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COVID-19 lethality reduction using artificial intelligence solutions derived from telecommunications systems

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1. Introduction

A large-scale medical urgency, such as the coronavirus disease 2019 (COVID-19) worldwide pandemic, requires suitable analysis and resource management tools that are optimized for large-scale macroscopic applications. In this chapter, the authors suggest borrowing such tools from a different domain, in particular the telecommunications domain, where the management and orchestration of large-scale systems are well understood and deployed on a worldwide basis. Obviously, the usage of such tools requires adjustments to consider new datasets as well as medical paradigms. A literary survey is presented in Section 2, whose findings build the basis for the further selection and parameterization of tools taken from the telecommunications field.

The choice of telecommunications system is considered legitimate, as it has proved its efficiency for decades. Indeed, such base stations deployed on a large scale are providing access to cellular communication, and they increasingly apply artificial intelligence (AI) and machine learning tools in order to manage the inherent complexity efficiently. In September 2019, the European Telecommunications Standards Institute (ETSI) has issued an innovative group specification (GS) developed by the Industry Specific Group (ISG) Experimental Network Intelligence (ENI). This GS introduces a system architecture [1] and related building blocks supporting an automated processing of data and related decision-making. In this chapter, our intention is to bridge two worlds—we illustrate how ETSI’s architectural proposals may be exploited in the field of data analytics by public services, particularly in the field of pandemic data analytics (forecast, prediction, and resource optimization).
We further illustrate how the components of such a system can be directly mapped to the context of a pandemic and the involved stakeholders. We present a proposal for the first implementation of data intelligence to fight against COVID-19. This implementation relies on specific data such as the number of available face masks, the presence of enough staff, the time to detect a contamination, the availability of drugs and ventilators, etc. As a consequence, available tools and findings can be straightforwardly exploited to improve the handling of a worldwide pandemic. It is furthermore considered how to adjust the government policy to make new decisions in the confinement: protection gestures, social distancing, movement interdiction, etc. Finally, information may be provided to define de-confinement scenarios and facilitate the postconfinement rebound.

Today, funding for medical services is typically declining, as governments seek to reduce their health expenses in order to reduce their debt to its gross domestic product (GDP) ratio. For instance, the European Union constrains European countries to respect a maximal ratio of debt equal to 3%.

In many countries, the healthcare system was forced to cut expenses in terms of staff, equipment, and facilities during the past decade. The effects of this reduction are emphasized by the rapid evolution of the pandemic. As many COVID-19 patients have severe respiratory problems, they often need to be hospitalized for 2 or 3 weeks using specific and dedicated ventilators, as well as specialized staff (reanimation teams).

To lessen this problem of resource scarcity, the basic and necessary decision is to confine the population. However, this confinement can also worsen the stamina and psychological state of people, as well as the debt of a country and the healthcare system itself. Therefore it is essential to pay attention and propose optimization schemes that can help optimize the allocation of every available resource. In this chapter, multiple solutions are proposed to do so and reduce the scarcity of resources.

The key proposals are to gather resources on a regional or national level and not to address the problem on a hospital-centric or single-patient-centric approach. Moreover, the authors propose a holistic optimization problem statement involving the entire health system including retirement homes and general practitioners. Finally, it is outlined how to resolve the optimization problem using advanced mathematic tools such as Lagrangian optimization.

The structure of this chapter is as follows: Section 2 provides a review of literature concerning resource allocation, AI, and the fight against COVID-19 pandemic. Section 3 introduces the ETSI ENI architecture and related building blocks, and Section 4 comments on the specific needs of data analytics in the context of pandemics, in particular for modeling the spread of disease and the way the population is affected. Section 5 includes a proposal on a modified architecture adapted to the need of data analytics for pandemic-related predications inspired by the ETSI approach; while Section 6 finally gives a conclusion and perspectives for this work.
2. Literary review

Before developing a new AI system, the initial step is to investigate the core topic, available information, and recommendations. In this context, the publication by Emanuel et al. [2] is providing a suitable basis as the authors propose ethical values to define how to manage the resource scarcity. The authors establish six specific recommendations for allocating medical resources in the COVID-19 pandemic. Their proposal consists of maximizing benefits, prioritizing health workers, avoiding to allocate resources on a “first-come, first-served” basis, being adaptive to scientific evolution and evidence, recognizing research participation, and applying the same principles to all COVID-19 and non-COVID-19 patients. This approach is necessary to ensure ethical behaviors but does not tackle the resource allocation problem itself. Mesko et al. [3] advocate that AI is becoming widespread, affordable, and reliable. It helps physicians to analyze data collected by multiple sources (oxygen saturation, blood pressure, X-ray images, tomography, etc.) and highlights the key parameters required to make a medical decision. However, the authors underline the importance of taking into account ethical concerns to set up the limit between technology and human medicine. They believe that intelligence augmentation (IA) will probably reduce the cost of healthcare, as many actions could be automatized. At the same time, the healthcare system could improve in quality, as physicians should evolve to better accompany medical decisions and provide explanations to patients. Unfortunately, these long-term perspectives do not provide any short-term solution.

More generally, many researchers also focus on how information technology (IT) software or machines articulate with human decisions. Thus Hassani et al. [4], provide a comprehensive review, which examines the differences between AI and IA, that is to say technology dedicated to improve human comprehension, decision, or behavior. The authors propose a clear vision for different domains: enterprise, vehicles, robots, and drones. They also insist on the role of education to associate creativity and technology. Their discussion also proposes to ensure that AI is not used to copy human intelligence but to develop complementary skills. Thus mankind capability could blossom. Another approach was proposed by Jones et al. [5]. Indeed, the authors propose to distinguish healthcare AI into two parts: (1) the mining of information from raw data to provide useful information on treatment patterns or diagnoses and (2) the assistance to clinicians in delivering care to patients. Moreover, they insist on the importance of considering AI on a new tool useful to improve medical decisions. Physicians base their decisions not only on evidence but also on advice, experience, and reassurance. Therefore they are both complementary.

Some researchers also underline the importance of defining clear rules before collaborating with private entities. For example, Powles and Hodson [6] analyze the collaboration of Google DeepMind with the British National Health Service, especially
the difficulties in the openness of algorithms and results. The authors provide some warnings and recommendations about the management of personal data to private entities. First, they insist on the risk of giving access at a large private and confidential healthcare dataset to major companies, especially the GAFAM (Google, Apple, Facebook, Amazon, Microsoft). Second, they recommend to preserve the privacy of personal healthcare information, which should only be treated by public institutions. Similarly, Mikhaylov et al. [7] underline the importance of cross-sector collaboration to develop AI and ensure its operational dimension. They indicate that all around the world, the best AI centers associate researchers from universities, public and private sectors. Therefore the authors propose management strategies to manage those collaborations: define leadership, align objectives of the involved parties, ensure an efficient communication strategy, take into account nonexpert vision to provide operational solutions, and give priority to practical situations to ensure a proximity management.

The interest toward patient health benefits and rights is also described in Ref. [8]. In this paper, Wahl et al. provide a review of AI to improve patient health in resource-poor settings. They underline that AI will play an important role to transform healthcare services in such a context. They propose to combine the use of smartphones and the investments in supporting technologies to improve public health outcomes in low-income-country settings. They also indicate the importance to take into account legal and ethical questions such as privacy, confidentiality, data security, ownership, and informed consent.

At present, the research on healthcare focuses on the fight against COVID-19. Vaishya et al. [9] address the healthcare delivery using AI, big data, and machine learning. They provide a brief review of AI for COVID-19 using research material published on PubMed, Scopus, and Google Scholar. The authors also identify seven potential applications of AI for COVID-19 pandemic: diagnosis, treatment, tracing, drugs, vaccine, etc. This paper provides an interesting digest of the domain but does not tackle precisely the problem exposed.

Jiang et al. [10] provide a large review of the usage of IA in the healthcare context. They underline the interest of IA to provide assistance in cancer, neurology, and cardiology. They also give some details on the two major categories of current AI devices: machine learning and natural language processing. Although the results are really encouraging (for instance, IBM Watson provides 99% of coherent recommendation in oncology), they indicate that the AI technologies also face serious implementation difficulties in real-life implementation. Two classic hurdles are regulations to ensure patient safety and the difficulty to obtain data to ensure continuous learning. Davenport and Ravi [11] advocate that AI will play an increasing role in the healthcare system. It will offer better decision based on larger sets of data and will probably provide efficient diagnosis and treatment in the nearby future. The authors underline that the major challenge of AI in the healthcare domains are to be adopted in daily clinical practice. This requires a legal basis as well as a process to ensure the reliability and standardization of results, which should be understood by the appropriate practitioner (surgeon, physician, nurse, etc.).
He et al. [12] provide an analysis of the practical issues slowing the adoption of AI into real-life healthcare systems. The authors underline the difficulties encountered, which involve data management (especially information privacy), transparency of algorithms, data standardization, and interoperability, as well as concern for patient safety. They also provide a specific analysis of regions outside the United States and insist on the protection offered in Europe by the General Data Protection Regulation, as well as the favorable context for AI in China. Indeed, the China State Council decided to set up a development plan for AI, ensuring a large promotion of AI applications in the Chinese healthcare system.

Hick et al. [13] propose a review of the principles of crisis standards of care initially framed by the Institute of Medicine in 2009. These principles improve the resource allocation of staff, material, or facilities by using a large panel of management strategies such as preparing, conserving, substituting, adapting, reusing, and reallocating resources. The paper is originally intended to healthcare planners and clinicians. However, the key indicators and triggers proposed may also be injected into any AI solution in order to feed it with valuable medical practices.

Alimadadi et al. [14] provide a short paper that underlines the limit to deploy AI and machine learning in the current pandemic. The availability of COVID-19-related clinical data, which can be managed and processed into easily accessible databases, is a key current barrier. Therefore the development of cyberinfrastructure to fuel worldwide collaborations is important. The interest toward the proposal made in the current paper is that it does not require any confidential data. The model can help optimize patient allocation without any private or personal data.

Jiang et al. [15] proposed a method based on an AI framework, with predictive analytic capabilities applied to real patient data. Their dataset is limited to 53 Chinese patients, which reduces the capability to verify the proposal. However, the model proposed offers some clues to clinicians so that they better take into account some specific data. On the contrary, they underline that the usual key characteristics of diagnosis, including fever, lymphopenia, and chest imaging, were not as predictive of severity.

Sethy and Behera [16] present a method to detect infected patients based on X-ray images using a support-vector machine that distinguishes infected and healthy patients based on deep features. The dataset is limited to 50 images with 50% of safe patients. These features are extracted using a convolutional neural network and multiple models. The ResNet50 is statistically superior to the other eight models and has more than 95.38% of accuracy in COVID-19 detection. These results are really interesting in COVID-19 treatment strategy but do not enable to anticipate the situation, as they require the use of an X-ray image of patients.

Wang et al. [17] provide AI learning methods based on computed tomographic images. They possess a dataset of 453 images from persons infected with COVID-19 and used approximatively 50% of them to build the model and the remainder to validate it. The accuracy of their detection method reaches 82.9% with internal validation and 73.1% with external validation. The approach has similar advantages and drawbacks as the
proposal of Sethy and Behera [16]. Zheng et al. [18] also propose to build a deep-
learning-based model using computed tomographic images of lungs. Their approach
is slightly different, as their model relies on a segmented 3D lung region used to predict
the probability that a patient should be infected with COVID-19. The dataset is
composed of 499 images and the validation set has 131 images. The accuracy obtained is
better and reaches 90%. The algorithm proposed is also shared on GitHub, which
enables anyone to verify the results or conduct further research. This method requires to
perform computed tomography of lungs and does not improve resource allocation
between hospitals or other medical establishments.

Pham et al. [19] performed a large review of AI and big data applied to the struggle
against COVID-19 and highlight the results in various directions: prediction and spread
tracking, early diagnosis, and disease analysis, as well as potential treatments or vaccines
against severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). They also
underline the remaining challenges in terms of regulation, data obtention, or personal
privacy. They finally provide useful recommendations: enhance the accuracy and
reliability of the data analytics for better COVID-19 diagnosis and treatment, combine AI
and big data to other emerging technology to improve them, and do not forget
nontechnologic basic measures such as social distancing.

Hu et al. [20] proposed a method inspired from AI to ensure COVID-19 prediction.
The proposal models the transmission dynamics of the epidemics using a modified
stacked autoencoder. The learning stage was performed using data collected in China
from January 11 to February 27, 2020, by the World Health Organization. The authors
also modelize the 34 provinces/cities that were grouped into 9 clusters. The results
obtained were very close to reality, as the error was from 1% to 2%. A future improve-
ment of the proposal will be to taken into account for public services intervention to
propose forecasts on different decision scenarios.

Some researchers also highlight the ethical challenges raised by AI. Sun and Medaglia
[21], provide an analysis of challenges (social, economic, ethical, political, technologic,
etc.) raised by AI and their different perceptions of AI among three groups of stake-
holders (government policy-makers, hospital managers/doctors, and IT firm managers).
The authors illustrate the importance to identify the factors that can explain this
difference, to explain what can be the precise usage of AI in the healthcare context, and
to adjust AI to the local dataset because the way of life may differ from one continent to
another (and the adjustment should be refined to a country or a region if possible).

Desouza et al. [22] provide a review of the different types of usage of AI in organi-
zations. They underline the common usage of chatbots to replace human assistance to
customers as well as prediction to detect fraud or analysis to help decision-makers. They
provide a classification of cognitive computing system issues in four axes: data,
technology, organization, and environment. This classification also distinguishes the
difference between public and private sectors. They conclude their paper in an optim-
mistic manner as they highlight the potential of AI (“the fourth industrial revolution”),
which also introduces many organizational and managerial challenges.
Mikalef et al. [23] underline the importance of AI in the private sector and the lack of attention for public usages. They analyze the current state of AI use in municipalities in Norway and the future developments. To fulfill these objectives the authors interviewed managers in different Norwegian municipalities. They underline that the public decision-makers are willing to develop AI and anticipate many challenges to face the transition.

There are also many papers that describe how to benefit from medical data in order to help physicians make a diagnosis, select a treatment, or define and organize their activities. Zhou et al. [24] underline that COVID-19 is characterized by a long incubation period, strong infectivity, and difficulty of detection. They propose Geographic Information Systems (GIS) and big data technology to allow rapid responses and analyses to provide strategic information on the epidemic. The proposal illustrates the development of COVID-19 in China using a spatial representation of the disease, material, population, and social psychology. These elements enable to visualize efficiently the pandemic dispersion, but, to our knowledge, it does not propose any direct solution to tackle the resource allocation problem.

Alhashmi et al. [25] provided a survey on AI acceptance by decision-makers, physicians, nurses, and patients within the United Arab Emirates Healthcare Sector. They propose and verify the results of a Technology Acceptance Model (TAM) to explore critical success factors based on perceived usefulness, attitudes, and behavior in usage. They also proved that managerial, organizational, operational, and IT infrastructure factors have a positive effect on IA acceptance. These elements should be taken into account before deploying any IA implementation in production.

Reis et al. [26] analyze how AI impacts research, digitalization, and public policies. They consider a large scope of research publications and highlight that the current digital transformation is mainly focused on business and industries. However, AI has an increasing impact on public policies with a direct support within the United States and a collaborative approach with industries within Europe. To enhance this research, they propose to take into account the impact of AI on citizen as well as business economics.

Vermeulen et al. [27] provide a framework to optimize resource scheduling of patient appointments, especially for scarce resources such as computed tomography scan. They take into account resource capacity and divide patients into specific groups (depending on the emergency, duration time, and specificities of the examination). They also divide calendars into small time slots to help the resource allocation process. Mathematically one can notice that the underlying optimization process is similar to a common mobile radio allocation problem: time-division multiple access (TDMA). The results obtained enable to optimize the usage of scarce resources within one hospital, for instance, but do not mutualize resources within a larger perimeter.

Abbas et al. [28] proposed a framework to combine cognitive radio with AI. They also present state-of-the-art machine learning techniques based on different AI techniques. Their proposal confirms that mobile communication techniques combine easily with AI, which explains our initiative to reuse the ETSI architecture to perform AI in the healthcare context.
The abovementioned extensive literature study reveals that the application of AI is traditionally limited to local optimization, including support for the diagnosis of a specific patient, improved interactions with patients, etc. In the present contributions, the authors propose to apply a further level of abstraction and employ AI on a macroscopic level. The objective is to identify and track the spread of a pandemic over a geographic space and time and to automatically process the findings and generate reports in an automated way to inform government agencies about the current status; finally, the solution is able to optimally determine local confinement strategies and allocate patients to available treatment resources (hospitals, intensive care, etc.). The basic principle is outlined in Fig. 33.1.

With the objective to improve the current localized application of AI on a per-patient level and to move toward a macroscopic application of related tools, we first propose to analyze the architecture proposal by GS ENI [1] and illustrate how the proposed building blocks may be repurposed for the needs of public service data analytics. In this context, the introduction of new tools is proposed, such as model driven engineering with the objective to create machine readable models for the specification of functional blocks. Suitable processing tools are then applied to create software codes at a minimized overall development time and effort.

3. European Telecommunications Standards Institute architecture

The ETSI architecture as introduced by ETSI ENI [1] is illustrated in Fig. 33.2 and will be detailed in the following. The relationship of the various components to a pandemic situation is indicated through examples in Fig. 33.2.
The first step to be addressed is the provision of information to the proposed architectural framework. Data may indeed originate from different sources and must be processed such that it can be represented using a well-defined format. The various building blocks of the architecture will then be able to use and process the data. In the context of a pandemic, “Data” may relate to observations on the spreading of the disease over time and characteristics of the population (age, population density, health information, etc.).

This process is typically referred to as “Data Ingestion” and may include the following steps:

i. Data Filtering for removal of unnecessary or not useful information;
ii. Data Correlation to create an association or relationship between data;
iii. Data Cleansing for detection and removal of corrupt, incomplete, inaccurate, and/or irrelevant data;
iv. Data Anonymization and Pseudonymization for removing or protecting (encrypting) data that may be used to identify people;
v. Data Augmentation for adding other types of data to the existing dataset to enrich it;
vi. Data Labeling to add class labels to datasets.

In the context of pandemic-related data analytics, data may be provided by various means, e.g., hand-filled forms, data provided through official institutions (hospitals,
government agencies, etc.), data being extracted from automated processing, etc. Also, data originates typically from different sources, e.g., private persons, public services, not-for-profit organizations, etc. In some approaches, the data ingestion functional block is complemented by a “data normalization functional block,” which creates datasets of a specific common format.

The functional blocks of ingestion and data normalization are typically fed by the “knowledge management functional block.” A knowledge management entity is fundamental in the context of AI. Typically, knowledge representation defines a set of formalisms that define information and knowledge in a computer-readable form. Formal and consensual knowledge representation also enables machine learning and reasoning. To extend the knowledge base of the system, an inference system is being applied.

In the context of pandemic-related applications, suitable hypotheses may relate to a refined classification of data sources, to identify typical patterns characterizing the spreading of a disease, etc.

The “context-aware management functional block” enables the system to gather information about itself and its environment and thus finally to make the system adapt its behavior according to changes in the context. Indeed, policy decisions are typically driven by the contextual history of a user (or data source), etc. In the context of a pandemic, information may be included related to lockdown (confinement) of the population, movement restrictions and other protective measures (e.g., wearing of masks), etc. Contextual data typically includes personal and group information of a user or data source (such as contact information, profile and preference information), etc.

In the context of public services, the sources of information may be typically classified in terms of (home) address information, professional context of a data source, ownership of assets, etc.

The “cognition framework functional block” targets to imitate the function of the human brain to understand concepts; this is achieved using a set of specialized data structures and computational procedures operating in a similar way to the human brain. Cognition is used to process new data, applying inferences and to compare the results to available knowledge. Typically, a cognition entity comprises at least the following three functions:

i. interfaces interacting with the environment providing data;
ii. processing that can analyze and manipulate data, information, and knowledge;
iii. storage to hold data, information, and knowledge.

In practice, cognitive systems are built based on one of the following two approaches: the symbolic approach (computationalism) and the connectionist approach, assuming that all cognitive processes are the same and are derived from neural activity dynamics. Knowledge is obtained through processing of training samples.

In the context of pandemic-related applications, the connectionist approach may be used to feed a model with existing data, indicating which samples imply specific patterns
of spreading of a disease, persons not obeying to medical requirements (e.g., confinement, wearing of masks), etc.

The “situational awareness functional block” enables the system to understand what has just happened, what is likely to happen, and how both may affect the objectives of the system. Typically, the process comprises five actions: gathering data (perception), understanding the significance of the data (through facts and inferences), determining what to do in response to the given event, making a decision, and executing those actions.

In the context of pandemic-related applications, situational awareness may relate to the current situation of a user (data source) and anticipated follow-up events, such as further spreading of a disease, contamination of new regions, etc.

The “model driven engineering functional block” is responsible for enabling software development based on models instead of codes. Related models are machine readable. In our context, the use of such models fulfills three key purposes:

i. The model ensures that all different data models maintain a consistent definition and understanding of concepts.

ii. The model enables different policies at different levels of abstraction to communicate with each other using a common vocabulary and data dictionary.

iii. The model decouples the need for policy (defined by the situational awareness functional block) from the specification of policy from the implementation of policy.

In the context of pandemic-related applications, the model driven engineering approach is applying models suitable to characterize the spread of a disease, the behavioral information of a population, medical coverage and saturation level of the medical system, etc., and is thus able to accelerate the development of new functions and software applications.

Finally, the “policy management functional block” provides a set of uniform and intuitive mechanisms for consistent recommendations and commands meeting the following requirements:

i. to be able to transform data and information to a common format that facilitates generating outputs,

ii. to use a set of models including data types and structures for producing outputs,

iii. Data Denormalization may be achieved by a separate functional block.

In general, policy is a natural way to express rules and restrictions on behavior and then automate the enforcement of those rules.

In the context of pandemic-related applications, a policy management framework will enable nonexperts to apply a data evaluation system by providing evaluation requirements and objections through easy-to-read policies.
4. Data required to reduce COVID lethality

Multiple data are involved in COVID lethality:

1. The probability that an infected person transmits the infection to others. This probability depends on different decisions such as confinement rules, availability of masks and tests, public services organization, etc.

2. The probability to die when a person is infected. This probability depends on different factors such as the presence of sufficient staff, the time to detect a contamination, the availability of drugs and ventilators, etc.

3. The resilience of the health system organization. This axis represents the financial, human, and social capacity to ensure the functioning of the normal health system (general practitioners) as well as the hospital health system (public and private) or retirement residences during the time.

It is interesting to underline that the probability to die also depends on the health status of persons. Therefore there could be a different approach for specific populations such as retirement residences.

Consequently, the objective may be to reduce the global lethality within the country, that is, to minimize the sum of

1. the number of deaths within a hospital \( \sum_i \sum_j P_{i,j} \alpha_{i,j} \), where a person \( i \) admitted to hospital \( j \) has a probability to die \( \alpha_{i,j} \), and the hospital capacity is \( C_i \);

2. the number of deaths outside a hospital \( \sum_i \sum_k P_{i,k} \beta_{i,k} \), where a person \( i \) cared by a medical doctor \( k \) has a probability to die \( \beta_{i,k} \), and the medical capacity is noted as \( C_k \);

3. the number of deaths outside hospital and retirement residences \( \sum_i \sum_l P_{i,l} \gamma_{i,l} \), where a person \( i \) living in residence \( l \) has a probability to die \( \gamma_{i,l} \), and the residence capacity is known as \( C_l \).

Therefore the allocation problem is expressed as follows:

Minimize \( \sum_i \sum_j P_{i,j} \alpha_{i,j} + \sum_i \sum_k P_{i,k} \beta_{i,k} + \sum_i \sum_l P_{i,l} \gamma_{i,l} \)

where

- for each hospital \( i \), \( \sum_i \sum_j P_{i,j} \leq C_i \);
- for each medical doctor \( k \), \( \sum_i \sum_k P_{i,k} \leq C_k \);
- for each retirement residence \( l \), \( \sum_i \sum_l P_{i,l} \leq C_l \).

With all data elements being known, the problem can be relatively easily solved with the resolution method developed in Ref. [29]. This method is based on solving the dual problem with convex optimization techniques. **Fig. 33.3** illustrates the basic principles of
the optimization, namely, identifying the optimum “working point,” i.e., the optimum mapping of patients to available medical resources such that the overall fatality rate is minimized.

However, we advocate the usage of more recent techniques based on AI to solve the allocation problem in different situations:

- the AI should be able to solve the problem even if some information is missing,
- the AI should be able to refine the optimization problem in order to take into account new data.

As the lethality highly depends on different parameters described at the beginning of this section, the different functions $\alpha_{i,j}$, $\beta_{i,k}$, and $\gamma_{i,l}$ may differ along time according to

- equipment, staff, and drug availability, which can increase or decrease; it is interesting to underline that the lethality depends on the weakest link;
- experience and learning on the disease and its treatments, which tend to improve along the pandemic;
- the confinement measures and respect, which can evolve in opposite directions (increasing coercive measures vs. decreasing respect and tolerance).

Moreover, the new data obtained could be used to refine the fraud detection model. For instance, an order of equipment could be injected in the model to improve the pandemic forecast in a short term.
Obviously, these elements should be confirmed by other methods such as using feedback from practitioners in the field, researchers, and managers.

For instance, our proposal should integrate the crisis standard-of-care principles described by Hick et al. [13]. Continuous feedback could also be obtained through appropriate spreadsheets or simple web applications filled by the medical staff. Every information obtained should in any case respect the national law on private rights and confidentiality.

It seems very important to buffer a sufficient quantity of data to enable machine learning such that the machine estimations are sufficiently reliable. Errors could effectively occur if only specific establishments are taken into account. For instance, if the data is only available for overwhelmed establishments, then the forecasts could be too pessimistic. On the contrary, if the majority of data is obtained from peaceful regions, then the results could be too optimistic. In both cases, this could lead to a misinterpretation.

Furthermore, the functioning of AI relies on permanent learning and improvement. Thus the cognition framework should compare the results obtained with the algorithm to the results obtained with the following allocation of person:

- a nearby hospital allocation where the infected persons are assigned to the closest hospital if necessary; in this scenario, nothing is done for retirement residences except standard confinement;
- a nearby hospital allocation combined with a basic reallocation of dangerous retirement residences toward secured places (if the threshold of lethality is reached, then the riskier residents should be moved to secure places).

Lastly, it is important to notice that the model may be refined to take into account a variation of lethality probability over time. The probability that a person dies depends on the available equipment, drugs, staff, etc. For example, if a person gets the virus at the beginning of the pandemic, it will be more likely to survive than at the peak. Contracting the virus at the end of the pandemic could also imply a different lethality, which depends on the resilience of the health system (capacity to refuel from drugs and to adjust to new treatments).

The global immunity of a region (highly contaminated at the beginning of a pandemic) could also be an advantage to take care of infected persons when another region becomes overwhelmed by the pandemic. This “solidarity effect” is in particular important to cope with peaks of the pandemic.

5. Adaptation of the European Telecommunications Standards Institute architecture to the needs of public services

We propose to integrate the ETSI support architecture as introduced in Section 2 into a classical AI approach. Furthermore, we outline the type of information to be processed
in the new functional blocks in order to address the needs to model and predict pandemic-related characteristics, as outlined in Section 3.

In the novel approach proposed in Fig. 33.4 the elements are discussed in the following.

The functional blocks of the ETSI architecture are as introduced in Section 2. We provide further details on the exact mapping to a pandemic-related decision-making system:

![Diagram of the ETSI architecture](image-url)

**FIGURE 33.4** European Telecommunications Standards Institute architecture for artificial intelligence integrated into a pandemic-related detection system.
1. The Data Bases relate to one or multiple classical Data Bases as usually used by government agencies and medical institutions to track the spread of the pandemic.

2. The Data Mining Algorithms support the “Pandemic-Related Detection System” by extracting relevant elements from the plethora of available information.

3. The Pandemic-Related Detection System uses all available inputs to process pandemic-related information and to identify any inconsistencies. As a novelty, we propose that the system provides information back to the ETSI framework on the relevance of context information and other elements such that the ETSI system can perform self-optimization and improve its efficiency (see feedback arrow in Fig. 33.4).

4. Reports to government agencies and medical institutions are finally creating human-readable reports providing information related to the spread of the disease and other pandemic-related information. The reports should propose government and medical organizations to control by order of priority. It typically provides proposed decisions to be implemented to improve the overall situation in terms of spread of the disease, containment to a specific region, etc.

It is important to underline that Table 33.1 proposes the first model for the architecture proposed. Obviously, this model needs to be refined when building the specific operational solution. This enables to take into account not only unexpected human behaviors or adjustments to control through experiments or interviews relevant to government agencies and medical institutions but also the acceptance dimension described in Ref. [25].

To do so, we propose to add different thresholds to ensure a better usage of respiratory equipment:

- The absolute need of reanimation: in this case, the patient should be directly moved to the closest reanimation center, except if there is an agreement from both a specialist and the person to stay at home.
- The highly probable need of reanimation: in this case, the person should be moved to the closest available hospital with a reanimation place. A medical examination should be performed to confirm the requirement of reanimation. This examination should enable to refine the allocation and could offer alternatives if the patient is stable.
- The probable need of reanimation: in this case, the person should be moved to an available hospital in a perimeter to define (50 km, for instance) and with a reanimation place. A medical examination should be performed on arrival to confirm the requirement of reanimation. This process ensures better distribution of patients before their arrival and before they need a respiratory equipment. This also should respect the health security, as the perimeter could be reduced in high-density regions.

It is important to notice that the health system effectiveness is enhanced by using simplified procedures.
| ETSI functional entity                  | Usage for patient allocation in the context of a pandemic                                                                 |
|----------------------------------------|------------------------------------------------------------------------------------------------------------------------|
| Context-aware management functional block | The context-aware management framework will be used to gather further information about whether individuals (at least statistical information or on a voluntary basis) are infected or not. Information about hospitals, retirement residences, and practitioners should also be gathered.  
  - For individuals the context may be fed by home address (city), age, ability to stay at home, distance to the closest hospital, etc.  
  - For hospitals the context may be fed by the number of medical beds, the number of reanimation beds, the number of ventilators, the amount of staff by professional ability, the current occupancy rate, the capability to create new reanimation beds, etc.  
  - For retirement residences the context may be fed by the number of residents, the number of medical beds, the number of ventilators, the amount of staff by professional ability, the current occupancy rate, etc.  
  - For general practitioners the context may be fed by the number of patients, abilities especially in terms of reanimation, the capability to coordinate with the emergency system, etc.  
  
  **Note:** It is often difficult to predict which type of context information is providing hints to be exploited by the AI. It is thus suggested to provide a maximum amount of input and then let the AI feedback mechanisms identify relevant contributions. |
| Cognition framework functional block    | The cognition framework is used to acquire and use new data available for individuals, hospitals, retirement residences, and general practitioners. This enables to derive inferences and finally to compare new results and conclusions with past available knowledge; examples are as follows:  
  - For individuals a misbehavior derived through inference could be that potentially infected individuals always go to the closest hospital even if it is overburdened and do not use a mask before accessing the emergency room.  
  - For hospitals an underoptimized organization could be that the emergency does not separate common patients from those potentially infected by the pandemic. |
| Situational awareness functional block  | The situational awareness framework analyzes relevant current events of individuals, hospitals, retirement residences, and general practitioners; predicts what will happen as a consequence in the future; and determines how both affect the objectives of the system (i.e., allocation of patients or resources) and derives required decisions, examples are as follows:  
  - For individuals the awareness of situation can refer to the event of being infected or being in contact with another infected person (this information could be obtained if tracing is allowed or if the person declares himself/herself this personal information). Individuals could also change status, becoming unemployed or being in partial work, which decreases the probability of infection if the person respects confinement rules.  
  - For hospitals the awareness of situation can refer to the arrival of new patients as well as the departures. The creation of a new room with staff and equipment (beds and ventilators) may also be another important event, as well as reprogramming nonurgent surgery.  
  - For retirement residences or practitioners the arrival of masks may decrease the lethality of persons and staff. On the contrary, the detection of a contamination should imply some isolation measures. |
6. Conclusion

In this chapter, we proposed to apply AI solutions originally developed for telecommunications systems to the field of patient allocation and modeling of disease spread in the context of the fight against pandemics. We analyze the problem of resource allocation in three levels: hospitals, retirement residences, and city medical doctors.

We furthermore illustrate how the available structure defined for telecommunications systems can be adapted to the needs and analysis of the spread of a disease and which learning and decision-making processes may be applied for the extraction of information related to the evolution of a pandemic. This illustration is based on the ETSI architecture that is adjusted to the pandemic detection context. An important part of the proposal consists of providing a feedback path to the ETSI system in order to improve the decision process.

The authors suggest engaging with data scientists of health system administrations to implement the novel approaches in a practical and operational context. It is anticipated that the proposed solutions will considerably improve the efficiency of AI-based modeling of pandemics. Also, the presented methodology can be straightforwardly applied to other data-mining-related applications and provide similar benefits.

References

[1] ETSI Group Specification (GS) ENI 005, V1.1.1, 2019. Available at: http://www.etsi.org.

[2] E.J. Emanuel, G. Persad, R. Upshur, B. Thome, M. Parker, A. Glickman, C. Zhang, C. Boyle, M. Smith, J.P. Phillips, Fair allocation of scarce medical resources in the time of Covid-19, N. Engl. J. Med. (2020), https://doi.org/10.1056/NEJMsb2005114.

[3] B. Mesko, G. Hetényi, Z. Györrfy, Will artificial intelligence solve the human resource crisis in healthcare? BMC Health Serv. Res. 18 (2018) 545, https://doi.org/10.1186/s12913-018-3359-4.
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[4] H. Hassani, E. Silva, S. Unger, M. Tajmazinani, S. MacFeely, Artificial intelligence (AI) or intelligence augmentation (IA): what is the future? Artif. Intell. 1 (2020) 1211, [doi:10.3390/ai1020008].

[5] L.D. Jones, D. Golan, S.A. Hanna, M. Ramachandran, Artificial intelligence, machine learning and the evolution of healthcare, Bone Jt. Res. 7 (3) (2018) 223–225.

[6] J. Powles, H. Hodson, Google DeepMind and healthcare in an age of algorithms, Health Technol. 7 (2017) 351–367, [doi:10.1007/s12553-017-01791].

[7] S.J. Mikhaylov, M. Esteve, A. Campion, Artificial intelligence for the public sector: opportunities and challenges of cross-sector collaboration, Philos. Trans. Math. Phys. Eng. Sci. 376 (2128) (2018), [doi:10.1098/rsta.2017.0357, 20170357].

[8] B. Wahl, A. Cossey-Gantner, S. Germann, et al., Artificial intelligence (AI) and global health: how can AI contribute to health in resource-poor settings? BMJ Global Health 3 (2018) e000798.

[9] R. Vaishya, M. Javaid, I. Haleem Khan, A. Haleem, Artificial intelligence (AI) applications for Covid-19 pandemic, Diabetes Metab. Syndr. ISSN: 1871-4021 14 (4) (2020) 337–339, [doi:10.1016/j.dsx.2020.04.012].

[10] F. Jiang, Y. Jiang, H. Zhi, et al., Artificial intelligence in healthcare: past, present and future, Stroke Vasc.Neurol. 2 (2017). [doi:10.1136/svn-2017-000101].

[11] T. Davenport, K. Ravi, The potential for artificial intelligence in healthcare, Future Healthc. J. 6 (2) (2019) 94–98. [doi:10.7861/futurehosp.6-2-94].

[12] J. He, S.L. Baxter, J. Xu, et al., The practical implementation of artificial intelligence technologies in medicine, Nat. Med. 25 (2019) 30–36. [doi:10.1038/s41591-018-0307-0].

[13] J. Hick, D. Hanfling, M. Wynia, A. Pavia, Duty to plan: health care, crisis standards of care, and novel coronavirus SARS-CoV-2, NAM Perspect. (2020). [doi:10.31478/202003b].

[14] A. Alimadadi, S. Aryal, I. Manandhar, et al., Artificial intelligence and machine learning to fight Covid-19, Physiol. Genom. 52 (4) (2020) 200–202. [doi:10.1152/physiolgenomics.00029.2020].

[15] X. Jiang, M. Coffee, A. Bari, J. Wang, X. Jiang, J. Huang, J. Shi, J. Dai, J. Cai, T. Zhang, Z. Wu, G. He, Y. Huang, Towards an artificial intelligence framework for data-driven prediction of coronavirus clinical severity, Comput. Mater. Continua (CMC) 62 (2020) 537–551. [doi:10.32604/cmc.2020.010691].

[16] P.K. Sethy, S.K. Behera, Detection of coronavirus disease (Covid-19) based on deep features, Preprints.org (2020). [doi:10.20944/preprints202003.0300.v1].

[17] S. Wang, B. Kang, J. Ma, et al., A deep learning algorithm using CT images to screen for coronavirus disease (Covid-19), medRxiv (2020). [doi:10.1101/2020.02.14.20023028].

[18] C. Zheng, X. Deng, Q. Fu, et al., Deep learning-based detection for Covid-19 from chest CT using weak label, medRxiv (2020). [doi:10.1101/2020.03.12.20027185].

[19] Q.V. Pham, D. Nguyen, T. Huynh-The, W.J. Hwang, P. Pathirana, Artificial intelligence (AI) and big data for coronavirus (Covid-19) pandemic: a survey on the state-of-the-arts, (2020). [doi:10.13140/RG.2.2.23518.38727].

[20] Z. Hu, Q. Ge, L. Jin, M. Xiong, Artificial Intelligence Forecasting of Covid-19 in China, 2020 arXiv preprint arXiv:2002.07112.

[21] T.Q. Sun, R. Medaglia, Mapping the challenges of artificial intelligence in the public sector: evidence from public healthcare, Govern. Inf. Q. 36 (2) (2019) 368–383. [doi:10.1016/j.giq.2018.09.008].

[22] K. Desouza, G. Dawson, D. Chenok, Designing, developing, and deploying artificial intelligence systems: lessons from and for the public sector, Bus. Horiz. 63 (2019). [doi:10.1016/j.bushor.2019.11.004].
[23] P. Mikalef, S. Fjortoft, H. Torvatn, Artificial Intelligence in the Public Sector: A Study of Challenges and Opportunities for Norwegian Municipalities, 2019. https://doi.org/10.1007/978-3-030-29374-1_22.

[24] C. Zhou, F. Su, T. Pei, A. Zhang, Y. Du, B. Luo, Z. Cao, J. Wang, W. Yuan, Y. Zhu, et al., Covid-19: challenges to GIS with big data, geography and sustainability, Geogr. Sustain. (2020).

[25] F.S. Alhashmi Shaikha, S.A. Salloum, C. Mhamdi, Implementing artificial intelligence in the United Arab Emirates healthcare sector: an extended technology acceptance model, Int. J. Inf. Technol. Lang. Stud. 3 (2019) 27–42.

[26] J. Reis, P. Espírito Santo, N. Melao, Artificial Intelligence in Government Services: A Systematic Literature Review, 2019. https://doi.org/10.1007/978-3-030-16181-1_23.

[27] I. Vermeulen, S. Bohte, S. Elkhuizen, H. Lameris, P. Bakker, H. Poutré, Adaptive resource allocation for efficient patient scheduling, Artif. Intell. Med. 46 (2008) 67–80. https://doi.org/10.1016/j.artmed.2008.07.019.

[28] N. Abbas, Y. Nasser, K. Ahmad, Recent advances on artificial intelligence and learning techniques in cognitive radio networks, J. Wirel. Commun. Netw. (2015). https://doi.org/10.1186/s13638-015-0381-7, 174 (2015).

[29] C. Gaie, M. Assaad, M. Muck, P. Duhamel, Distributed discrete resource optimization in heterogeneous networks, in: IEEE Workshop on Signal Processing Advances for Wireless Communications (SPAWC 2008), 2008. https://doi.org/10.1109/SPAWC.2008.4641670.

[30] ISO/IEC 19505-2:2012 [ISO/IEC 19505-2:2012], Information Technology — Object Management Group Unified Modeling Language (OMG UML) — Part 2: Superstructure, 2012. Available at: https://www.iso.org/standard/52854.html.