoing COVID-19 pandemic has demonstrated that the bridging of not only professional silos but also the use of multi-tech approaches is much essential to generate synergistic effects in combatting global pandemic of such scale[38,39]. To cite, various countries have used modern technologies in the form of data science[40], computational biology[41], medical image processing[42,43], disease tracking[44], prediction models[45,46], and machine learning and artificial intelligence[47] to aid the fight against COVID-19. For examples, the use of software enabled smartphones[48], wrist bands[49] and facial recognition cameras[50] helped in rapid identification of cases, proper source tracking, outbreak forecasting and monitoring of the compliance of quarantine rules. In hospitals, robots for delivery of food and medicines to patients[51] and drones for patrolling and broadcasting awareness messages and site disinfections, were employed[52]. Taiwan, which was applauded globally for its COVID-19 containment efforts, has successfully coupled the information of their national medical insurance database with the immigration and customs database for rapid isolation and tracking of suspected patients[53]. The use of artificial intelligence in rapid diagnosis of the cases (*e.g.*, use of computational tomography scans[43] and radiology images)[42], prediction of the possible disease outcomes among patients by virus-host interaction[41], new drug molecule discovery[54] and development of various suitable vaccine candidates by possible protein structure predictions has been widely employed[55-57].

## Public health surveillance

The public health surveillance is known as the radar of public health, with the two-core objectives of assessing existing disease burden and pattern to guide the control programmes effectively, and early

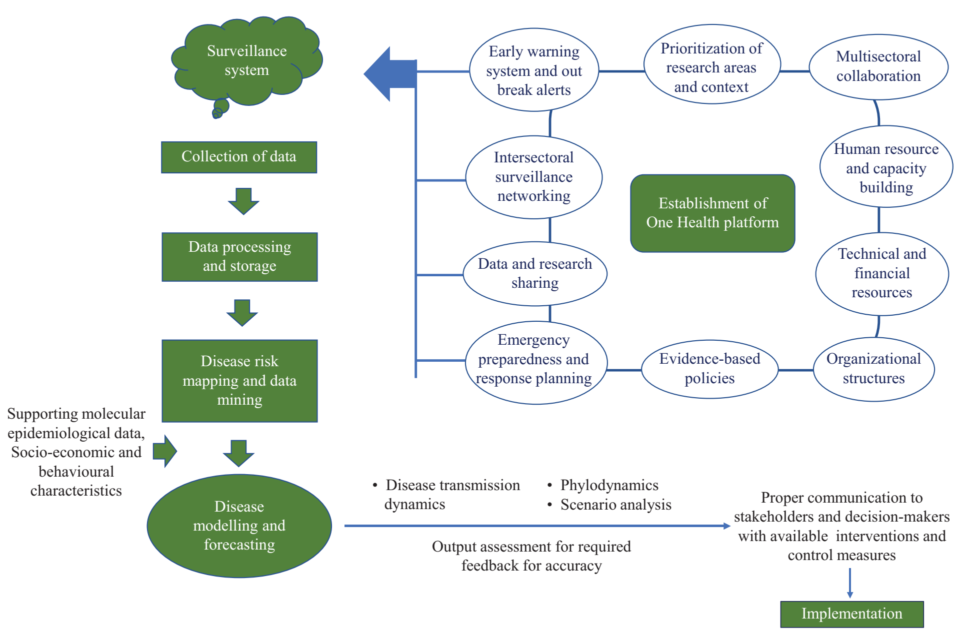


**Fig. 1.** Various components of public health preparedness.

warning and detection of novel pathogens for the rapid instigation of responses[22]. These systems should have adequate sensitivity and feasibility to be vigilant to detect the alerts from various sources, without compromising the specificity of surveillance system[58]. The core steps in the design of any surveillance system are depicted in Figure 2.

The complex scenario in developing countries with numerous drivers of infectious diseases at animal and human interface urges the need to strengthen the existing surveillance systems[59]. The various surveillance systems established for diseases of regional importance need upgradation to tackle numerous emerging infectious diseases[59]. For example, the Food and Agriculture Organization's (FAO) Emergency Prevention System for Transboundary Animal and Plant Pests and Disease (EMPRES) was initially built on the foundation of community surveillance efforts for Rinderpest eradication[60].

Most of the laboratory-based surveillance protocols rely on the conventional culture techniques for identification and isolation of pathogen from the collected samples. These isolates can be further characterized by array of available molecular typing tools, *viz.,* conventional and real-time polymerase chain reaction (PCR); pulsed-field gel electrophoresis (PFGE); amplified fragment length polymorphism (AFLP); random amplification of polymorphic DNA (RAPD); repetitive-element PCR (rep-PCR), variable-number tandem repeat (VNTR) typing; single locus sequence typing (SLST); multi-locus sequence typing (MLST), DNA microarray *etc.*[61]. Moreover, the advent of whole-genome sequencing (WGS) as tool with much higher resolving power than traditional molecular methods, greatly improved the speed and accuracy of epidemiologic investigations[62]. However, implementation of these novel molecular tools to assist conventional laboratory surveillance require proper validation of protocols and trained manpower for their standardized application. The use of molecular tools for the investigation of malaria outbreak included the demonstration of zoonotic transmission of *Plasmodium simium* in people of the Atlantic Forest in Rio de Janeiro by sequencing of the parasite mitochondrial genome[63]. The importance of molecular surveillance to prevent the foodborne outbreaks has been highlighted by the researchers, where the use of forensic microbiology

**Stakeholders**
- Selection and participation of relevant stakeholders (*eg*., for any zoonotic outbreak: Public health officials, Veterinary professionals, Epidemiologists, Ecologists, *etc*.)

**Surveillance objectives**
- To minimize public health and socio-economics impact due to the infectious disease(s)
- Early detection of new and emerging cases
- To confirm the absence of specific disease(s) in a country or region
- Estimation of prevalence and disease trends in endemic regions
- Monitoring of outcome of disease control programme and their prioritization

**Surveillance protocols**
- Description of the health event
- Case definition (suspected, confirmed, *etc*.)
- Description of type of surveillance (active/passive, targeted/scanning *etc*.)
- Data transmission: Methods and means (reports, forms, samples *etc*.)
- Data analysis
- Data processing and returning the results to field officers and relevant stakeholders
- Time span of the protocol (continuous or limited surveillance)

**Data collection**
- **Sources of data**
- Compulsory notification
- Voluntary notification: Public awareness and motivation are essential
- Laboratory reports: Regional or national laboratories provide essential information
- Outbreak investigations
- Structured surveys: It involves selection of a sample of the target population for surveillance, looking for the health event of interest.
- Sentinel surveillance: Certain groups or areas (sentinel units) are recruited to collect information because these are at higher risk of the health event.
- Participatory and rapid appraisals: In marginalized areas of developing countries, with poor infrastructure, alternative resources of data collection must be developed using qualitative data collection, face-to-face interviews, and so on.

**Data analysis and interpretation**
- Information flow and information systems (*eg*., Geographical information system)

**Data dissemination**
- Transparent flow of information to the stakeholders

**Organization**
- Management, legal framework, training and funding

**Fig. 2.** Core steps in the design of surveillance system.

based on the WGS of *Listeria monocytogenes* isolates successfully traced the source of the invasive listeriosis outbreak occurred during 2012-2016 in southern Germany[64].

The early detection of the outbreaks allows the public health professionals a window period for coordinating efforts to contain the spread of outbreak and prevent it locally. The early warning and response systems rely on the epidemic intelligence gathered from sentinel and event-based surveillance data[22]. In sentinel surveillance programmes, the monitoring of at-risk population can generate the outbreak alerts, for example, entry screening of passengers at airport for H1N1[65], receiving data on influenza like illness from selected healthcare centres[66], or designated sentinel sites to monitor the HIV outbreaks among high-risk groups in epidemic areas (*e.g*., drug users, sex workers, long-distance truck drivers and clinic attendees of sexually transmitted diseases)[67]. The population based epidemiological tools such as wastewater-based surveillance approaches have been used as an early warning signal in the tracking of infectious agents at the community level, such as, adenoviruses[68], hepatitis A[69], rotavirus[70], poliovirus[71] and also for the presence of SARS-CoV-2[72,73].

In addition, the application of zoonotic surveillance for predicting human risk has been highlighted during animal-sentinel approaches which drew the association between crow mortality and mosquito abundance and emergence of West Nile virus among human population[74]. The identification of potential reservoir hosts and their longitudinal surveillance for the detection of pathogen shedding and related ecological interactions are essential for early prediction of spillover of zoonotic pathogens[75,76].

The effective implementation of public health surveillance requires the breakage of the sectoral silos by adopting a multisectoral and multi-disciplinary approach. The Global Early Warning System (GLEWS) and World Animal Health Information System (WAHIS) are the two important ongoing supranational global surveillance systems where the multi-institutional coordination and collaboration across disciplines remain a cornerstone component to predict, prevent and control the emerging health threats. GLEWS has been devised as an alert mechanism for major animal diseases including zoonoses at human-animal-ecosystems interface. It is a joint collaborative effort of FAO, World Organization for Animal Health (OIE) and WHO to carry out the disease tracking, analysis and joint risk assessment to generate early warning alerts, and essential response to outbreaks[77]. The OIE-WAHIS is a web-based system that collects and processes data to monitor the status of OIE listed diseases and to generate the alert messages by its early warning system on animal diseases in real-time to update the member countries[78]. The risk assessment and modelling are carried out as per the data availability on reported outbreaks, vaccination coverage, livestock movement, land use, wildlife interactions, climatic conditions and surveillance activities carried out by the member countries[77,78]. Thus, the proper standardization of the data and transparent reporting are must for proper dissemination of information to the member countries.

The upgradation of the traditional laboratory based and syndromic surveillance to build hybrid systems with their integration to digital data can improve the speed, sensitivity and specificity of existing surveillance indicators[79]. The use of participatory surveillance approaches for modelling and forecasting of epidemics has strengthened the real-time response in emergency conditions such as pandemic influenza[29]. The heterogeneity of data sets in health sector poses a technical challenge for their integration at various spatial scales. However, the use of novel analytical and modelling tools (*e.g*., multilevel Bayesian statistical approaches) aids in alleviating this challenging issue[80]. The reliability and validation of surveillance systems highlights the importance of the constant evaluation and subsequent improvement of the methodology.

**Disease modelling and forecasting**

The models are considered as simplified representation of complex phenomenon which remain an important decision support tool and an aid to communication[81]. The various uses of epidemiological models include formulation of hypothesis, retrospective analysis from past epidemics, rapid characterization of infectious disease outbreaks, transmission modalities associated with disease outbreaks, contingency planning and facilitating emergency response(s), disease forecasting, resource planning and implementation of public health policy, economic consideration for available intervention tools, and training of public health professionals[21,82-84].

The ongoing COVID-19 pandemic highlighted the applied aspects of epidemiological modelling in terms of disease dynamics[85], projected basic reproduction number (R0)[86], disease control interventions like social distancing, regional or national lockdown, healthcare capacity estimations[87], pharmaceutical distribution and immunisation campaigns[88] and other requirements. In such emergency scenario, the experimental studies would have many inherent limitations such as, time consuming, unethical, impractical, or sometimes impossible.

It should be remembered that biological systems are inherently more difficult to model due to their complexity and variability, thereby the input data are more difficult to collect and analyse[89]. To build a model of disease outbreak, the knowledge of epidemiological parameters of disease is needed so that the relevant components of the model can be put together accurately with correct interactions. Therefore, it is important to match the accuracy of disease modelling with the dynamics of real-world disease transmission. In the past years, dramatic increase in understanding of multifactorial disease dynamics paved to the development of many relevant models with significant implications *(e.g.*, Ebola epidemic-Liberia and Sierra Leone, 2014-2015[90], COVID-19 pandemics)[91]. For the development of model for global Zika virus spread, the movement of high-risk population for Zika virus, the ecological niche of the mosquito vectors (*i.e.*, *Aedes aegypti* and *Ae. albopictus*) and the data of the environmental temperature profile were used to locate the risk zones[92]. The risk of the COVID-19 spread outside China was statistically modelled using the aviation data integrated with the numbers of confirmed cases at each potential destination[93]. However, comprehensive predictive modelling of infectious diseases remains a challenging due to inadequate access to the data on various factors that affect the disease dynamics. Some of the important inputs for robust predictive modelling of infectious diseases have been presented in the Table[81,82,84,89,94].

**Development and types of epidemiological models**

The important aim of epidemiological models are to provide a systematic, data-driven, transparent, reproducible output, with the ability to describe the uncertainty and key data needed, and comprehensible decision-making framework. The development of epidemiological models remain a complex dynamical system which need coordination of several systems as presented in Fig. 3[94].

The models can be classified into various types; however, the two well-known classifications of epidemiological models are:

1. *Deterministic and stochastic models*: Deterministic models use a pre-determined relationship between the model structure and inputs and the associated outputs, whereas, the stochastic models include the 'effect of chance', thereby, can produce varying outputs according to the calculation of individual probabilities[81,94].
2. *Compartmental (or state-based) and individual-based (agent-based) models:* On the basis of approach to represent the population, compartmental

**Table.** Characteristics and associated parameters for epidemiological disease modelling of infectious diseases

| Characteristics | Associated parameters |
|---|---|
| Agent | Inherent characteristics: virulence, infectivity and pathogenicity<br>Transmission dynamics: within cell and cell-to-cell transmission; within tissue and tissue-to-tissue transmission; host and multi-host level and population level dynamics<br>Molecular characterization: genetic make-up, genotypic resistance, genetic relatedness, *etc*. |
| Host | Age, sex, immunity status, underlying disease conditions, disease carriers, demographic characteristics, population susceptibility and immunity, geographic networks and host movement |
| Environmental | Environmental hygiene, environmental reservoirs, transmission vehicles, temperature and other climate indicators |
| Socio-economic and behavioural | Personal hygiene and sanitation, cultural/religious practices, prevalence-elastic behaviour |
| Disease related parameters | Latent period, incubation period, infectious period, non-symptomatic cases, chronic cases, possible co-infection dynamics and synergism, deliberate epidemics as in case of bioterrorism |
| Disease surveillance data (if prior outbreaks occurred from same/similar agent) | Transmission dynamics and pathways, sensitivity and specificity of available diagnostic (s), data collection methodology, consideration of previous under reporting, interactions of multiple risk factors, followed medical countermeasures, availability of regional, national and global health resources and infrastructure, availability of novel therapies and interventions, and possible synergistic effects of the interventions |

*Source*: Refs 81, 82, 84, 89, 94

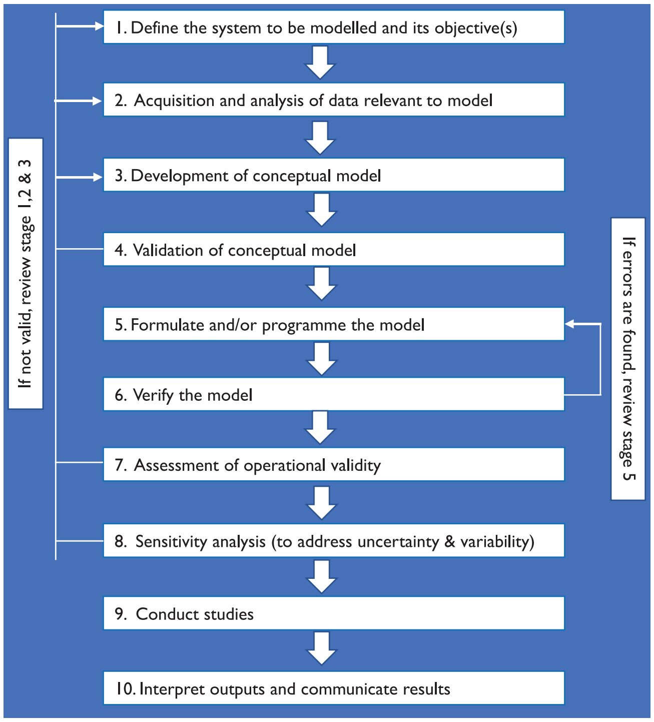


**Fig. 3.** Different stages of epidemiological model development.

(or state-based) models group individuals into states on the basis of characteristics relevant to the infectious disease processes. *e.g.*, the popular SIR (susceptible–infected–recovered) model[95] and its variants. These are quick to form and works best when risk factors of infection are uniform in the population. Whereas the individual-based (agent-based) models explicitly represent the differentiation in biology or behaviour of individuals. Being stochastic, these offer more value when individual heterogeneity in transmission and structure of intervention is important[89].

The British statistician George E. P. Box stated that "All models are wrong, but some models are useful"[96]. The continuous refinement of models to optimally respond to natural outbreaks is important. The realism in the model can be improved by incorporating the treatment of space (*e.g.*, spatial distribution, population contact structure and contact rates) and the effect of available health related infrastructure. It should be remembered that the impact of behavioural factors in a population could have effect on disease dynamics, thus can produce different results from homogeneously mixing populations[97]. Other major inherent characteristic of models is that the accuracy of the models can be improved only by proper assessment of the real-world data after the outbreak[98].

For the infectious diseases, where the quality data is available, but the epidemiological knowledge is lacking, analytical modelling, such as regression of various types can be applied to assess the risk factors. Later, with appropriate epidemiological knowledge, these risk factors can be included in simulation models.

Many times, due to incomplete assumptions and inaccuracies in data assessments, the practicality of disease models have been questioned due to overestimation or underestimation of progression of disease outbreak[99]. In a recent systematic review on the use of prediction models for diagnosis and prognosis of COVID-19, the authors concluded that the prediction models are getting way to the medical literature to support the decision-making process. However, the majority of the models are poorly reported and pose high risk of bias in delivering the information. In addition, the promising models need to be validated appropriately in multiple cohorts through proper data sharing with collaborative efforts to assess their stability and heterogeneity across the various populations settings[46].

One of the other limitations of the epidemiological models include multiple interpretation by different stakeholders resulting in the loss of core essence of the conveyed information from the initial model. Sometimes, especially in developing countries, the intervention measures derived from models lacks ground reality in terms of implementation capacity, quarantine limits, availability of logistics, timing, compliance, or extent of completion. Moreover, the lack of required technical skill and the knowledge-practice gap restrict their use by the stakeholders in these regions[100]. It must be noted that regular examination and frequent model validation is required[21], especially in consideration of currently available diagnostics, therapeutics, and other interventions. The generation of participatory approaches in the preparation of policy-oriented models aid in increased incorporation of local knowledge to effectively address the associated environmental and socio-economic implications of infectious diseases[101].

## Capacity building

The early detection of the pathogen in the 2018 Nipah outbreak in Kerala, India, within a quick time span of 12 hours, due to the presence of trained manpower and the use of advanced genomic tools such as next generation sequencing (NGS), aided in the prompt response and deployment of the multidisciplinary team for the containment of the outbreak[102]. The detection of such novel pathogens requires well-equipped laboratory networks integrated with robust surveillance system, community participation and knowledge of the socio-economic and environmental factors[103].

The standardization of laboratory protocols and their accreditation through periodic assessment assures the accuracy and reliability of the results[104]. The reference diagnostic frameworks need to be routinely upgraded to equip with latest diagnostic facilities at national, regional, or global levels. The success of the 'Diagnostic and Laboratory Systems Program (DLSP)' in Kenya in early detection of infectious disease outbreaks has exemplified the necessity of capacity building of the diagnostic framework and trained manpower[105].

The measures for public health preparedness also focus on preparing the public health taskforce with well-defined roles and responsibilities by developing competent training resources, enhancing communications, establishing and sustaining response systems, and providing evaluation parameters for effectiveness and efficiency[106]. The global public health agencies such as the Centers for Disease Control and Prevention (CDC) have initiated Preparedness and Emergency Response Research Centers (PERRCs) as well as Preparedness and Emergency Response Learning Centers (PERLCs) across the United States to aid in developing such a public health workforce[106]. The deployment of such trained taskforce in the frontline of emergencies enhances capacity for a timely response to turn aside the global threat. The field epidemiology training programmes exists in many countries to train resource persons and thereby efficiently improving core capacities in the human and animal health sectors[107]. The tripartite collaboration between FAO, OIE and WHO exhibits a long-lasting strong advocacy for effective multisectoral, multidisciplinary, and transnational collaboration at various levels. The recently published tripartite zoonoses guide provides operational guidance and tool to implement One Health approach at human-animal-environment interface to address emerging zoonoses[108].

## Conclusion

The advancement in medical education and public health infrastructure coupled with technological development helped in reducing the morbidity and mortality due to infectious diseases in 20th century. These changes were appreciated in terms of increase in life expectancy and shifting of major mortality cause from infectious to chronic degenerative diseases[109]. However, the recent emergence of public health threats in the globalized world of the 21st century increases the vulnerability of the nations across the world, further demanding the expansion of the present capacity for emergency preparedness and prevention by establishing better early warning systems. A robust surveillance system with the capacity of rapid reporting of newly diagnosed threats; publicising best practices to public health workers, epidemiological disease modelling enabled interventions, simulating transmission dynamics and enhanced forecasting is crucial to mitigate the upcoming emerging public health threats. The multisectoral cooperation and coordination across all the stakeholders under the umbrella of One Health is essential to mount rapid and swift response to the public health challenges.

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