Towards a Unified Pandemic Management Architecture: Survey, Challenges, and Future Directions

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The pandemic caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) has impacted the economy, health, and society. Emerging strains are making pandemic management challenging. There is an urge to collect epidemiological, clinical, and physiological data to make an informed decision on mitigation. Advances in the Internet of Things (IoT) and edge computing provide solutions for pandemic management through data collection and intelligent computation. While existing data-driven architectures operate on specific application domains and attempt to automate decision-making, they do not capture the multifaceted interaction among computational models, communication infrastructure, and data. In this article, we survey the existing approaches for pandemic management, including data repositories and contact-tracing applications. We envision a unified pandemic management architecture that leverages the IoT and edge computing paradigms to automate recommendations on vaccine distribution, dynamic lockdown, mobility scheduling, and pandemic trend prediction. We elucidate the data flow among the layers, namely, cloud, edge, and end device layers. Moreover, we address the privacy implications, threats, regulations, and solutions that may be adapted to optimize the utility of health data with security guarantees. The article ends with a discussion of the limitations of the architecture and research directions to enhance its practicality.

CCS Concepts: • Computer systems organization → n-tier architectures;

Additional Key Words and Phrases: Pandemic management, IoT, optimization, machine learning, privacy

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1 INTRODUCTION

Coronavirus disease 2019 (COVID-19) is an infectious disease that has had major health, economic, and social impact on the world. It has cumulatively infected over 750 million people and claimed over 6.9 million lives globally [1]. The manifestation of COVID-19 ranges from asymptomatic/mild symptoms to severe respiratory illness, hospitalization, and death, while the survivors are afflicted with several long-term effects [2]. The efficacy of vaccines is challenged by the rapid and unabated emergence of new strains varying in virulence and transmissibility [3, 4]. COVID-19 is expected to acquire an endemic status over time while causing intermittent outbreaks. Hence, it is imperative to design policies around clinical management strategies, rehabilitation, and human behavior [5–7].

The proliferation of digital technology has resulted in the generation of volumes of pandemic-related data made available in public repositories. These clinical, epidemiological, physiological, socioeconomic, genomic, and so on. Data not only disseminate information on the latest developments but have opened up a new vista of computational research on COVID-19 [8–11]. The goal of this research is to create management plans to combat epidemic outbreaks by optimizing the allocation of human and material resources such as manufacturing production, human labor, transportation, and so on [12]. It identifies the limitations in the existing technological deployments and ways to make them more practicable [13]. These computational frameworks propose the application of a wide array of methodologies such as artificial intelligence, machine learning, deep learning, optimization, statistics, network science, epidemiology, bioinformatics, and so on to meet two primary goals [11].

(1) They inform the researchers, policymakers, and general public of the spatiotemporal and behavioral trends that are associated with the onset of severe outbreaks [14].

(2) They recommend the decisions that will contribute towards curbing contagion [15].

For example, these models may prescribe resource (e.g., vaccine) allocation based on socioeconomic and demographic factors, human mobility, effective duration, or timing of lockdowns [16].

The advent of the Internet of Things (IoT) has revolutionized the field of healthcare. We have seen a barrage of healthcare solutions that rely on the mobility, clinical, physiological, and epidemiological data generated by the IoT devices [17]. Moreover, the abundance of IoT devices and the data generated therefrom creates a problem of plenty, necessitating a comprehensive pandemic management architecture for intelligent decision-making. It is necessary to provide a blueprint for (1) communication technologies for the collection of data from personalized devices as well as data repositories, (2) data offloading from the user equipment to compute/storage infrastructures, and (3) the use of computational models for data analysis to enable decision-making [18].

We are witnessing nascent efforts to design data-driven architectures that automate decision-making related to pandemic management. With regard to healthcare, they propose (1) smart aggregation of clinical big data collected from wearables and implantable IoT devices, automation of patient monitoring, and emergency care facility, and (2) technology-driven policy enforcement through industry-academia collaboration (as we have discussed in Section 4.1 dedicated to existing pandemic management architectures). However, these architectures work on specific application domains, whereas pandemic management is realizable only when healthcare, policymaking, and communication technologies work in tandem and not in silos. To this end, we attempt to answer key questions pertaining to the gap in existing works on (1) the relevant communication framework and the interaction among cloud, fog, and edge devices; (2) the kind of data they generate, store, and manage; (3) the computational models for real-time decision-making; and (4) the potential security and privacy challenges of managing personalized and heterogeneous clinical data.
In this article, we present an architecture that leverages the capabilities inherent in existing IoT and edge computing frameworks to achieve pandemic management. It will gather sensory physiological, clinical, and epidemiological data from the general public, harness computational approaches to process ground and historical data, and send periodic recommendations to civic authorities and participating users. The pandemic management architecture operates on three levels, namely, individuals possessing smart (or IoT) devices infused with data analytic capabilities, a cloud layer comprising servers enabled with high data storage and processing power, and an intermediate edge layer offering on-demand computation, communication, and caching services to applications running on IoT devices (Figure 1). Hence, the requests from IoT devices are not directly sent to the back-end cloud but are offloaded to intermediate edge nodes that are at the edge of the users’ networks, resulting in improved latency and better bandwidth utilization for the rest of the Internet.

We discuss the studies on the online data repositories and mobile contact-tracing applications and the representative pandemic management tasks, namely, vaccine distribution, dynamic lockdown, contact tracing, and pandemic prediction (see Section 3). Next, we cover existing architectures for pandemic management (see Section 4.1), before delving into the details of the proposed architecture (Section 4.2). Specifically, we cover the three layers of the architecture, followed by how the edge computation layer pulls time-series data from cloud-hosted repositories and mobile devices, runs them through the computational models, and recommends human actions regarding vaccines, social distancing, lockdowns, and so on. We explore the privacy concerns of sharing confidential data and strategies to achieve data utility and necessary data anonymity (see Section 4.4). Finally, we highlight the shortcomings of the framework that hinder practical implementation and motivate future research directions (see Section 5). The keywords and their abbreviations are summarized in Table 1.

2 PRELIMINARIES

2.1 Vaccine Distribution

The vaccines are housed in the warehouses and transferred to the vaccination sites of the zones (see Figure 2(a)). (The warehouses can have their own sites as well.) The vaccine recipients from the neighborhood visit the sites to get inoculated [19].
Table 1. List of Abbreviations

| Term                                                                 | Abbreviation          |
|----------------------------------------------------------------------|-----------------------|
| Severe Acute Respiratory Syndrome Coronavirus 2                      | SARS-CoV-2            |
| Coronavirus disease 2019                                             | COVID-19              |
| Autoregressive Integrated Moving Average,                            | ARIMA                 |
| Attribute-based Access Control                                       | ABAC                  |
| Contagion Potential                                                  | CP                    |
| Differential Privacy                                                 | DP                    |
| Federated Learning                                                  | FL                    |
| Graph Attention Network                                             | GAT                   |
| Giant Connected Component                                           | GCC                   |
| General Data Protection Regulation                                   | GDPR                  |
| Global Positioning System                                           | GPS                   |
| Grant Recurrent Network                                             | GRU                   |
| Health Insurance Portability and Accountability Act                  | HIPAA                 |
| Intensive Care Unit                                                 | ICU                   |
| Internet of Things                                                  | IoT                   |
| Internet Protocol                                                   | IP                    |
| Internet Service Protocol                                           | ISP                   |
| Local Area Network                                                  | LAN                   |
| Long-Term Evolution                                                 | LTE                   |
| Multi-access edge computing                                         | MEC                   |
| Machine Learning as a Service                                       | MLaaS                 |
| Oblivious Transfer                                                  | OT                    |
| Organization-based Access Control                                    | OrBAC                 |
| Private Information Retrieval                                       | PIR                   |
| Radio Access Network                                                | RAN                   |
| Role-based Access Control                                           | RBAC                  |
| Radio Network Controller                                            | RNC                   |
| Received Signal Strength Indicator                                   | RSSI                  |
| Susceptible-Exposed-Infected-Recovered                               | SEIR                  |
| Susceptible-Exposed-Infected-Recovered-Death                         | SEIRD                 |
| Single Instruction Multiple Data                                     | SIMD                  |
| Susceptible-Infected-Recovered                                       | SIR                   |
| Spatiotemporal Attention Network                                    | STAN                  |
| User Equipment                                                       | UE                    |

2.2 Epidemic Model

The susceptible-exposed-infected-recovered-death (SEIRD) epidemic model is applied to the mathematical modeling of infectious diseases [20]. The susceptible (S) class comprises individuals who are not exposed to the infection. Once exposed to infected individuals, they may transfer to the exposed (E) category with a rate $\beta$. The E class comprises asymptomatic or untested individuals, who transition to the (tested) infected (I) class with probability $\sigma$. The individuals in I transition to another state with a probability $\gamma$; this other state can be either recovered (R) or dead (D) with probabilities $1 - \alpha$ and $\alpha$, respectively, as shown below. Note that $\beta = \gamma \times R_0$, where $R_0$ is the basic reproduction number (defined as the number of new infections a single infectious individual
Fig. 2. Vaccine distribution and contact tracing; (a) warehouse, zones, and neighborhood; and (b) message exchanges between server and mobile devices in the centralized and distributed mobile contact tracing apps.

creates in a susceptible population [21] that has a median value of 3 but can be equal to 5.7 or even more as per previous literature [22, 23]. Thus, unlike, \((\gamma, \rho, \alpha), \beta\) is not a transition probability.

\[
S \xrightarrow{\beta} E, \\
E \xrightarrow{\sigma} I, \\
I \xrightarrow{\gamma \times (1-\alpha)} R, \\
I \xrightarrow{\gamma \times \alpha} D. 
\]

2.3 Graph Theory

A graph is an ordered pair \(G = (V, E)\) where \(V\) is a finite, non-empty set of objects called vertices (or nodes); and \(E\) is a (possibly empty) set of 2-subsets of \(V\), called edges [24]. A directed graph is a graph in which edges have directions. A directed edge \((u, v) \in E\), allows unidirectional information flow from vertex \(u\) to \(v\) and not necessarily from \(v\) to \(u\). In a weighted graph, \((u, v) \in E\) is associated with a weight \(w_{u,v} \in [0, 1]\), measuring the strength of influence of \(u\) on \(v\).

2.4 Components of Wireless Communication Architecture

The major components in our envisioned pandemic management architecture are as follows:

1. **Core network**: It specifies the backbone network for the Internet, which interconnects geographically dispersed computer networks and constitutes several core routers. The core routers are owned by cellular companies and are managed by regional and national Internet Service Providers (ISPs). Each router has multiple high-speed interfaces for faster exchange of Internet Protocol (IP) packets among communicating networks and supports many protocols.

2. **Cloud servers**: They are high-performance computing clusters hosted in a remote network and managed by infrastructure service providers. The servers handle application requests from the end device users and cater to thousands of user requests simultaneously, they have significant capacities of computation, storage, and network bandwidths. Each cloud server can host multiple application containers/content servers that handle requests in parallel and store volumes of time-series data obtained from/by APIs managed by external data sources.
Radio Access Network (RAN): A radio access network (RAN) is a part of the mobile telecommunication system, and it provides a predefined range of frequencies (frequency spectrum) for enabling wireless communication between mobile phones or any wirelessly controlled machines (laptops, tablets, wearables, and so on) with the mobile core network [25]. With the accustomed support of mobile Internet using RAN long-term evolution (LTE), 4G/5G now has the edge over other wireless mobile telecommunication technologies providing the best user experience. RAN covers a wide geographical area divided into cells, and each cell is integrated with its base station. Each base station has a radio network controller (RNC) that carries out mobile management functions and supports a high data transfer rate [25].

Users’ Equipment (UE): Users’ equipment consists of mobile, handheld devices such as smartphones, laptops, and wearables. They are equipped with multiple sensors and are invoked by mobile applications for collecting heterogeneous data. These devices are intelligent as they can receive feedback from applications and perform actuation to adapt to varying physiological conditions. Users can use their UEs to participate in data acquisition tasks by sharing personal or environmental data. Such devices communicate with remote content and compute servers using Wi-Fi, LTE/4G/5G technologies, and can communicate with peer devices using short-range protocols such as BLE/Bluetooth, ZigBee, and Wi-Fi direct protocols.

Multi-access edge computing (MEC) servers: MEC constitutes geo-distributed servers with built-in IT services [26]. These servers have fair amounts of computing, storage, and communication bandwidth. MEC servers may be deployed at a fixed location, such as at an LTE base station or a multi-technology (3G/LTE) cell aggregation site [27] and offer cloud computing capabilities within the RAN by pushing cloud resources to the mobile edge, enabling mobile applications to offload requests to the MEC servers rather than sending them to the content servers in the cloud. Such offloading helps to fulfill the QoS requirements of resource-intensive, delay-sensitive, and high-bandwidth applications on end devices.

3 COMPUTATIONAL PANDEMIC MANAGEMENT FRAMEWORKS

We survey online repositories, contact-tracing apps., and frameworks for COVID-19 management.

3.1 Online Repositories

We discuss databases that are periodically updated with emerging information on COVID-19.

3.1.1 Publication Repositories. These repositories shortlist the global scientific publications specific to COVID-19. The standard repositories include WHO COVID publication repository [28], NIST COVID-19 repository [29], CDEI COVID-19 repository and public attitudes retrospective [30], and the Elsevier Coronavirus Research Repository [31].

3.1.2 General Data Repositories. These repositories, such as NIH Open-Access Data and Computational Resources [32], Google Health COVID-19 Open Data Repository [33], iReceptor Repository [34], Stanford Research Repository [35], Humdata [36], and so on, house the genomic, biomedical, clinical, sensor and behavioral data collected on COVID-19.

3.1.3 Epidemiological Information Repositories. These databases record and visualize daily infected cases, deaths, and so on, in the US and the world. Some examples include Johns Hopkins COVID resource center [37], Our World in Data [38], and CDC COVID Tracker [39], and so on.

3.1.4 Resource Repository. These repositories help organize resources necessary for pandemic management. For example, Faith and COVID-19: Resource Repository [40] offers a web platform that allows people to participate in COVID-19 response, WASH Resources [41] offers intellectual
resources to the staff and practitioners of Water Sanitation and Hygiene, Sages COVID-19 Medical Device Repository [42] offers information on a medical toolkit for treatment of COVID-19, and COVID-19 Toolkit: Federal Depository Library Program [43] provides information on library closures, virtual work environments, and virtual service environments.

3.2 Mobile Contact Tracing Applications

Let us briefly discuss the two design architectures of contact tracing applications [44] (see Figure 2(b)).

3.2.1 Centralized Architectures. These applications, like Singapore’s TraceTogether [45] and China’s Health Code [46], rely on the centralized back-end server to process the contact tracing information. The server carries out the authentication, risk analysis as well as user notification. We outline the four salient processes in centralized architecture-based apps (marked red in Figure 2(b)).

(1) The user registers their device with the server. User identity is authenticated by exchanging a one-time password.
(2) The user app exchanges Bluetooth encounter messages with peers. The timestamp and the Received Signal Strength Indicator (RSSI) are locally recorded.
(3) If a user has tested positive and has volunteered to share their medical status, the location information as well as the list of recent encounters, are offloaded to the server.
(4) The server estimates the risk of exposure of the peers who came in contact with the infected person. The assessment is based on RSSI and transmission power. Subsequently, the likely exposed individuals are notified and prompted to isolate and get tested.

3.2.2 Distributed Architectures. These architectures, like Google-Apple contact tracing apps [47], do away with the dependency on the server, by performing computational tasks on the user end. We discuss the key steps in distributed architecture-based applications (marked green in Figure 2(b)).

(1) The devices do not register with the server nodes. They periodically exchange short messages, comprising pseudo-random key and current time, with their peers.
(2) If someone has tested positive, (s)he voluntarily uploads these messages (and not all recent encounters) to the server.
(3) The server advertises the message from the infected user to all mobile users.
(4) Users accessing the advertising messages do risk analysis locally based on proximity and duration of exposure.

3.3 Vaccine distribution strategies

These approaches address (1) equity and fairness and (2) epidemiological goals, such as minimization of infection, hospitalization, and mortality in the course of vaccine allocation. Emanuel et al. discussed the three fundamental values of vaccine distribution, namely, maximizing people and limiting harm, prioritizing the disadvantaged, and equal moral concern [48, 49].

3.3.1 Optimization Formulation. The standard approach to designing vaccine distribution solutions is to model it as an optimization with constraints on the supply. Roy et al. designed a generalizable, multi-vaccine distribution measure that allocates vaccines based on the socio-economic, epidemiological, and demographic profiles of zones [19, 50]. In this approach, there is a matrix of decision variables $x_{w,b}^v \in X$ (where $x \in [0, 1]$) that represents the fraction of vaccines of type $v$ transported from the warehouse $w$ to zone $b$. Optimization allocates $|Z|$ vaccines among $b \in B$ zones while minimizing the cost, denoted by $d(w, b)$, between the warehouse $w$ and zone $b$. 
Number of vaccinations. The formulation allows the optimizer to distribute $|Z|$ vaccines, where inequality is replaced by equality in Constraint 1 (C1, Ineq. 6). It preserves the inequality sign ($\leq$) if the goal is to minimize the number of distributed vaccines while meeting the following goals.

Fairness based on demography and epidemiology. The optimizer allocates vaccines based on the susceptible, infected, or population density, modulating the value of $c$ in Constraint 2 (C2, Ineq. 7).

1. Susceptible. Vaccines are allocated to zones based on the proportion of the remaining susceptible population (after $r_v \times \sum_{w} X_{w,b}^v$ have acquired immunity).

   \[ c = \frac{S_b - \sum_{v \in V} r_v \times \sum_{w} X_{w,b}^v}{\sum_{b \in B} S_b} \]  

   (9)

2. Population Density. Vaccines are assigned based on the population density of a zone $b \in B$.

   \[ c = c \times \delta_b \]  

   (10)

   In the above equation, $\delta_b = \frac{D_b - \mu(D)}{\sum_{b \in B} D_b}$, where $D_b$ is the population density of zone $b$.

3. Infected. Vaccines are allocated based on the ratio of the infected population for a zone $b \in B$.

   \[ c = c \times \iota_b \]  

   (11)

   Here $\iota_b = \frac{\rho_b - \mu(\rho)}{\sum_{b \in B} \rho_b}$, where $\rho_b$ is the infected ratio of zone $b$ given by $\frac{I_b}{S_b}$.

Here, $\delta_b$ and $\iota_b$ denote the scaled population density and infected proportions for a zone $b$. If $\delta_b$ (or $\iota_b$) is greater than 1, its population density $D_b$ exceeds mean density $\mu(D)$, and vice versa. Summing over all $\delta_b$ (or $\iota_b$), i.e., $\sum_b \delta_b = \sum_b \frac{D_b - \mu(D)}{\sum_{b \in B} D_b} = \sum_b \frac{D_b}{\sum_{b \in B} D_b} - \sum_b \frac{\mu(D)}{\sum_{b \in B} D_b} = 1 - 1 = 0$. They consider a tradeoff parameter $\tau \in [0, 1]$ balancing the economics vs. demographic or epidemiological factors. Specifically, a high $\tau$ distributes vaccines on the basis of the factors discussed under Constraint 2; conversely a low value of $\tau$ causes the optimizer to emphasize economic cost.

There are several works that utilize a similar optimization formulation that distributes vaccines among communities based on their direct and herd immunity and mortality minimization [51, 52]. Bertsimas et al. proposed a model that combines DELPHI epidemiological model with a bilinear, non-convex optimization to minimize exposure, mortality, and distance between vaccination centers and population centers [53]. Shim et al. learn the parameters of the age-structured model of COVID-19 spread in South Korea to design vaccine deployment policies such that infections and deaths could be mitigated, given the parameters of age distribution and social contact [54], while Meehan et al. [55] and Buckner et al. [56] use the age-structured model and epidemiological model, respectively, to suss out high-priority individuals to be vaccinated based on their contact rates and risk of infection.
Fig. 3. SEIR model proposed by Roux et al. [61], where \( S, E, I_p, A, I_h, I_{nh} \), and \( R \) represent susceptible, exposed, pre-infected, asymptomatic, symptomatic infected, hospitalized, non-hospitalized and recovered, respectively.

3.3.2 Measures for Vaccine Distribution. Jadidi proposed using Bluetooth on mobile devices to create a social graph to identify well-connected individuals to be vaccinated to achieve herd immunity [51]. These individuals, \( u \), in a social graph have a high connectivity centrality measured as:

\[
C_{con}(u) = \sum_v c(u, v).
\]  (12)

Given the weight of the social tie between individuals \( u \) and \( v \), \( w(u, v) \) measuring the likelihood of disease transmissibility based on the duration and frequency of contacts, the distance, and their locations; and the number of simple paths between nodes \( u \) and \( v \), \( h(u, v) \), we get \( c(u, v) = \frac{w(u, v)}{h(u, v)} \).

Xu et al. presented a vaccination coverage metric that determines the percentage of vaccinated individuals [57]. The proposed metric improves upon the transportation accessibility and demographics constraints of the existing coverage metrics. Different zones are assigned levels \( k = 1, 2, \ldots \) depending on the increasing amount of time needed to reach the vaccination site of the zone from the neighborhood (refer to Section 2.1). The measure for zones in level \( k \) to be covered by site \( i \) is

\[
\alpha_{k}^* = \min(1, \alpha_k + b \times N_i).
\]  (13)

In the above equation, \( \alpha_k \) is the baseline of coverage for level \( k \) zones as per Lim’s study [58], \( N_i \) is the total number of public transportation stops in the vicinity of site \( i \), and \( b \) measures the convenience rendered by adding a stop near a given site \( i \).

3.4 Dynamic lockdown strategies

We discuss the models that prescribe varying levels of lockdown based on the epidemiological and clinical parameters, such as infected cases, mortality, contact rates, healthcare facilities, and so on.

3.4.1 Supervised Models. Tadano et al. employed artificial neural networks (namely, extreme learning machine, echo state network; multilayer perceptron, and radial basis function networks) to predict the effect of lockdown in Sao Paulo City, South America on air pollution levels [59]. Roy et al. propose a dynamic pandemic lockdown strategy that leverages reinforcement learning and queueing models to regulate inter-zone traffic on the basis of hospitalization and healthcare budget [60]. Roux et al. proposed an age-structured Susceptible-Exposed-Infected-Recovered (SEIR) model (see Figure 3 and refer to Section 2.2) to estimate the number of hospitalizations, hospital beds requirements, and hospital deaths that a timely lockdown could have prevented in France [61].

3.4.2 Unsupervised Models. Rahman et al. proposed an unsupervised machine learning-based dynamic lockdown framework. The clustering algorithm identifies dynamic clusters based on the infected cases and mobility data. The clusters are marked for hard, moderate, or no lockdown depending on the number of active or suspected clusters in them [62]. Gollier incorporated the uncertainty of the infection status of an individual into the Susceptible-Infected-Recovered (SIR) epidemic model to infer the economic impact of the lockdown imposed [63].
Pestieau studied how the lockdown strategies, namely uniform lockdowns and age-differentiated lockdowns, align with social welfare criterion, balancing the tradeoff between economy and lives lost [64]. Bosi et al. challenge the notion of indefinite immunity of the recovered (or immunized) individuals [65]. They employ a dynamic equilibrium model to show that a positive lockdown is useful when the society is altruistic (i.e., willing to maximize collective rewards), while zero lockdowns are an optimal lockdown policy if the agents are selfish. Fajgelbaum et al. proposed an optimization to solve the planning problem of determining the traffic flow across districts in two Korean cities that reduce the economic overheads due to uncoordinated lockdown measures and the loss of lives [66]. The social planner optimization formulation works as follows:

\[ W = \max_{x(t)} \int_0^{\infty} e^{-(r+v)t} \sum_j \left[ U(j,t) + \frac{v}{r} \times U(j,t) - \omega \gamma D I(j,t) \right] dt. \]  

(14)

This equation maximizes discounted real net income considering the loss of lives, where \( U(j,t) \) is the real income of location \( j \) at time \( t \) based on the distribution of infected cases and lockdown and \( \tilde{U} \) is the income if the vaccine is freely available with probability \( v \). The variable \( \omega \) represents the expected income of the COVID victims (measured as their expected lifetime times annual income minus the discounted value of wages) and \( I(j,t) \) is the daily infected at location \( j \) at the time \( t \).

### 3.5 Mobility Scheduling

The contact-tracing applications discussed in Section 3.2 already inform human mobility [67]. While they are yet to get traction in the realm of pandemic management, the apps possessing simple user interfaces and visual depictions of infection hotspots are truly the future of pandemic management [68]. These apps are connected to smart mobile devices or embedded in wearables. We discuss the models implemented as mobile applications to recommend human mobility.

Hu et al. used computational approaches to compare the attributes of mobility data sources on the basis of privacy, quality of information, storage, processing, and access [14]. Similarly, Grantz discussed the applicability of mobile apps in the control of contagion as well as the implication of selection bias in mobile phone data [69]. Oliver et al. delve into the shortcomings of data-driven research to overcome them through the involvement of government and domain experts [70]. Based on Global Positioning System (GPS)-based mobility data from US counties, Tokey employed space-time cube, curve-fitting, and regression to study the evolving relationship between mobility and COVID daily infected cases over time with alteration in socioeconomic, demographic, and geographic policies [71]. Basu discussed how increasing dependency on private vehicles and dwindling mass transit ridership is a hindrance to affordable and sustainable urban mobility [72].

Roy et al. leveraged network science to propose three optimization strategies, which will result in social networks that minimize contact between the infected and susceptible individuals [73]. As part of the same goal, they introduced the notion of contagion potential that measures, on a scale of 0 to 1, the likelihood of individuals acting as spreaders of contagion (CP). Instantaneous CP \( (P_t(u)) \) of an individual is measured as the number of infected people (s)he comes in contact with at time \( t \) (see Figure 4). The overall CP till time \( T \) is calculated as the mean instantaneous value CP, as follows:

\[ Z_T(u) = \begin{cases} 
0, & u \in R, D \\
1, & u \in I \\
\frac{1}{T} \sum_{t=0}^{T} P_t(u), & \text{Otherwise.}
\end{cases} \]

They introduced a mobile app, called MyCovid, which includes a case study on optimization strategies and guides the users’ mobility to minimize contagion. With prior user permission, the
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Fig. 4. Evolution of CP over time. Every panel shows the location of nodes at time $t$ ($1 \leq t \leq T$) and the spectrum of colors - dark red, light red, light blue, and dark blue - represent increasing CP of the observed node (large circle) on contact with infected individuals (small circles).

Fig. 5. A 6-node network with $K = 2$, where 2-core and 1-core nodes are marked red and green, respectively.

app creates a repository of mobility traces and enables research on informing mobility during outbreaks.

Serafino et al. explored the GPS traces of mobile devices in Latin America to infer a social contact network, based on the duration of contact and proximity between the infected and susceptible individuals [74]. They employ percolation theory to explain this idea. In bond percolation, the connectivity is reduced by removing a small fraction of links (bonds) in the contact network. Serafino measures network connectivity in terms of the size of the giant connected component (GCC) (calculated as the largest set of nodes such that each node is reachable from every other node). Through network analysis, they depict that the lockdown measures cause a drop in GCC, causing the dense contact network to be reduced to several strongly connected modules.

However, despite the drop in GCC, the number of cases continued to grow, albeit at a slower pace. Serafino used the notion of $K$–core [75] to explain this phenomenon. $K$–core is obtained by iteratively pruning the lowest degree nodes from the network (see Figure 5). The high K-cores possess a high disease transmission persistence. Similarly, Roy et al. also employed machine learning and network science concepts, like coloring and clustering, on daily infected cases in New York City to propose interdiction strategies that mitigate contagion, while meeting economic goals [76].

3.6 Pandemic Trend Prediction and Travel Policy

The current subsection is dedicated to a survey on efforts to make spatiotemporal predictions that determine global pandemic-related travel policy. Gao et al. proposed a spatiotemporal attention network (STAN) approach for pandemic prediction [77]. The proposed framework leverages
Fig. 6. Spatiotemporal prediction architecture [77], which employs GAT and GRU to predict future trends in infection and recovery.

static features (namely, geographic and demographic data of states and counties) and dynamic features (namely, daily infected counts). Figure 6 shows that the framework constructs location graphs with zones as nodes and inter-zone interaction as links for the static and dynamic features.

STAN utilizes a graph attention network (GAT) to learn the spatiotemporal interaction across zones. GAT network employs a multi-head approach to learn attention scores denoting the interaction between any pair of zones (refer to Section 2.3 for a summary on graph theory) and combines the attention scores to infer the embedded representation of the zones. Subsequently, STAN processes the graph embedding with a gated recurrent unit (GRU) – a type of recurrent neural network – to predict epidemiological parameters and infection and recovery counts and update the loss terms.

Pinter et al. introduced a hybrid model that combines a network-based fuzzy inference system and a multi-layered perceptron-imperialist competitive algorithm to predict the infected and death counts in Hungary [78]. Kumar et al. used PROPHET and autoregressive integrated moving average (ARIMA) disease forecasting models to gauge contagion in the US, Spain, Italy, France, Germany, Russia, Iran, United Kingdom, Turkey, and India [79]. Singhal et al. also proposed a mathematical series-based model and Fourier decomposition method to predict contagion trends [80].

Like Kumar, Oguntokun et al. and Alzahrani et al. employed the ARIMA model to evaluate the possibility of air- and water-based transmission of the pathogen and the impact of preventive measures on contagion in India and Saudi Arabia, respectively [81, 82]. Luo discussed the variables influencing time-series prediction models, namely, new strains, human behavior, politics, and so on, and emphasized the need for predictive monitoring to better understand their efficacy [83].

Roy et al. introduce a spatiotemporal network-inference approach that uses a sliding window to scan daily infection numbers. The resultant temporal networks quantify the potential of inter-zone infection spread and help identify zones with a high outflow of link weights as ones acting as disease hotspots [84]. Zhang et al. introduced a minimization formulation that determines the extent of intervention over a period of $J$ days in terms of the population size $N$ [85], measured as

$$\min_{N} \frac{1}{J} \sum_{j=1}^{J} e_j(N).$$

Here, $e_j(N)$ denotes the prediction error in cumulative infection for a given population count $N$.

Mehta et al. implemented a machine learning approach on fused health statistics, demographics, and geographical datasets to gauge the course of the pandemic. They predicted the risk of outbreaks in the US counties on the basis of their urban and vulnerable population demography [86]. Ahmad et al. discussed the role of big data analytics and IoT in designing a neural network-based
Table 2. Classification of Existing Pandemic Management Architectures by Application Domain (City Planning CP; Contagion Mitigation CM; Healthcare Management; and Public Policymaking PP) and Approach

| Approach               | CP             | CM            | Health        | PP             |
|------------------------|----------------|---------------|---------------|----------------|
| IoT/mobile application | [91, 93]       | [90, 94]      | [93, 95, 96]  | [91, 97–99]    |
| AI/ML                  | [93]           | [91, 92, 100, 101] | [93]         |                |
| Big data integration   | [89, 94]       | [102, 103]    |               |                |

health monitoring framework that possesses diagnostic, predictive, and prescriptive capabilities to predict the future of the pandemic [87]. Similarly, Kavadi et al. presented a Nonlinear Global Pandemic Machine Learning model for global pandemic prediction. They applied the model to demographic, clinical, and epidemiological data of Indian states to show its efficacy in pandemic prediction [88].

4 PANDEMIC MANAGEMENT ARCHITECTURE

4.1 Existing Pandemic Management Architectures

These architectures are a means to a coordinated, data-driven, and agile response to pandemics [89]. We discuss (and summarize in Table 2) the existing architectures with the following four focal points: (a) **public policymaking** amalgamates real-time data, such as epidemiological data, hospital capacities, and socioeconomic indicators, to inform decision-making. The policies created therefrom incorporate the evolving nature of the pandemic, identify high-risk areas, and allocate resources effectively; (b) **smart city planning** leverages advanced technologies, such as IoT devices, data analytics, and artificial intelligence, into urban infrastructure. Future cities will enhance their preparedness and response capabilities. Smart sensors will monitor crowd density, air quality, and temperature, enabling early detection of potential outbreaks and facilitating targeted interventions; (c) **contagion mitigation** aims at adaptable strategies to minimize the spread of the virus. This includes measures like contact tracing, testing protocols, and vaccination campaigns. Using advanced AI and analytics techniques, they identify patterns and trends in the spread of the virus, enabling more effective and targeted interventions; and (d) **healthcare management** provides a framework of health records, hospitals, and medical professionals into a cohesive network. These architectures enable the deployment of resources, such as personal protective equipment (PPE), ventilators, and healthcare personnel, based on real-time data on infection rates, hospitalizations, and healthcare capacities. They also facilitate telemedicine and remote monitoring solutions, ensuring access to healthcare services while minimizing the risk of transmission. Below we discuss the literature on existing architectures (summarized in Table 2) in greater detail.

The Smart Cities Mission is a government-led project to promote economic growth and development across four strategic planning pillars: city improvement, city rehabilitation, city extension (Greenfield development), and pan-city development [91]. This study discusses numerous obstacles and constraints in three categories: technical, socioeconomic, and environmental. This article investigates the feasibility of applying technology in an existing city and transforming it into a smart city using the most advanced technologies, as well as smart strategies and automated judgments; the research uses the 10th of Ramadan city as a case study. In addition, the predicted outcome of this article is the implementation of smart city policies as a best practice for the COVID-19 pandemic in Egypt. Finally, it is predicted that more cities would use technology in future policymaking.

Megahed et al. presented one such smart city architecture to automate mitigation and control measures, comprising four levels: (1) **application layer** comprising the smart services, such as
healthcare and industrial management, weather forecasting, surveillance & security, and so on; (2) a data management layer that manages data to be used by the application layer; (3) transmission layer uses wireless technologies, like 3G, 4G, LTE, and so on to transfer the sensed data to the management layer; and (4) sensing layer for data collection by means of the IoT devices. Myriad sources of big data, like social media, immigration, and customs databases, COVID-19 database/healthcare data, mobile data, transportation systems, bank card transactions, security cameras, and GPS, can provide first-hand insights into the direct outcomes of the management efforts. Alfonso P. Ramallo-González et al. presented another IoT framework that helps policymakers and healthcare systems monitor and act over the pandemic. Their framework comprised data collection through sensors and actuators, followed by its storage and fusion (Figure 7). The data is pushed into an AI pipeline for risk analysis and the inference is shared with the stakeholders, i.e., the public and policymakers.

Others have also focused on the role of data management, particularly in healthcare. Sheikhtaheri et al. and Brakefield et al. focused on this aspect while discussing an electronic health record-based COVID-19 surveillance system, whereby hospitals can exchange electronic health records, such as billing summaries, laboratory test results, prescriptions, and diagnoses via router nodes that form a mesh network. Their goal is to integrate data from multiple medical centers to provide near real-time access to COVID-19 data for prompt decision-making. Similarly, Mohammad et al. conceive a smart city that employs cutting-edge technology, automation, and a scientific approach to policymaking to mitigate outbreaks. Mowafi et al. discussed an emergency care system that is activated by the public in the event of a mass emergency, such as an outbreak. Such a system will monitor and provide life-saving healthcare facilities from the scene of injury till they are transported to the emergency care system. Similarly, Awotunde et al. and Aman et al. discussed an Internet of Medical Things framework, comprising wearable and implantable body area network systems, to ensure quality healthcare and patient monitoring.

There have been a few attempts to enable these architectures to implement necessary policy guidelines necessitating the design of more robust frameworks. Huang et al. discussed a data-driven machine learning approach for efficient testing, while Alam et al. presented a technology-driven policy enforcement framework, consisting of five phases: (1) Monitoring and Break-the-Chain assess potential pandemics by monitoring the environment through IoT-based and social media sensing; (2) Cure Development and Treatment that aims at developing vaccines and drugs to curb pandemic spread; (3) Resource Planner plans the provisioning of testing and medical equipment, treatment centers, and human resources; (4) Data Analytics and Decision Making makes use of advanced AI tools to enable decision-making and (5) Data Storage and Management aims at managing and storing big data. There is an increasing focus...
on industry-university partnerships towards modern pandemic management, such as the IBM-Oxford collaboration [99] or the asynchronous digital contact tracing framework proposed by INRIA and other industry partners [97, 98].

4.2 Proposed Architecture Overview

We propose a multi-layer architecture for managing future pandemic situations. Most Federal governments’ systems for the COVID-19 pandemic management are ad-hoc and loosely coupled. These systems lack a proper and coherent ecosystem needed for dynamic decision-making. Our envisioned ecosystem is hierarchically organized into three tiers, and they handshake among themselves by sharing data and computation models. At the lowest layer, sensory data from citizens (such as co-location information, the health status of the individual, and so on) will be gathered and shared dynamically over the network to the middle layer comprising several multi-access edge computing servers. In this layer, a few computation modules will be hosted that feed on the sensory data obtained from the crowd and help in real-time decision-making. As a part of the feedback loop, this layer sends messages to civic authorities and users to take appropriate measures. The middle layer periodically pushes the ground-level sensory data to the top layer comprising cloud servers and storage. The ground data is fused with the historical time-series epidemiological data fed from various other sources, and AI/ML models are executed to predict future outbreaks.

The architecture draws inspiration from the existing implementations of multi-tier architectures by Internet-based video companies like Google, YouTube, Netflix, and others to address the challenges associated with delay, bandwidth inefficiency resulting from redundant content sharing, and the vulnerability of a single point of failure within the conventional client-server architecture. Internet companies employ Content Distribution Networks (CDNs) for disseminating multimedia data to geographically dispersed users [104]. CDNs are an intermediary layer of interconnected servers between the end user and cloud data center layers. Operating a cluster of servers across multiple geographically diverse locations, a CDN stores content duplicates within its servers. It strives to direct each user request to the most suitable CDN location, optimizing the user experience [105]. These CDN server clusters are strategically placed within access networks of Internet Service Providers or at selected key locations, often referred to as Points of Presence (PoP), and are interconnected via a private high-speed network [106]. Next, we highlight that the edge computing layer in this architecture, analogous to the CDN, positions content servers from cloud data centers at the edge of access networks, bridging the gap between the cloud and edge device layers.

A schematic representation of our envisioned architecture is given in Figure 8. It consists of three distinct layers – (1) the cloud layer; (2) the edge computing layer; and (3) the end device layer. We propose using the edge computing paradigm to provide networking support for collecting and sharing data across the different layers. Edge computing aims at introducing an intermediate computing layer between the end device (bottom) and cloud layers (top) so that computing, storage, and communication services can be brought to the edge of the end devices’ network. Another motivation behind using edge computing is to handle the massive scale of the end devices and the digital footprint they create nowadays. Offloading sensory data onto remote servers creates bandwidth bottlenecks in the backhaul networks, increasing delay and performance loss. Thus, if the sensory data are delegated to edge nodes that are near the network edge, bandwidth wastage in backhaul networks can be avoided, and response time, throughput, and latency can be improved. We describe the components of this architecture below.

4.2.1 Core Network. The core network (Internet), managed by several regional ISPs, hosts a plethora of epidemiological, healthcare, and demographic data hosted by Worldometer, CDC-USA, Johns Hopkins CSSE, and Ministries of Health or other Government Institutions and Government
Fig. 8. Pandemic management architecture comprises the cloud, edge computing, and mobile user layers. Authorities’ social media accounts, and so on. Some of the features of such data are – population count, population density, number of cases (infection count), mortality rate, R-factor, number of vaccine doses administered, number of tests performed, the spread of infection in terms of count per ten thousand/hundred thousand/million and so on. Also, healthcare data on the number of hospitals, number of beds in the COVID ward per hospital, availability status of COVID-19-related medicines, and so on, are made available in these data stores of different granularities depending on the macro-level or micro-level views. Most of them are time-series data updated tentatively after every 24 hours.

4.2.2 Cloud Layer. This layer consists of an array of high-performance servers hosted in the cloud capable of handling large data volumes and carrying out massive computation tasks in parallel. The cloud-hosted servers will periodically (maybe once in a few hours) pull data from different
sources and maintain an updated repository. The servers use IPv4/IPv6 routing as the backbone network technology to pull data from the public/paid APIs provided by various sources on the Internet. This data is used by the following four modules (discussed later in Section 4.3) running in these servers:

- **Vaccine allocation**: This module will find optimal vaccine allocation strategies across different zones of geographical space (city, county/district, state, and so on).
- **Dynamic lockdown**: This module is responsible for determining if any zone requires lockdown (partial or complete) based on the healthcare facilities, infection spread, mobility, and so on.
- **Contact tracing and mobility scheduling**: This module finds people who are close to an infected individual. If any zone is found to have many unvaccinated and exposed individuals, then a spatiotemporal schedule can be recommended to curb the movement of large masses.
- **Pandemic prediction**: One or more prediction algorithms will be running to infer the likelihood of an outbreak of the pandemic situation at a particular zone. The algorithm will use healthcare infrastructure data, epidemiological data, and mobility and contact tracing information for making the prediction. Such predictions will enable decision-makers to allocate additional resources to that zone and prevent an unforeseen health crisis owing to the pandemic.

4.2.3 Edge Computing Layer. The edge computing layer consists of a network of MEC servers [107], each co-located with a cellular base station. MEC servers are managed by different mobile network operators and have heterogeneous system resources (CPU, memory, storage, bandwidth). A MEC server uses the RANs of its co-located base station to collect sensory data from citizens of a borough in an urban city. There can be more than one reserve MEC server co-located at a RAN to guarantee the continuity of services in the presence of failures. Therefore, several MEC servers will be deployed in different boroughs to maximize coverage and collect as much human-sensed data as possible from different neighborhoods across the city.

The pandemic management agencies need to roll out the smartphone-based app(s) for the collection of citizens’ data who are in different neighborhoods. We assume this/these app(s) is/are installed by the users on their devices, and necessary permissions are granted for data collection. One of the objectives of the application(s) hosted in MEC is to send alerts to the individuals if they are currently present in a large gathering with a few infected people or if their health status necessitates isolation. For communicating with cloud servers, the MEC servers will use Wi-Fi/WiMax as carrier technologies, while for gathering ground-level public data, wireless technologies will be used.

The MEC servers can provide on-demand computing, cache, and communication services to data collection application(s) running on the user devices. The server instances for these applications run on the MEC servers. They collect information on vaccination status and epidemiological condition (i.e., susceptible, infected, or recovered) from individual users and location (waypoint) information from the devices. The periodic waypoint information enables the server to trace out the mobility of the users and also the places they are making visits. The past application data collected from the users are pushed to the back-end cloud servers periodically. This is useful when mobile users migrate to a new neighborhood beyond the control of their current MEC. The architecture handles this handoff by allowing the new MEC to download the pertinent information of that user.

The instances of three modules (viz., vaccine allocation, dynamic lockdown, and contact tracing and mobility scheduling) running on the cloud servers will also be hosted in the MEC servers to enable decision-making at the edge of the users’ networks. These modules are real-time
decision-making engines. They are concerned with borough-level local issues, and they must be hosted at the edge of the users’ network to minimize network delay and save network bandwidth. On the contrary, the pandemic trend prediction module operates in offline mode to predict outbreaks which enables the federal bodies to plan for contingency measures and design various policies. Thus, to ensure higher prediction accuracy, this module will run on centralized cloud servers where the AI/ML models and a large volume of data are co-located.

The computation modules hosted in MECs will leverage the sensory data collected from the public and fuse them with the historical ones (pulled from the back-end cloud storage) to develop recommendation(s) for the stakeholders (civic authorities, healthcare specialists, caregivers, public). However, if any MEC server is overloaded or unequipped with computational resources, the computation of the modules will be offloaded to the cloud. If any MEC server encounters a failure, then the **High Availability (HA)** service will ensure that the pandemic management architecture does not go for an outage but recovers from the faulty condition within a prespecified delay bound. Below we discuss high-availability services in the context of the proposed architecture.

**High Availability (HA):** Complex enterprise applications that are essential cannot tolerate a prolonged fail-over period. To prevent such an adverse situation, these applications typically use a **HA manager** deployed on top of the **High Availability Cluster (HAC)** to provide secure service guarantees with minimal downtime [108]. In the context of pandemic management architecture, the three computational modules, as well as the mobile application for collecting crowd-sourced data, are critical, and they cannot be at fault for an arbitrary length of time. Thus, the **HA manager** should be available with the MEC servers to provide near-uninterrupted services.

The **HA manager** performs two major tasks to ensure high availability for the modules and applications under the pandemic management. First, it continuously monitors the layers of the modules, such as the compute/application server, application core, database, operating system, virtual machines, network, storage, and so on, in order to identify and resolve faults before they lead to errors and errors before they trigger failures [108]. The second task for the **HA manager** is triggered if, despite monitoring, a fault occurs at any application component. The **HA manager**’s objective is to offer continued operation of the application layer, despite a failure. To this end, it identifies the critical components of the modules across the layers. Then, they are replicated in multiple **HAC nodes** that are connected via the backbone network but are geographically apart.

In the context of the proposed architecture, the multiple MEC servers across the different boroughs can serve as **HAC nodes** and maintain the redundant deployments of critical components of the computational modules and the sensory data collection app(s). For any radio access network (RAN), if multiple MEC servers are present, one of them acts as the primary node and others are the secondary. Thus, if one of the layers at the primary MEC node is at fault, the **HA manager** can activate the corresponding layer at a secondary MEC and ensure the service sustenance. There may be some delay during the hand-off, but it removes single-point failures and prolonged outages.

#### 4.2.4 End Device Layer

The end device layer comprises hundreds of intelligent hand-held IoT devices possessed by citizens moving around an urban area. We collectively refer to them as **user equipment (UE)**. These users, present in different neighborhoods and boroughs, are expected to install and register with the COVID-19 app(s) and allow it/them to collect UEs’ location information opportunistically. Besides this, the app(s) will also request the users to share information related to his/her vaccination status, current health condition, and previous health history (if any). The app(s) will push notifications, asking the user to update the information provided if required and also send notifications regarding the appropriate measures the individual has to undertake.

The UEs can either use Wi-Fi or LTE/4G/5G communication or a combination of the two (in hand-off scenarios to support mobility) to upload data to the application server(s) running on the
MEC servers. To support dynamic decision-making in mobility, the proposed architecture should enable the migration of relevant data if any user changes position from one RAN to the other. In such a scenario, following the network hand-off, once the user signs back into the app, his/her location is updated, and corresponding epidemiological data will be migrated from cloud storage to the nearest MEC server for sending health advisory alerts and recommendations.

Finally, let us discuss a pandemic stack (see Figure 9) that captures the logical flow of the proposed architecture. The first layer is the application layer that operates in two ways: (1) use of the mobile applications (refer to Section 3.2) to collect individual clinical, epidemiological, and physiological data and (2) the application programming interfaces to store and access data from the cloud servers. The next layer is the privacy (and security) layer that ensures the data is obfuscated so that the sensitive user information is hidden away while maintaining data utility (refer to Section 4.4). Next, the storage layer, comprising the data servers as well as local smart device memory, stores the anonymized data. As depicted in Figure 8, the network layer allows the interaction between (1) cloud and edge layers, (2) edge and mobile layers, and (3) mobile users (see Figure 5.2) through WLAN, WMAN, LTE, 4G/5G, Wi-Fi, and so on technologies. Finally, there is the computational layer that applies the models on the structured data to make predictions and recommendations over time.

4.3 Details of Intelligent Computation Layer

Figure 10 shows the flow of data between the sources (i.e., public repositories and mobility, epidemiological and physiological data from individuals in the end device layer of the pandemic management architecture shown in Figure 8) and the four computational modules. Specifically, the modules receive inputs from the static and dynamic prediction model and from one another, based on which decisions regarding vaccine allocation, dynamic lockdowns, mobility scheduling, and pandemic trends are determined. The effect of these decisions is reflected in the form of outcome
variables and indicators, recording the daily new infections, deaths, and the consequent pressure on the healthcare infrastructure of the zones. The computation layer needs to (a) access socioeconomic, demographic, and epidemiological data from diverse sources, such as surveys, census data, healthcare records, and social media that may inform policies on different population groups and their social and economic implications; (b) harmonize data from various sources, such as health systems, laboratories, surveillance systems, and external databases after rigorous cleaning, validation, and quality assurance; and (c) use artificial intelligence, machine learning, data science, and statistical modeling to find emerging patterns or evolving circumstances from new data for prompt decision-making and response strategies. We discuss the aforementioned tasks in the following subsections.

4.3.1 Socioeconomic, Demographic, and Epidemiological Factors. We discuss the colored factors that serve as inputs (marked blue in Figure 10) to the four modules. (In Section 3, we have discussed the computational studies on vaccine distribution, dynamic lockdown, mobility scheduling, and pandemic prediction that utilize these factors to draw inferences.)

Vaccine distribution. The vaccine distribution module determines the number of vaccines received by zones based on the following key factors (delineated during the survey in Section 3.3.1). (This module can be extended to distribute drugs to treat symptoms of the virus.) Since population density determines the frequency and duration of interaction among individuals, the vaccine distribution modules may attempt to distribute more vaccines to densely populated zones [19, 56]. The module may distribute vaccines based on the disease transmissibility, gauged in terms of reproduction number (see Section 2.2), among the zonal population [109]. The proportion of the elderly individuals with comorbidities may be a determinant of vaccine distribution [55]. Poor socioeconomic condition of the population or urban planning of a zone may be grounds for the inoculation of its population [58].
Dynamic lockdown strategies. This module determines the duration and extent of lockdown imposed on zones depending on the changing socioeconomic and epidemiological conditions, age, and comorbidity profiles. The module may recommend the imposition of stricter lockdowns in zones with a poor healthcare infrastructure [60, 61]. Since lockdowns have economic overheads, the module must strike a balance between contagion and economy [63, 64]. It may assess how the restrictions disrupt the supply-demand chain of industrial sectors.

Mobility scheduling. Based on the epidemiological data, this module informs individuals of their next location (via mobile applications) to protect them from disease contraction. We have discussed in Section 3.5 that mobility and contact pattern of the zones is a key factor influencing the identification of hotspots [73]. Similarly, the knowledge of urban planning can help determine the regions of high human contact [72]. Also, age and medical history are essential considerations in determining the level of priority in protecting individuals from exposure to infection.

Pandemic trend prediction. This module considers bulk population mobility (and not individual mobility traces like the mobility schedule module) to determine future trends. Since trend prediction requires global knowledge, this module, unlike the other modules runs on the cloud and not the edge layer. Time-series infected and mortality numbers of the population is essential to predict the course of the pandemic [78]. Age and comorbidity distribution of the zones help determine the extent and duration of the infection spread [86]. Human behavior is another factor influencing the prediction of these modules since the level of adherence to lockdown restrictions affects how promptly contagion can be mitigated [83]. The latest information on the number of hotspots and severity of outbreaks in them is necessary for drawing up public policies related to the pandemic [84].

4.3.2 Data Integration. The prediction models may employ these models to aggregate inputs received from the data sources and the health and epidemiological indicators. There exists a rich volume of literature on data integration algorithms. For example, Rao et al. solve vaccine allocation based on effective reproduction number [109], whereas Shim et al. address the same problem based on age and contact pattern [54]. Evidently, consensus algorithms are necessary to aggregate the solutions proffered by myriad frameworks. Monti et al. proposed an iterative sampling-based consensus algorithm, which uses a consensus matrix to assign cluster identity to each datapoint (i.e., solutions in our context) [110]. Subsequently, the consensus clustering strategies by Hoadley et al. attempt to reassign cluster labels to solutions based on vectors denoting solution clusters from different approaches [111]. Shen et al. employed probabilistic matrix factorization [112], while Wang et al. exploited network similarity for integration of heterogeneous data [113]. For every module, the edge device can adopt the above models to infer the aggregated decision.

4.3.3 Prediction Models. There can be two types of prediction models: static and dynamic. The static prediction models could be supervised machine learning models (namely, Naive Bayes, Decision Trees, Linear Regression, Support Vector Machines, Multilayer Perceptron, and so on) and unsupervised machine learning models (clustering, associative rule mining, and so on) [114]. The dynamic models incorporate the time-series feature data from the past to predict the present outcomes [115]. These models include univariate and multivariate time-series forecasting models, such as autoregressive integrated moving averages, vector autoregressive models, long short-term memory, and so on. Although both the static and dynamic models work on (1) past feature data X (comprising the factors) and the corresponding decisions from the four modules D and (2) observed outcome Y (i.e., infected, death, impact on health infrastructure), they operate in two different ways:
The dynamic models are meant to predict the course of the pandemic based on the feature data at time \( t \) \( (X_t) \) based on the data from earlier timepoints, i.e., \( X_0, X_1, \ldots, X_{t-1} \), as follows:

\[
X_t = c + \phi_1 \times X_{t-1} + \phi_2 \times X_{t-2} + \cdots + \phi_p \times X_{t-p} + \epsilon_t.
\] (16)

Here, \( p \) is the number of past time points being considered, \( c \) is a constant, \( \phi_i \) is the coefficient measuring the contribution of the \( i^{th} \) timepoint on the prediction, and \( \epsilon_t \) is the error term. This model is useful to derive proxy feature data when the actual feature data is missing.

Machine learning algorithms are functions (say, \( f \)) that map the input features \((X)\) to a target variable \((Y)\). The static models learn the parameters of a function \( f_{\text{static}} \) to quantify the effects of \( X \) and decision data \((D)\) on the observed outcomes as \( Y = f_{\text{static}}(X, D) + \epsilon \).

Using the past decisions as input, these models inform a module, say the vaccine distribution module, of the predicted outcome in terms of infected cases, deaths, impact on healthcare infrastructure, and so on.

### 4.4 Privacy Considerations

We discuss the concerns over abuses of health-related information and its potential solutions.

#### 4.4.1 Challenges

We first discuss some of the privacy challenges.

**Data utility vs. privacy tradeoff.** Figure 8 shows that the architecture is processing data of varying privacy demands. The data from the repositories are publicly available, whereas the data reported by mobile users are more sensitive as they pertain to personal physiological, clinical, or epidemiological information. This leads to a dilemma of privacy-utility tradeoff, summarized as, how much data utility can be compromised to achieve the desired data privacy guarantees and vice-versa, and clearly, it is a critical part of the privacy module (in Figure 9) when dealing with user data. In order to achieve perfect privacy for the users, one can model the privacy-utility trade-off as generalizations of the information bottleneck and privacy funnel problems and come up with positive information utility under perfect privacy i.e., zero information leakage over a rate constraint [116].

**Policies and regulations.** The architecture must abide by a few data-based regulations such as the General Data Protection Regulation (GDPR) or the California Consumer Privacy Act (CCPA) that are created with the objective to protect persons’ rights to the protection of personal data from a variety of agents or organizations. These regulations deal with the following safeguards surrounding personal or sensitive data being shared using the user’s mobile applications.

- To establish architectural roles consisting of data Policing officers for malicious users.
- The cloud layer must maintain an audit trail and protect against malicious MEC accesses.
- Edge Computing and End Device Layers should provide data privacy control tools to users.

**Malicious intent and breaches.** Depending on the privacy guarantee required, the parties could be *semi-honest* or *malicious*. In a semi-honest adversary model, the adversaries or parties follow their protocol definition. However, while doing so, they are allowed to learn anything from the intermediate data that is exposed to them in the defined course of computations as specified by the protocol, while in the malicious adversary model, the adversaries can deviate from the protocol definition by changing their inputs [117]. In either case, the cloud, MEC, and mobile layers must be protected (in decreasing order of priority) from access by individuals who can tamper with the data and computational model parameters and cause inaccurate recommendations.
4.4.2 Off-the-shelf and Potential Solution. We discuss ways to resolve the stated privacy challenges.

**Differential privacy (DP).** It is a widely-used privacy-preserving mechanism guaranteeing certain statistical bounds over the loss of privacy [118]. It is a randomized query mechanism that defines a privacy loss parameter $\epsilon$. The higher the value of $\epsilon$, the greater the utility and consequent privacy loss, and vice versa. Similarly, there are $k$-anonymity techniques that operate on the idea that sensitive information about users can be obscured by combining multiple datasets with similar attributes. The privacy layer can invoke one of these privacy-preserving techniques to control the data utility vs. privacy tradeoff depending on data provenance and type.

**Privacy preserving inference.** As described in Section 4.1, the edge computing layer provides on-demand computational services in the form of time-varying recommendations. This can be modeled as privacy-preserving inference problems [119, 120], involving two parties, namely mobile end users and edge devices, who respectively share and receive sensitive data. Among existing solutions, Hesamifard et al. provides a framework to enable privacy-preserving machine learning as a service (MLaaS) for applying deep neural network algorithms on encrypted data [119]. Luo et al. propose a privacy-preserving clinical decision support system using a Naive Bayesian classifier to enable secure disease prediction and patient health status monitoring, both of which could be used in the ML modules of dynamic lockdown, pandemic prediction (see Section 4.3.1) and the prediction of medical requirements in critically affected regions. Their privacy guarantees are achieved through fully homomorphic encryption scheme and single instruction multiple data integer circuits.

**Private information retrieval.** The pandemic architecture carries out information exchange in the form of queries. Queries may be inference-based (i.e., regarding recommendations from the lockdown, mobility scheduling, prediction, and so on models) or aggregation-based (i.e., regarding gross percentage or a number of vaccinated individuals in an area). To achieve secure information retrieval, a class of privacy-preserving techniques, called Private Information Retrieval (PIR), can be employed. A client in PIR can request access to records from a public repository, which may be hosted by multiple servers, without revealing information to the server(s) about the requested record [121]. One can leverage the privacy guarantees provided by $k$-out-of-$N$ Oblivious Transfers to fetch the statistic of interest, thereby protecting the access pattern. Moreover, differential privacy could be applied to each category of aggregation-based query issued to protect the actual data.

**Hybrid privacy-preserving techniques.** These models combine privacy-preserving mechanisms to enhance privacy and utility. For example, to enable the MEC server to compute the vaccine demand, the end device nodes can encrypt their vaccination status (say, $E(1)$ for vaccinated or $E(0)$, otherwise) using some additive homomorphic cryptosystem like Paillier [122] or other fully homomorphic system and report it to the server. The MEC server, not knowing the private key, can use the additive properties to obtain the encrypted aggregate value, and then add the differential privacy (DP) noise to protect the output using homomorphic properties. Finally, the encrypted DP perturbed value is sent to the end device(s), who can then decrypt it to get the actual value [123].

Privacy of data needs to be handled at every layer of our architecture to preserve user privacy and to conform to the privacy regulations such as GDPR, by enabling Health Insurance Portability and Accountability Act (HIPAA). It may be important to classify data into categories: (1) user-generated and (2) public repository. We delve into the details of privacy preservation on two levels.
End device. User physiological or clinical data is generated by the end device layer, and thus privacy mechanisms must be applied within the applications, devices, and protocols involved at the layer. We know that the End Device Layer is the main source of private health information (PHI) and as a result, plays an important role in controlling privacy loss. For example, the mobility scheduling module could leak information for some types of side-channel attacks. To avoid such attacks, Cho et al. [124, 125] provide privacy-preserving ways to address privacy issues in end-device applications. Moreover, user-provided data should only reside on the user’s device, and a federated learning-based approach can be used to compute over such private user data. For computations, the data must be anonymized or perturbed and encrypted such that the user is in control of their data. The data utility aspect must be taken into consideration during perturbation due to the tradeoff between utility and privacy. Due to the textual nature of data utilized within the architecture, the end device layer can incorporate the deep-confidentiality approach [126] based on textual sanitization.

Edge Computing Layer. The public repositories are likely to desensitize data before release. While processing multiple repositories simultaneously, care needs to be taken in order to avoid side-channel attacks and ensure data confidentiality. Additionally, the MEC servers interact with heterogeneous devices and protocols, which could potentially identify an individual or their demographics. Privacy-enhancing techniques such as secure multi-party computation (MPC), PIR, and data sanitization, can be applied within the architecture. However, they work well with specific datatypes only. Rao et. al. [127] propose privacy-enhancing solutions centered on DP and homomorphic encryption systems for edge-based applications. The addressed edge-based applications and their corresponding architecture services could be data aggregation for Dynamic Lockdown, and Pandemic prediction, point-of-interest services for contact tracing and mobility scheduling, vaccine allocation, traffic information services, and crowd-sourcing. Moreover, MECs can glean information such as application usage patterns. This can be addressed using the task offloading scheduling [128] based upon the Markov decision process (CMDP).

Overall, the best practices of standards and regulations need to be applied to address potential security and privacy issues. Architectural security can be ensured by abiding with the NIST cybersecurity framework. NIST 800-66 aims at addressing concerns with respect to patient data like prescriptions, results, hospital visit records, and vaccinations. The NIST 800-66 standard addresses security issues while enabling the HIPAA act [129]. This is achieved using NIST 800-53 [130]. For analysis and management of security risk, NIST Cyber Security Framework can be used. GDPR and CCPA are key standards for privacy and protection frameworks, which need to be met [131].

5 DISCUSSIONS
We discuss the limitations of the proposed pandemic architecture and future research directions.

5.1 Limitations of the Architecture
The pandemic architecture suffers from several computational and data-centric challenges. First, recall from our discussion from Section 4.3, the architecture ensures scalability and reduced computation time, by performing the bulk of the computation at the edge on the basis of the inputs received from the cloud layer as well as the mobile users. While it may be expected that the information housed in the data servers is structured, the personal and crowd-sourced data emanating from the mobile users are not. Thus, the architecture may need human intervention, i.e., an AI expert who filters the incoming data of misinformation, bias, and so on, and lends structure to it. The domain expert may be tasked with the processing of a sizable body of scientific literature to ensure the method and data sources being utilized by the architecture are effective and cutting-edge.
**Second**, the accuracy of the prediction from the AI-based forecasting models hinges on a steady influx of data. However, a significant portion of the world population will not embrace digital technology for quite some time, bringing into question the pervasiveness of architecture. Its adoption is further stymied by the limitations in steady access to wireless communication technology around the world. For instance, we discuss the use of mobile applications in Section 3.2 as ways to model social contagion. Unfortunately, individuals do not always carry mobile devices, or their devices are not enabled with the necessary communication technology to record contacts necessary for tracing contagion, and so on [132]. Hence, the validity and reliability of prediction by the computational models are hindered due to the sporadic data influx from a small section of the human population.

**Third**, in contradistinction to traditional mobile computing architectures, the pandemic architecture requires decisions to be taken based on clinical parameters. Recently, the community of computational scientists are using AI for the automatic classification of COVID-19 and its physiological effects. For instance, there have been efforts to exploit computer vision to identify COVID-19 from radiological images. The radiological societies have expressed doubt that these ML models rely on features that are not necessarily related to the pathology they are classifying [8]. Understandably, the accuracy of the architecture employing a vaccine allocation (as discussed in [56]) or a dynamic lockdown recommendation (as proposed in [64]) based on vision-based COVID-19 detection rests largely upon the latter’s clinical robustness and generalizability.

5.2 Future Directions

Let us discuss a few immediate research avenues that emerge from this pandemic architecture.

**First**, a considerable amount of research effort needs to go into data sensitisation and structuring [133]. Thankfully, the data housed in public repositories, such as the COVID Tracking Project [134], of respectable organizations (refer Section 3.1 for details) allow domain experts and the general public to participate in the data reporting, dissemination, and debugging. As described in Section 4.3, the personal or crowdsourced data reported by the mobile users can be comparatively noisy and inaccurate, begging questions on their trustworthiness and authenticity [135]. One of the many ways to mitigate this hurdle is to assign fitness scores to mobile users based on their (1) overall reputation, (2) memory, residual energy, and communication capabilities of smart devices, and so on. In exchange for incentives, the system will periodically nominate the fittest individual as a cluster head or group owner and require them to collect the data from the peers in their neighborhood, pre-process it to eliminate potential noise, redundancy, and inaccuracy, and transfer the data to the MEC nodes [136, 137]. Anomaly and outlier detection mechanisms [138] could be adapted at the MEC layer to bolster the accuracy of the static and dynamic prediction models in place.

**Second**, as discussed in Section 4.4, there will be multiple stakeholders involved such as government agencies, healthcare departments, police departments, third-party companies responsible for development and management tasks, users, and so on. Moreover, the data that the architecture will be collecting and using are often sensitive. Therefore, traditional hard security mechanisms that entail authentication and authorization (access control) need to be implemented. The objectives are to ensure that only authenticated stakeholders can use the data and the services and implementation of a fine-grained authorization to enforce conflict-free separation of duties by taking into consideration spatiotemporal aspects. Henceforth, potential research directions are the determination of the “best” authentication mechanism such that identity keys can be generated, distributed, and verified seamlessly across all platforms, and choosing a suitable access control model (viz., **attribute-based access control (ABAC)** [139], **role-based access control (RBAC)** [140], **organization-based access control (OrBAC)** [141], and so on) that enables secure accesses. Also, soft security mechanisms implemented through suitable trust/reputation...
models may be integrated with authentication and access control to prevent unauthorized disclosure or manipulation of information.

Third, a key feature of edge computing is to bring computation closer to the edge, thereby minimizing computation delay. **Federated learning** – an ML technique in which multiple distributed nodes can use their local data to collaboratively learn a shared prediction model [142] – may be employed to optimize this feature of edge computing. Specifically, instead of the MEC layer, mobile devices can pool their memory and processing resources to collectively run the prediction model. While FL enables mobile devices to run applications requiring high computational power [143], research should go into ensuring fairness, and realizability of FL applications in the edge [144].

Fourth, yet another key aspect of the pandemic management architecture is **fault-tolerance**. Mobile devices are energy constrained and prone to energy depletion, whereas the MEC and cloud servers are likely to experience hardware faults from time to time. The implication of either of these faults is data starvation leading to incorrect recommendations. Thus, research efforts need to be directed at the installation of maintenance modules that oversee the functioning at each of the three layers. There are models that improve system resilience against the intermittent connectivity of mobile devices and present preemptive measures to control the failure of cloud servers [145]. The big research question then will be to integrate these models into the pandemic architecture.

Finally, the architecture hinges on its capability to ensure data trustworthiness and fault tolerance. The flip side of such sophisticated mechanisms for both is the communication overhead resulting in challenges pertaining to **energy efficiency**. We know that the researchers of participatory sensing and mobile computing have studied the criticality of cost-to-benefit tradeoff for mobile users at length and proposed ways for intelligent energy-efficient data reporting [146]; additionally, the energy overheads of data centers and their consequent exorbitant demand on worldwide power consumption is also an open research area [147]. Overall, the overheads for the myriad generations of wireless communication technologies (4G, 5G, Wi-Fi, LTE, and so on) employed by the cloud, MEC, and mobile layers also warrant adequate consideration during the realization of the architecture [148].

6 CONCLUSION

In this article, we proposed a pandemic management architecture that automates recommendations on vaccine distribution, dynamic lockdowns, human mobility scheduling, and pandemic prediction, by leveraging the pandemic-related data collected through IoT technology. We survey the relevant computational frameworks in the field of pandemic management, online data repositories, and contact-tracing mobile applications. The proposed architecture delves into the wireless communication among the three layers, namely, cloud, edge, and mobile layers, as well as the prediction models at the edge computational layer that run the computational models on the physiological, clinical, and epidemiological data to make time-varying recommendations. We discuss the data utility versus anonymization tradeoff, privacy threats, regulations, and potential solutions, before covering the limitations and future research directions to enhance the applicability of the architecture.

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