Healthcare Fusion: An Innovative Framework for Health Information Management

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Abstract: Perhaps the main goal of healthcare management is the attainment of effective, efficient, equitable, timely, safe, and patient-centered care. At the core of this lies the need for an integrated pathway for healthcare data storage, analysis, and utilization. The potential exists for a centralized, cloud-based system that links physicians, hospitals, public health agencies, insurance and pharmaceutical companies, and most importantly, patients. Such a system could improve clinical quality management and support the delivery of consistent and effective treatments. Undoubtedly, massive integration of personalized health and large-scale epidemiological and molecular data, coupled with the use of artificial intelligence and machine learning, is already in process. Here, we envision the healthcare fusion framework, which unites all stakeholders in healthcare. This fusion aims to achieve culturally and demographically relevant outcomes in precision medicine and population health, in ways that are convincing to stakeholders and investors. In addition, the proposed framework may prove relevant in informing governmental and private sector responses to sudden public health crises.

Keywords: healthcare fusion, big data, ROBIN, medical records, machine learning, artificial intelligence, cloud computing, precision medicine, population health

1. Introduction

Despite recent innovations in medical technologies, individual patients could become increasingly voiceless in the care process. Leaders in western medicine have therefore advocated for patient-centered care, in which patients' perspectives are heavily weighted in health-related decisions (Barry and Edgman-Levitan, 2012). Patient-centered care improves clinical outcomes and efficiency (Stewart et al., 2000).

To describe a data-driven, patient-centered care system, Leroy Hood proposed the term "P4 Medicine," where the four "P's" stand for predictive, preventive, personalized, and participatory (Hood, 2013). In recent years, health data have expanded along three vectors: volume, variety and velocity. Substantial progress has been made along the data trajectory, as advanced data analytics platforms are now available. However, lack of collaboration between the various stakeholders in healthcare continues to constitute a major barrier which prevents a complete rollout of patient-centered care and P4 medicine.

Even today, healthcare data are largely siloed and scattered across various discrete points of storage and exchange; this hinders medical progress, patient-centered care, and the effective management of population health risks. An enormous amount of data needs to be managed, and the advancement of precision medicine depends tremendously on interoperable and standardized data and systems.

To address these challenges, we propose a new framework, healthcare fusion, for the consolidation and leveraging of medical and data technologies to achieve culturally and demographically relevant outcomes in precision medicine and population health. Healthcare fusion centers upon the development of a single cloud-based repository for a nation's health and biological (omics and biobanking) data. In the interest of realizing financial and non-financial returns, stakeholders in healthcare, including healthcare providers, insurance companies, and pharmaceutical corporations, would participate and contribute data. Artificial intelligence (AI) and machine learning (ML) would be leveraged for data analysis. To this end, we propose a set of criteria,

Reference this paper: Zhai, K., et al., 2022. Healthcare Fusion: An Innovative Framework for Health Information Management. *The Electronic Journal of Knowledge Management,* 20(3), pp. 179-192, available online at www.ejkm.com

enumerated within the acronym ROBIN (Responsive, Open, Bridging, Interoperable, Network-based; see Textbox 1), for the optimization of data processing machinery. Through stakeholder collaboration and data sharing, healthcare fusion could facilitate the widespread adoption of patient-centered care.

2. The Healthcare Fusion Framework

To advance patient-centered care and improve interoperability within healthcare systems, we propose the healthcare fusion model. In developing this concept, we aim to create an organized, regulated framework for healthcare data delivery and management.

At the core of our framework lies a centralized, cloud-based information management system (IMS) which would contain a nation's healthcare data (Figure 1). Stakeholders – including patients, healthcare and insurance providers, pharmaceutical corporations, social media, and governments – would contribute data to the IMS. Cloud computing platforms would leverage AI and ML to interrogate these data. Patient- and population-level health data, biological (omics and biobanking) data, and epidemiological, demographic, and socioeconomic patterns would be stored in the IMS. Stakeholders would have varying levels of access to these data. Healthcare and insurance providers, for example, would have access to personally identifiable data, while pharmaceutical corporations and epidemiologists would be limited to blinded (de-identified) clinical data. This framework could be applicable to a broad spectrum of healthcare systems, including public, private, and hybrid models; it could be modified and optimized to meet the needs of individual nations. In most cases, we anticipate that governments would ultimately bear responsibility for the implementation and regulation of the healthcare fusion framework. Depending on the jurisdiction, day-to-day technical operations could be managed by the government, a public-private partnership, or a contractor(s). As such, our proposed framework encompasses not only a shared data repository, but also effective stakeholder participation and rigorous system-wide oversight mechanisms, as explained below.

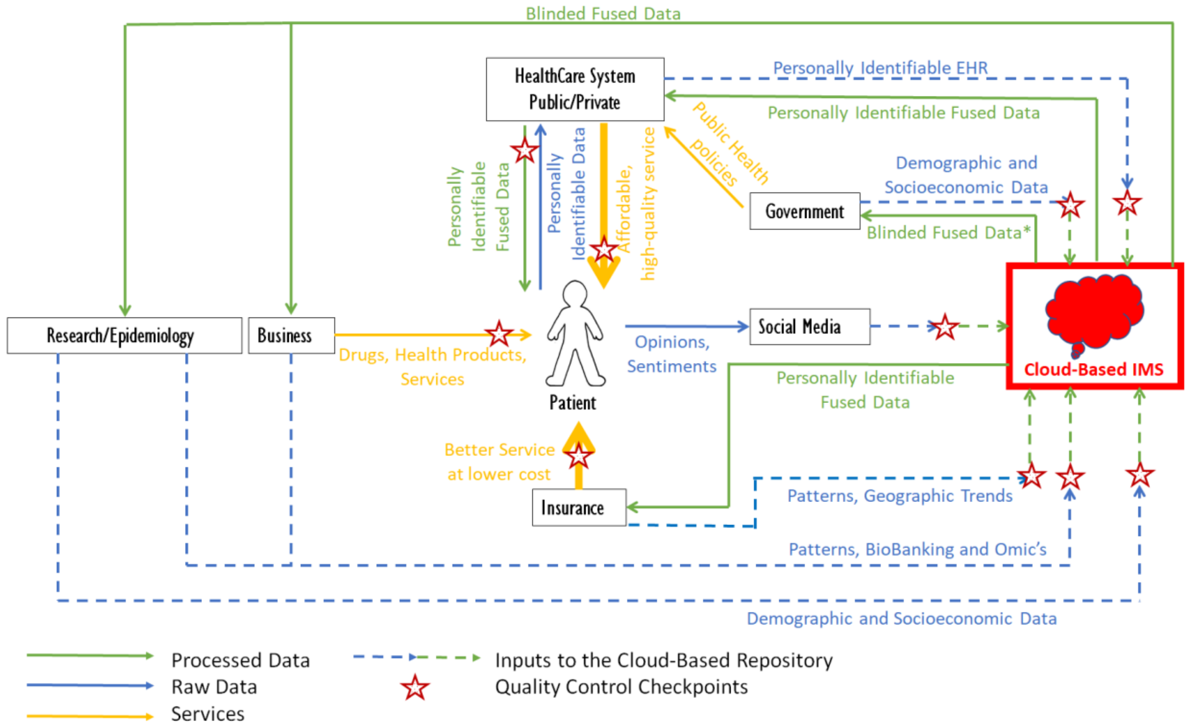

Figure 1: Overview of the healthcare fusion framework, a patient-centered approach

Stakeholders contribute to and oversee health-related data exchanged with a centralized, cloud-based repository. Artificial intelligence platforms are leveraged to analyze these data with high precision and throughput. In the interest of advancing patient-centered care, stakeholders will have varying levels of access to data within the repository. Healthcare providers and insurance companies would have access to personally identifiable records, while the business and research sectors would be limited to blinded data. To ensure system-wide interoperability and proper data packaging, security, and utilization, we suggest a number of quality control checkpoints (indicated by red stars; see the ROBIN criteria in the text). *While we envision that governments would be limited to blinded data, governmental access privileges will vary between jurisdictions.

3. Stakeholders in Healthcare Fusion

The stakeholders in our proposed framework include all parties with a vested interest in the success of a healthcare system (as defined by measures such as patient satisfaction, profitability, and efficacy of care):

3.1 Patients

Patients are the primary beneficiaries of healthcare fusion. They seek accessible, timely, and effective care, delivered in the context of their physical, social, and emotional needs. They also desire participation in the care process and value continuity of care (Peckham et al., 2021). Data access, privacy, and security are also of great concern. Patients can contribute to the fused macrocosm by relaying their health data to healthcare providers, and by sharing their opinions on social media platforms. In exchange, patients would receive affordable, personalized, and evidence-based care. Moreover, our proposed IMS would create complete personal health records that could be seamlessly transitioned between various healthcare and insurance providers. Patients would therefore benefit from flexibility and improved consistency and continuity of care.

3.2 Healthcare Providers

Healthcare providers (*e.g.* hospitals, physician practices, etc.) may be governmental bodies, non-profit organizations, or private corporations. These entities interface directly with patients; they offer preventive and curative care, promote health maintenance, and field inquiries. Currently, healthcare providers have access to large bodies of data and medical expertise. Hospitals, multispecialty groups, and physician practices can contribute complete datasets – with patients' symptoms, treatment regimens, and outcomes – to our proposed IMS. In return, these stakeholders could benefit immensely from healthcare fusion. Firstly, by utilizing the IMS, healthcare providers would transfer data management responsibilities to an external entity. As such, these providers would no longer bear the overhead costs associated with data storage, transmission, and security. Furthermore, by adopting our proposed big data-driven framework, healthcare providers could optimize preventive and curative interventions, reduce readmissions, and improve patient satisfaction.

3.3 Insurance Companies

In privatized healthcare systems, insurance companies are financial intermediaries between patients and healthcare providers. Insurance agencies reimburse healthcare providers on patients' behalf. As such, these corporations benefit from preventive measures that reduce the need for costly curative ones. Like healthcare providers, insurance companies have access to vast repositories of personal health data. Insurance records may even be more complete than hospital records, as they include data from all parties that have cared for individual patients. Therefore, insurance providers can contribute valuable datasets to a fused healthcare system. In addition, given the large number of patients they cover, insurance agencies can also extract patterns with epidemiological relevance. With the adoption of healthcare fusion, insurance companies (like healthcare providers) stand to benefit from reduced data-related overhead costs. Additionally, via the IMS, insurance providers could rigorously monitor patient health, identify and respond to anomalies early on, and suggest preventive and lifestyle interventions. These capabilities could ultimately reduce the incidence of preventable diseases, and minimize spending on unnecessary treatments.

3.4 Pharmaceutical and Biotechnology Corporations

Pharmaceutical and biotechnology corporations are essential components of modern healthcare systems. The pharmaceutical sector develops drugs and other therapies, while biotechnology firms propose innovative treatments and solutions to challenges in healthcare. These entities aim to outcompete rivals and maximize profits. Medically-related businesses can contribute biological samples and data for biobanking, as well as a variety of omics data. In return for their valuable contributions to the IMS, these businesses would have access to aggregated, de-identified health data. These data could support drug discovery and market research, and allow corporations to anticipate and profit from major market events (*e.g.,* COVID-19).

3.5 Social Media Platforms

Social media platforms are important public forums in health and medicine. For patients, social networks facilitate the sharing of opinions and sentiments related to healthcare. As such, social media companies have access to vast amounts of health-related data, which they can contribute to the fused cloud. Patterns extracted from these data could be harnessed for epidemiology, market research, and other beneficial purposes. Within our proposed framework, social media platforms could profit by establishing partnerships with healthcare providers and businesses for informatics and advertising ventures.

3.6 Research and Epidemiology Organizations

Academic and private research entities are important players in the advancement of modern biomedical science and public health. This group includes basic science researchers, clinical researchers, epidemiologists, and sociologists – who often depend on raw data from other parties (*e.g.,* patients, hospitals, insurance companies). Within our proposed framework, researchers can contribute epidemiological patterns, demographic and socioeconomic data, and biological data for omics and biobanking. In exchange for their support, the research and epidemiological sectors would gain access to vast datasets within the IMS. Complete, anonymized health records, for instance, would be available for retrospective and longitudinal studies. Moreover, data centralization could lower barriers to translational research, as the IMS would link biological data and clinical records.

3.7 Investors and Venture Capitalists (VCs)

This group of stakeholders constitutes the financial sector of a healthcare system. Through strategic investments, they seek to maximize returns. Investors and VCs possess financial resources which they can contribute to healthcare fusion. Their investments could support the development and modernization of data processing machinery, in the interest of advancing precision medicine and public health. As the healthcare field adapts to the digital era, investments in forward-looking businesses are likely to remain lucrative. Investors and VCs stand to profit immensely as corporations leverage data to optimize their operations, expand their market shares, and capitalize on market events.

3.8 Governmental and Regulatory Authorities

Governments are ultimately responsible for the health and wellbeing of their citizens. As such, legislative and executive bodies have an interest in ensuring timely, equitable, and effective healthcare delivery while containing costs. In pursuit of this goal, governments can contribute capital resources to the envisioned system. Additionally, public authorities can contribute demographic and socioeconomic data. Governments can moreover enact regulations and initiatives which protect stakeholder rights and encourage the adoption of healthcare fusion. In exchange for their investment, governmental agencies could realize substantial returns. A streamlined healthcare system would reduce national healthcare spending. Furthermore, our proposed IMS would facilitate the early detection of public health emergencies. Finally, governments could realize increased tax revenues as a result of increased profits by healthcare providers and businesses.

4. Data in Healthcare Fusion

4.1 Types of Data

Patient encounters, basic science research, clinical trials, and other healthcare activities generate a myriad of qualitative and quantitative data. The following types of data are prominent within the healthcare fusion framework:

4.2 Personal Medical Records

Personal medical records include vitals, medical images, laboratory results, medical histories, and free-text physician comments. Healthcare providers generate these data upon encounters with patients. Within our proposed framework, healthcare providers would package personal medical data and upload them to the fused IMS.

4.3 Patient Opinions and Sentiments

In advancing patient-centered medicine, individual patient opinions and sentiments are of great importance. Patients may express their sentiments during encounters with healthcare providers; these thoughts could be captured as free-text records and uploaded to the IMS. Social media is another avenue through which patients may openly convey their perspectives (Strang and Sun, 2019). Qualitative records from social media could be collected (1) in-house, by social media companies; (2) by governments; or (3) by third parties. These records would be de-identified and uploaded to the IMS.

4.4 Biological Data (Biobanking and Omics)

Biomedical research operations, biotechnology firms, and pharmaceutical companies generate diverse biological outputs. 'Omics' technologies, such as genomics, proteomics, and metabolomics, produce highly specific data at the patient and population levels (Hasin et al., 2017, Alyass et al., 2015). Biobanks store cell and tissue lines, pathogen specimens, blood, DNA, RNA, and other samples (Coppola et al., 2019). For the purposes of healthcare fusion, our proposed IMS would serve as a centralized repository for omics data. Applicable individual and population omics data would be attached to patient records and could enhance diagnosis. Moreover, the IMS would function as a comprehensive catalog unifying existing biobanks, in the interest of improving interoperability and data accessibility. The merits of centralized biobanking programs are demonstrated in countries such as Iceland and Finland, where interconnected biobank and EHR records facilitate population-level studies (Wolford et al., 2018).

4.5 Patterns

Epidemiological patterns are critical for public health. Elucidation of these patterns requires large quantities of healthcare data. Our envisioned IMS would aggregate, organize, and de-identify these data, and then make them available to research organizations and businesses. These entities could subsequently leverage AI platforms to analyze and extract patterns from the blinded data. Furthermore, insurance companies would have access to complete patient records; as such, they would also be well equipped to search for patterns. Identified patterns would be uploaded to the IMS, aggregated, and made accessible to relevant stakeholders.

4.6 Demographic and Socioeconomic Data

Geographic metadata pertaining to homelessness, familial status, tobacco use, and educational level can be highly beneficial in assessing the socioeconomic implications of disease. Through census, taxation, surveillance, and other records, governmental organizations have access to large volumes of relevant metadata. Under the healthcare fusion model, these data would be uploaded to the IMS and attached to patient records on a geographic basis. As such, healthcare providers could better understand and respond to patients' physical, social, and economic needs, without excessive intrusions of privacy.

4.7 Information Communication Technology (ICT)

Health-related data are stored and transmitted through Information Communication Technology (ICT). There are six major types of ICT:

1. Electronic Health Records (EHR)
2. Health Information Exchanges (HIE)
3. Patient Health Records (PHR)
4. Telemedicine
5. Apps and Wearable Sensors
6. Social Media

Currently, HIEs aggregate data and facilitate information sharing between disparate EHRs. PHRs, or Patient Portals, allow patients to view some of their medical data. Healthcare fusion would merge EHRs, PHRs, and HIEs to create a centralized, secure, cloud-based repository for health data. This IMS would enable the stakeholders in health to access relevant data in a streamlined and controlled fashion. In this way, patients and their PCPs are "kept in the loop" and can be assertive in the development of healthcare plans (Mamlin and Tierney, 2016). Additionally, the IMS would improve interoperability within healthcare systems. Currently, patients seeking to transfer between healthcare or insurance providers often face challenges migrating their medical records between disparate systems. A centralized IMS would facilitate smooth transitions for both patients and providers, and ensure continuity of care.

Another ICT, telemedicine, has progressed over the past two decades as a technology which facilitates healthcare delivery over long distances. One example is teleradiology, which minimizes the need for both on-site radiologists and patient travel to often distant hospitals. Our proposed cloud-based IMS would aggregate patient data (e.g. medical images) and streamline their transmission to relevant physicians. As such, our framework would improve interoperability between traditional and telemedicine providers through data centralization.

In the age of mobile phones, health data can be generated by wearable sensors, and processed and displayed in software applications (apps). It has been proposed that this ICT could be linked with EHRs, such that patients may access medical information on their mobile devices, and wearable sensors may input data directly into EHRs. Healthcare fusion takes a more limited approach with regard to mobile sensors. Within our framework, these sensors would provide data directly to patients in a comprehensible manner. Patients could retain these data for private use, or share them with healthcare providers. Physicians would then screen the data for validity and plausibility, and upload the data to the centralized IMS if appropriate. In this way, patients can retain control over their mobile data, as these data would not be pushed to EHRs or the IMS without their consent. Additionally, data screening by healthcare providers would prevent automatic population of patient records with inaccurate or inappropriate data.

Social media allows for rapid and large-scale communications which transcend socioeconomic barriers. Given their ubiquity among younger people of all backgrounds, social media platforms can reduce healthcare disparities (Huo et al., 2019). Furthermore, online networks for healthcare providers can promote best practices, knowledge transfer, and cross-checking of diagnoses and treatment plans (Grajales et al., 2014). Healthcare fusion would maximize utilization of valuable social media data to gather patient perspectives and sentiments. Social media is also an indicator of “buzz” or “hype” about diseases and treatments at the population level. Within the fused macrocosm, data on social media trends would be available to physicians, to enable them to better understand patients’ thoughts.

4.8 Big Data Analytics

The volume of quantitative healthcare data available today is vast and expanding exponentially; these data have important medical applications (Brown et al., 2018, Kayaalp, 2018, Mooney and Pejaver, 2018, Sanchez-Pinto et al., 2018, Zhang et al., 2017, Austin and Kusumoto, 2016). Today, the challenge is to store, transmit, and analyze these data on a sufficiently large scale. In this regard, an essential component of healthcare fusion is the synergy between various modern computing technologies, namely AI, ML, big data, and cloud computing, for analysis of qualitative and quantitative data (Figure 2). These technologies are described below:

4.9 Artificial Intelligence (AI) and Machine Learning (ML)

AI deals with independently intelligent systems which exhibit efficient, human-like cognitive and intellectual capabilities. These systems are driven by algorithms which facilitate self-learning and pattern recognition. Within the scope of healthcare, AI may expedite and optimize diagnosis and treatment, and minimize medical errors (Truong et al., 2019, Miller and Brown, 2018, Loh, 2018). In 2018, UK Prime Minister Theresa May announced that the UK will leverage AI to prevent and treat chronic diseases by 2030, indicating political recognition of the immense potential applications of AI.

ML, a subset of AI, is the ability to train machines to “learn” from data, self-improve, and make decisions. ML employs algorithms which iteratively leverage data to generate and refine decision-making and predictive models. Clinical, structured data (*e.g.* demographics, medical notes, physical examination and laboratory results, and images) can be used by AI applications for ML. Further, deep learning and natural language processing tools can “learn” from unstructured data (*e.g.* narrations and free-text records). Algorithms have already been trained with hospital data to predict outbreaks of chronic diseases such as cerebral infarction (Chen et al., 2017).

Our envisioned IMS would aggregate, store, and retrieve amounts of healthcare data that are far beyond the limits of human analysis. As such, AI and ML are indispensable. Appropriately “trained” AI platforms would scrutinize patient records for useful etiological and epidemiological patterns to feed into the IMS. Other systems could examine patient omics sequences to elucidate the molecular bases of disease. AI would also be leveraged to interrogate social media and other qualitative records. Finally, AI platforms would categorize data within the IMS, and control the release of data to stakeholders.

4.10 Cloud Computing

Healthcare data analytics programs are limited not only by human and intellectual factors, but by hardware as well. As data are largely siloed in discrete physical locations at present, each stakeholder is constrained by its in-house computational infrastructure. Healthcare fusion leverages cloud computing, or computing over the Internet, to address this. Cloud computing allows users to process and store vast datasets in remote data centers, and thereby makes big data analytics possible and cost-effective (Avula et al., 2012, Gao et al., 2018). Our proposed IMS would be a centralized, cloud-based point of information storage and exchange that would effectively circumvent the limits faced by individual stakeholders.

4.11 Databases

AI platforms can rapidly produce a large volume of data-linked outputs that can be utilized for ML if stored in appropriate databases. A goal of data mining is to discover patterns in datasets to enhance predictive and decision-making power (Itani et al., 2019, Mitchell, 1999). AI systems can undergo ML by scouring diagnoses and their corresponding data for patterns, and utilize the "learned" information to improve diagnostic efficiency and accuracy. In our proposed framework, data-linked outputs would be uploaded to the cloud-based IMS, which would eventually replace existing databases. We envision that through the IMS, AI platforms could iteratively leverage a nation's entire body of healthcare data for ML and data mining.

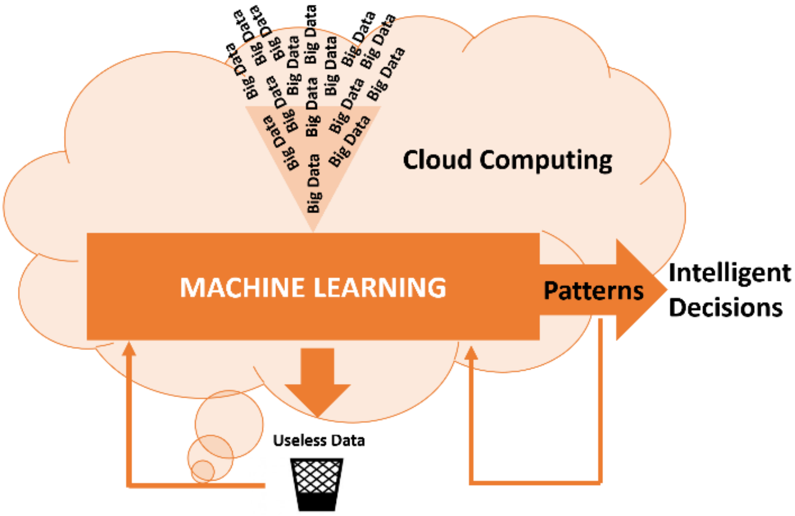

Figure 2: Synergy between modern machine learning, big data, and cloud computing technologies

Cloud computing facilitates storage and processing of immense amounts of (big) data by AI, while machine learning is a mechanism through which AI systems identify patterns and develop algorithms for data analysis.

4.12 ROBIN

To process healthcare data at an enormous scale and achieve the goals of healthcare fusion, data management systems must meet certain criteria for efficiency, accessibility, and efficacy. Five such criteria are enumerated within the acronym ROBIN, the components of which are presented in Textbox 1.

The ROBIN Criteria:

Responsive to shifting demands and technologies: in a rapidly changing field, big data analytics systems must be versatile enough to accept new types of data inputs and remain compatible with all sources of health data.

Open to patients and providers: to achieve patient-oriented precision medicine, all stakeholders in a patient's health should have access to relevant data. Patients, especially, should be able to view their data at-a-glance. However, big data systems must comply with HIPAA regulations and maintain rigorous security policies.

Bridges individual and population data: big data systems should contextualize individual patient data with relevant population-level data whenever possible. Utilizing stratification, diagnoses and treatment plans can be determined through pattern-matching between individual and population data.

Information is shared between systems: **I**nteroperability is key for efficient data analytics systems. Compatibility between ROBIN-ized systems facilitates efficient information transfer without the need for intermediaries (*e.g.* HIEs).

Networks with apps and wearable sensors: a key factor in patient empowerment is access to health data (as previously discussed). Patients must have an active role in the process of analysis, diagnosis, and treatment; as such, user-friendly data visualization interfaces are necessary.

Textbox 1: An overview of the five ROBIN criteria and their implications

In practice, the ROBIN criteria would constitute an oversight mechanism to maintain the quality and integrity of data in a fused system (see quality control checkpoints in Figure 1). Our proposed IMS would be fully "ROBIN-ized," such that it supports access to stakeholders, integrates patient-specific and epidemiological data, and remains relevant as new health-related technologies arise (see Textbox 1). Moreover, AI platforms within our framework would also adhere to ROBIN; in this way, data packets could be transmitted between stakeholders and the IMS without the need for extensive unpackaging and repackaging. The aim of capital investment in healthcare fusion is to facilitate the enhancement of existing big data analytics systems to meet the ROBIN criteria, as well as the design and implementation of new, "ROBIN-ized" systems. In the case of pandemic diseases and public health emergencies, healthcare systems constructed with ROBIN in mind are capable of early detection of abnormal cases, and can unify stakeholders to facilitate rapid and decisive responses.

5. Healthcare Fusion Outputs

5.1 Biomedicine and Personalized Medicine

Biomedicine is a form of evidence-based medicine (EBM) which utilizes medical, surgical, psychological, lifestyle, and other interventions to prevent and treat disease (Gaines and Davis-Floyd, 2003). Under the EBM approach, healthcare providers combine their individual medical expertise with basic science and clinical data for diagnosis and treatment (Sackett et al., 1996). The "evidence" which fuels EBM includes biological, epidemiological, socio-cultural, and mechanistic patterns. Data processing within the healthcare fusion framework would leverage AI to efficiently elucidate these patterns, and aggregate them in the proposed IMS. A centralized repository of "evidence" could improve biomedical knowledge and support the development and enhancement of evidence-based interventions.

At its core, healthcare fusion aims to promote patient-centric healthcare delivery and research, as patients are the greatest stakeholders in their own health. Within a fused macrocosm, our proposed IMS would create individual patient profiles by aggregating all relevant data. A profile would include the following:

1. Complete Patient Medical History
2. Complete Family Medical History
3. Omics Records (*e.g.,* gene and protein sequences)
4. Epidemiological and Treatment Patterns (based on the patient's age, gender, race, zip-code, etc.)
5. Non-Specific Demographic and Socioeconomic Data (based on the patient's zip-code)
6. Buzz/Hype on Social Media

Profiles of this nature would only be accessible to those parties who require personally identifiable health data – namely patients, healthcare providers, and insurance companies. Within our current framework, patients' requests for their profiles would be approved by their physicians, to ensure patient safety and avoid misinterpretation. In some jurisdictions, governmental authorities would also require access to the profiles.

With complete patient profiles at hand, physicians could consider the wide variety of genetic, environmental, and social factors at play. Omics records could be useful in understanding individual patients' molecular susceptibility to certain diseases. Epidemiological patterns may likewise prove relevant to diagnosis. Moreover, patterns in outcomes after treatment could be invaluable to physicians. Upon their output from the IMS, these outcome patterns would be stratified by patient age, gender, ethnicity, intervention type, and other attributes. Therefore, in an evidence-based manner, physicians could determine suitable treatments for each patient. In developing treatment regimens, physicians could also utilize non-specific demographic and socioeconomic data to account for non-medical constraints. Finally, physicians would be aware of and capable of adequately addressing the online hype their patients may have been exposed to.

Looking to the future, personalized medicine will constitute a merger between patients' clinical and biological (*e.g.,* omics) data (Karczewski and Snyder, 2018). Healthcare fusion would facilitate the combination of individual medical and biological data with epidemiological data. Together, these data could be leveraged to create personalized mechanistic models with predictive power (Viceconti et al., 2015, Shaikh et al., 2014, Costa, 2014). Furthermore, cloud computing, coupled with data from mobile applications and wearable sensors, can be utilized by patients for real-time health monitoring (Strang and Sun, 2019, Sobeslav et al., 2016).

5.2 Population Health

The components of healthcare fusion which drive biomedicine and personalized medicine can also deliver population-level impact. Key benefits of our proposed framework include surveillance and predictive power. The centralized IMS would contain all of a nation's health data; healthcare providers and other stakeholders would relay updates, amendments, and new data to the IMS regularly. Data aggregation would reduce record gaps and reporting delays, and support real-time population health monitoring. Analysis of aggregated data can reveal patterns and trends in the occurrence and spread of diseases (Strang and Sun, 2019, Grajales et al., 2014). As such, AI platforms would regularly scan records within the IMS in search of patterns and abnormalities; this could constitute an early warning system for infectious diseases. Discovered patterns could be utilized for ML, in the interest of developing predictive power.

Academic and research organizations would have access to blinded patient data from the IMS. Researchers could then conduct their own analyses, and relay patterns to the IMS. Governmental access to data within the IMS would vary between jurisdictions; in all cases, however, the IMS would relay epidemiological patterns and abnormalities to public health authorities. With access to up-to-date, comprehensive population data, governmental agencies could respond efficiently and decisively to public health emergencies. Furthermore, to provide nationwide equitable care, public funding could be allocated based on the epidemiological disease burden in each locality.

5.3 Profits

There are numerous ways to profit within the healthcare continuum. Outcomes in precision medicine and population health are highly profitable; investments in preventative and curative care drive revenue production (Cohen et al., 2008). Pharmaceutical and biotechnology corporations stand to profit from the vast amounts of data to be managed under healthcare fusion. Via the IMS, these businesses would have access to blinded health data; this data sharing model allows for corporate research and development without intruding excessively on patient privacy. Pharmaceutical companies, for instance, could leverage data within the fusion framework to accelerate drug discovery. De-identified omics and biobanking data could be utilized to identify therapeutic targets at the molecular level, while the centralized IMS could streamline clinical trial 187nrolment, monitoring, and data reporting. Moreover, these companies could scan anonymized clinical records to assess the demand for certain drugs on a geographic basis. They could subsequently optimize their operations to reduce costs while maximizing revenue.

Within the pharmaceutical sector, development of novel products and technologies is linked to high returns (Roberts, 1999). To realize these returns, pharmaceutical and biotechnology companies could use health patterns to anticipate and capitalize on market events. COVID-19, for instance, may have been detected early on in a fused system. Based on blinded data, businesses which anticipated the impending demand for masks, ventilators, and vaccines could have begun preparations in advance. Upon the full onset of the disease, those same businesses would be strategically positioned to maximally profit from the situation.

Finally, businesses in the health sector would have access to aggregated and de-identified social media records. These blinded data could prove instrumental for market research purposes. Utilizing patient sentiments, pharmaceutical and biotechnology companies could refine sales tactics, improve customer service, and identify niche roles within the market.

6. Implementation and Management of Healthcare Fusion

Ultimately, a governmental agency, public-private partnership, or private contractor(s) could oversee our proposed framework. Given the many stakeholders and interests in play, different expertise would be necessary to oversee each “arm” of a fused macrocosm. Here, we suggest several “departments” or sections that could be included in any supervisory body:

6.1 Technical Management Section

Day-to-day management of the IMS would be delegated to a section comprised of data scientists and software engineers. This branch could oversee AI platforms, implement system-wide software and firmware updates, analyze data, and resolve technical concerns.

6.2 ROBIN and Quality Control Section

Quality control checkpoints are necessary to ensure system-wide interoperability and streamline data transmission and utilization. A centralized quality control department would ensure that data entering or leaving the IMS are appropriately packaged (*i.e.,* “ROBIN-ized”).

6.3 Interface and Outreach Section

Staff within this section would maintain relationships with stakeholders in the fused macrocosm. Outreach personnel could encourage stakeholder participation through advertisements and incentives. Moreover, technicians and support staff would handle data-related inquiries. Finally, a public Relations team could compile data for public release.

6.4 Data Security Section

This section would maintain data integrity and patient privacy within the healthcare fusion framework. Data scientists and cybersecurity experts would oversee a rigorous security system for the IMS. These personnel would also develop solutions to protect data in transit. In addition, a centralized security department could perform audits to ensure stakeholder compliance with established regulations.

6.5 Regulatory Section

A regulatory branch would likely fall under the auspices of a governmental agency. Officials in this section would draft and implement system-wide policies on data management and security, stakeholder rights, and other pertinent matters. Importantly, regulators would balance patient and business interests in controlling access to data within the IMS.

Today, nations utilize a wide variety of healthcare and governmental models; as such, interactions between stakeholders vary on a national basis. Our proposed framework and business strategies could be adjusted and optimized to meet the needs of individual nations. Here, we discuss implementation and management strategies for healthcare fusion in three types of national healthcare systems. We are fully aware, however, that numerous intermediate and hybrid modalities also exist worldwide (*e.g.,* Canada and the United Kingdom, which have more socialized systems); our framework is agile enough to adapt accordingly.

6.6 Decentralized Government, Public Healthcare System (*e.g.,* New Zealand, Estonia)

In this group of countries, government hospitals and clinics constitute the majority of healthcare providers. Patients fund these providers through taxes, and receive low-cost or free care in exchange. As such, government is a dominant stakeholder in healthcare, along with patients and businesses in the health sector.

Implementation of healthcare fusion in government-run healthcare systems would be relatively straightforward. Based on central directives, system-wide changes could be made to modernize healthcare data infrastructure and link public care facilities to a cloud-based IMS. Importantly, private sector motivation and patient consent must be sought. In this interest, governments could provide incentives to patients and businesses in exchange for their participation. Finally, our proposed IMS would likely be publicly funded. We expect governmental agencies to take responsibility for data security and regulation. However, public-private partnerships may be established for technical management, quality control, and outreach. Based on public sentiment, limitations on data access by governmental organizations could be imposed (*i.e.,* governments may only have access to blinded data).

6.7 Centralized Government, Public Healthcare System (*e.g.,* Qatar, Oman, China)

Government is the major healthcare stakeholder within this category of countries. Through their tax dollars, patients fund government-run healthcare systems which provide low-cost care. Patients in these countries may have reduced control over their personal health data; this could streamline the adoption of healthcare fusion.

As discussed above, in-house changes within government-run healthcare systems could be accomplished efficiently. Patient participation and data sharing could be mandated through governmental directives. Health and social media corporations could likewise be required to contribute relevant data in order to continue business operations in a country. A cloud-based IMS could be constructed rapidly; governments may assume responsibility for all aspects of management of the fused macrocosm. It is likely that governmental agencies would have access to all data (unblinded) within the IMS.

6.8 Decentralized Government, Privatized Healthcare System (*e.g.,* United States)

Within countries such as the United States, a network of private care systems serves patients in exchange for insurance reimbursements. A limited number of public healthcare systems exist. Considering their financial role, insurance providers can exert great influence on healthcare delivery. These companies can regulate patient access to specialists and mandate diagnostic workups. As such, insurance companies are major stakeholders in healthcare. Other stakeholders include patients, healthcare providers, pharmaceutical and biotechnology corporations, and social media companies. Compared to the decentralized-public and centralized-public models, the role of government may be reduced.

In a landscape dominated by private interests, rollout of healthcare fusion may prove difficult. Governmental authorities facilitating the adoption of fusion would face the challenge of unifying a multitude of stakeholders and technologies. A variety of financial incentives could be utilized to accomplish this goal. Private healthcare providers, for instance, could be offered grants to modernize their data management infrastructure. These providers, along with insurance, pharmaceutical, biotechnology, and social media companies, could contribute data to the IMS in exchange for tax breaks. Further incentives could be offered to encourage patient participation. Our proposed IMS could be developed solely by the government, or via a public-private partnership. While a governmental agency would likely regulate the fused macrocosm, responsibilities for technical management of the IMS, quality control, outreach, and data security could feasibly be delegated to a private contractor(s).

American political institutions are notably willing to adapt to shifting healthcare technologies. Extensive political action in favor of EHR and electronic health data has taken place; some examples are presented in Table 1. In supporting a national health database, allocating funding for EHR, and regulating data privacy, the US has taken its first steps toward fusion.

Table 1: Examples of United States political actions pertaining to EHR and electronic health data

This list highlights some landmark actions encouraging the implementation of data storage and processing technologies in healthcare.

Legislation	**Purpose/Effect**
HIPAA (Health Insurance Portability and Accountability Act, 1996)	Regulates the sharing of personal health information.
ARRA (American Recovery and Reinvestment Act, 2009)	Provides $19 billion for health information technology.
HITECH (Health Information Technology for Economic and Clinical Health Act, 2009)	A part of ARRA which includes a set government incentive to encourage medical facilities to implement EHR.
CMIA (Confidentiality and Medical Information Act, 2012)	California state law that supplemented pre-existing federal protections of personal medical records.
All of Us Research Program, 2015	Federal program which aims to collect health data and metadata from 1 million volunteers, and create a national database to facilitate large-scale longitudinal studies (Sankar and Parker, 2017).

Concerns regarding data privacy and security are key points of contention in the implementation of healthcare fusion and related initiatives. Numerous perspectives on patient data rights and data management standards are currently available from all players in the healthcare sector. Pharmaceutical corporations and other health-related businesses could benefit immensely from access to patient data. On the other hand, patients may justifiably oppose the use of their data for commercial (or even research) purposes.

Conflicts between stakeholders have notably crippled fusion-related efforts in the past. In 2013, the UK government announced the care.data initiative, which aimed to create a centralized data repository with patient records and relevant metadata. This program was paused in 2014, and ultimately canceled in 2016, due to public discontent. Presser et al. identified the following major shortcomings of the initiative: (1) developers failed to properly consult with patients, providers, and other stakeholders; (2) unattainably high expectations were established for data management and privacy; and (3) healthcare providers faced contradictory regulations regarding data sharing (Presser et al., 2015).

To avoid the pitfalls of previous efforts, healthcare fusion aims to encourage stakeholder participation and shared returns. In all cases, universal best practices must be developed and implemented to prevent the stealing and selling of personal medical data (Mamlin and Tierney, 2016). Beyond this, stakeholder rights and responsibilities vary between nations. Implementation of our framework could be highly efficient in public healthcare systems and nations where stakeholder compliance can be enforced rather than encouraged. However, we believe that healthcare fusion is adaptable to a variety of political and social contexts.

7. COVID-19 and the Need for Healthcare Fusion

Amidst the COVID-19 outbreak, it is evident that the status quo of healthcare systems is unsustainable. Delays in drug development, legal barriers to public health measures, and equipment shortages place patients and medical staff at risk. Many of these shortcomings stem from incoherent data management and sharing schemes.

For early detection, valuable data can be gleaned from EHRs in an interconnected system. Emergency department triage diagnoses, for example, can be analyzed to detect outbreaks of epidemic disease with high sensitivity and specificity (Olszewski, 2003). Social media is another relevant ICT – posts by individuals may alert public health authorities to unusual outbreaks. Under healthcare fusion, governments, hospitals, patients, scientists, and private industry are connected. Elements of fusion were visible in China's initial response to COVID-19: due to efficient data sharing between hospitals and central authorities, the initial outbreak was detected and reported to the World Health Organization (WHO) after only 27 cases were diagnosed (Wu and McGoogan, 2020). New Zealand's COVID-19 response further demonstrates the value of collaborative, synergistic responses to public health crises.

In responding to pandemic diseases, hospitals and research institutes must interconnect to drive translational research. This was seen in China, as within a month of the detection of the first abnormal case in Wuhan, researchers identified the causal factor of COVID-19 (Wu and McGoogan, 2020). Pharmaceutical corporations are major stakeholders in vaccine development and drug discovery – both of which depend on reliable data from hospitals and epidemiologists; they should be connected to the governmental and clinical sectors to (1) access relevant, blinded clinical and basic science data for research and development, and (2) make incentivized contributions to local and national responses.

As the pandemic progressed, national and international efforts to promote fusion materialized and matured. The US government has increasingly adopted measures to connect local and national datasets – beginning in March 2020 with a mandate for all state laboratories and hospitals to report COVID-19 test results to the Centers for Disease Control and Prevention (CDC). At the international level, countries have formed consortia, while novel initiatives have linked basic and clinical COVID-19 researchers with other scientists worldwide. These are all emerging examples of international healthcare fusion.

8. Conclusions

A significant pitfall in today's notion of healthcare is the cavalier attitude toward synergy. This poses a serious barrier to entry for innovation in healthcare. We see an urgent need for a new healthcare macrocosm to link the currently isolated microcosms of governments, healthcare providers, private industry, and patients. In this regard, we propose healthcare fusion, a data-driven and holistic framework with a cloud-based IMS at its core, for patient-centered healthcare delivery. One immediate advantage of the fusion framework is that it aligns the interests of research, business, and government to ensure robust and profitable outputs.

Within our framework, a centralized, cloud-based IMS could efficiently connect stakeholders in health and medicine. Big data analytics systems, optimized through our proposed ROBIN criteria, could analyze aggregated medical data. Data-linked outputs of AI analysis could support personalized medicine, preventive care, epidemiology, market research, and other pursuits. By distinguishing between blinded and unblinded data, regulators can allow stakeholders to access data within the IMS, without compromising patient privacy. This is of paramount relevance to the emerging fields of personalized medicine, eHealth, and telemedicine.

Implementation of the healthcare fusion framework would firstly require political will, and then the contribution of patients, governmental authorities, healthcare providers, and the private sector. These stakeholders could be mobilized through incentives and regulations, which would vary between nations. A proof of concept may be examined in nations that are progressing towards comprehensive, digitized, big data-based healthcare systems.

In closing, we envision healthcare fusion as a novel, holistic approach to healthcare data management and utilization. Healthcare fusion is not only a centralized IMS. Rather, it is a comprehensive framework encompassing the stakeholders in healthcare, the healthcare data themselves, the system-wide quality control and oversight mechanisms, and the data repository. Our framework is novel in that it broadly leverages demographic and socioeconomic data in support of socially and environmentally conscious healthcare. Healthcare fusion also includes social media companies as key stakeholders in health, and utilizes "buzz" and "hype" from social media records to better inform and warn patients and physicians. Finally, we suggest the ROBIN criteria as a system-wide quality control mechanism.

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