Inefficiencies in the American Healthcare System and the Leap-Frogging Power of Predictive Care

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Abstract

The American Healthcare system is infamously inefficient; spending more money per capita and getting less in return than any other developed nation. When compared, preventative care emerges as a key difference between the U.S. Healthcare System and other more efficient national healthcare systems. Another characteristic of the American Healthcare System is that the data, although abundant, is highly fragmented, is owned by many different private entities, and is protected under federal laws such as HIPAA. Modern technological breakthroughs in Large Language Models and other Attention Networks have begun to show promise in merging complex databases into a coherent dataset from which powerful predictive models could be trained. These predictive models may be the exact leap-frogging technology that the American Healthcare System has been waiting for.

1 Introduction

1.1 Inefficiencies of the American Healthcare System

In a recent report, Dr. David Blumenthal et al. demonstrated the shortcomings of the American Healthcare System (The Commonwealth Fund, 2021). Despite spending nearly double the amount of money (around 18% of GDP) on its healthcare system compared to other nations in the study, the United States currently ranks last in overall performance. Dr. Blumenthal et al.'s report places the United States last in access-to-care, primarily due to lack of universal coverage, high out-of-pocket costs, difficulty in finding a primary care physician, and limited after-hours care availability. The United States also ranks last in health outcomes because of short life expectancies and superlative rates of preventable deaths. One, unifying shortcoming which is a contributing factor to all the aforementioned problems is the lack of a Universal Healthcare System.

1.2 Efficient National Healthcare Systems

There are many different metrics by which one could measure efficiency in a national healthcare system. One common metric is the ratio of life-expectancy to percent of GDP spent on healthcare. In this way, countries which spend a lot on healthcare without yielding a higher life expectancy are considered inefficient.

Efficient national healthcare systems often invest in preventative care systems. In general, these systems utilize public health education and medical screening to prevent a potential health issue from being exacerbated or from existing in the first place. Japan, a country well-know for its preventative healthcare system, emphasizes health and nutrition education at a young age and has a robust medical screening and vaccination system (The Japan Times, 2023).

Country	%GDP Spent on Healthcare	Life Expectancy (L.E.)	L.E.: / %GDP
United States	18	77.5	4.3
Australia	10.5	84.07	8.01
Netherlands	13.2	82.3	6.69
United Kingdom	10.9	81	7.43
Japan	9.8	84	8.6
Norway	8.1	83.46	10.30
Singapore	5.9	83	14.06

Table I: Data demonstrating Average Life Expectancy (L.E.) and %GDP spent on Healthcare. Data obtained from the following sources: (Australian Government Department of Health and Aged Care, 2024), (U.S. News, 2024), (Office for National Statistics, 2023), (NBC News, 2024), (Worldometers, 2024a), (Trading Economics, 2024), (Worldometers, 2024b), (Peter G. Peterson Foundation, 2024), (Worldometers, 2024c), (U.S. Department of Commerce, 2024b), (CNN, 2024), (Politico, 2024), (Statista, 2024b), (Statista, 2024a), (Insurance Hero, 2024), (U.S. Department of Commerce, 2024a), (Database Earth, 2024),

Early medical intervention tends to save a great deal of money downstream given that patients are spared the expense of a complex medical procedure and medical professionals are able to spend more time on the existing serious medical issues. Approximately 25% of U.S. healthcare spending is wasteful amounting with estimates ranging from $760-$935 Billion dollars per year (Peter G. Peterson Foundation, 2024), (McCracken, 2019). Broken down, the inefficiencies lie in the following categories:

- Administrative Complexity: $265 billion
- Pricing Failure: $230-240 billion
- Failure of Care Delivery: $102-166 billion
- Overtreatment or Low-Value Care: $75-100 billion
- Fraud and Abuse: $59-84 billion
- Failure of Care Coordination: $27-78 billion

A significant portion of this waste could be directly addressed and more thoughtfully analyzed if a comprehensive National Aggregated Healthcare Database existed.

2 Fragmented Datasets in the American Healthcare System

As the McKinsey Global Institute lays out in their Big Data Full Report textbook (McKinsey-G.I. *et al.*, 2011) the United States has four major pools of data that remain largely separate from one another. These pools of data are owned by many different actors and also are comprised of a variety of types of data-points. These datasets could contain everything from an ultrasound image to the cost of a particular prescription drug. Political and economic incentives are at play which keep these pools of data disparate, however these factors are outside of the scope of this paper. The third factor which keeps these datasets separated are the many technological hurdles which would need to be overcome for such a data-aggregation process to take place which is the main concern of this paper.

2.1 Clinical Data

Clinical data typically is collected in a hospital or clinic where a patient is interacting with a healthcare professional. These datasets can be comprised of ultrasound images, radiology reports, x-rays, or any other tests which the patient may have had done during their visit. These datasets are ideally well structured and coherently joined so that a patient's ultrasound image and the corresponding radiology report are easily linked. In practice however this is rarely the case since every practice and every doctor within a given practice may have a slightly different method for recording their findings.

These medical providers typically own these datasets in the United States meaning a large hospital network like the West Coast's Kaiser Permanente has a tremendous dataset of patient reports whereas a private practice would have a comparatively smaller dataset. Even within the pool of Clinical Data, there exist fragmentation which bottlenecks the quality of inferences which could be made with these datasets. Aggregating such datasets would require some data infrastructure capable of linking individual patients to all of their tests across potentially many different locations.

2.2 Pharmaceutical Research and Development Data

Research and Development of pharmaceuticals in the United States is a large industry, where several companies compete to be the first to market with a new drug. Healthcare as a market is unlike most others since the demand is effectively inelastic, especially when talking about a life-saving drug. For this reason, being the first to market means that company can capitalize on that demand without needing to share the market with other competitors. For this reason pharmaceutical data is often proprietary and is rarely shared between companies before bringing the drug to market.

To aggregate such a dataset, there would need to be infrastructure which can seamlessly combine the knowledge obtained by each of these individual companies, regardless of differences in data-structure from company to company. Such an aggregated dataset, if combined with the aforementioned aggregated clinical dataset, could be used to more efficiently iterate on the R&D process. A hypothesis could be made from within a company's R&D department and tested in a clinical setting across a wide number of practices and individuals. If a national aggregated dataset existed the validity of this hypothesis would be not only promptly available to the specialist who made it, but also to all other specialists who may not have thought to ask the same question. Such democratization of this data would mean an accelerated R&D process across the large companies present in the field and could lead to more rapid innovation. An important factor remember is that the faster these innovations are made, the fewer people will suffer unnecessarily.

2.3 Activity (Claims) Cost Data

This pool of data is comprised of datasets which measure factors such as utilization of care and cost of care. In general, it is concerned with how the financial system which underpins the United States Healthcare System operates and flows from one party to another; typically from patients, to healthcare insurers, to healthcare providers. These datasets are owned by these same healthcare providers and insurers. One problem which causes an undue inefficiency in the United State's Healthcare System is fraud. According to McKinsey, American insurance companies estimated that 2-4% of annual claims are fraudulent or unjustified; with that number rising up to 10% for Medicare and Medicaid. Identifying fraud is a labor intensive and potentially harmful practice, given that a claim flagged falsely as fraudulent could cause serious damage to the well-being of the patient. For this reason, an aggregated dataset of all cost data could be used to train Machine Learning models which identify fraud with a more consistent and effective methodology. Instead of a human examining each claim for fraud, a machine learning model could flag the potentially fraudulent cases for human review; meaning that individual need not examine as many cases and therefore will be able to move more quickly through their workload.

The actual mechanism through which this data could be aggregated is likely less complex, seeing as the data is comprised of financial time-series and other numeric values. It is likely that two different insurance providers are storing the same metrics and cost analyses; making the aggregation even less complex. Combining such a dataset with the more comprehensive national healthcare dataset would be more challenging, but realistically the cost of a particular drug or procedure and its utilization could be simply linked to each clinical usage of it and to the R&D data which produced it.

2.4 Patient Behavior and Sentiment Data

This dataset pool is perhaps the most spread out and the hardest to capture. One could imagine all of the data which a smart-watch takes during a run (including heart-rate, steps taken, average speed, etc.), which could be invaluable to certain healthcare professionals. Less personal datasets such as patient behaviors, preferences, and retail purchase history could also be used to make important inferences about someone's health. For example, an individual who spends a great deal of money on McDonald's and alcohol is, in general, more prone to health issues than someone who spends a great deal of money on workout clothes and gym classes.

The fragmented nature of this pool is due to the many different owners of these datasets: retail companies, tech companies, and the individual patients themselves. Combining these individual datasets would require a link around each patient to understand how each individual differs from another in their habits, eating patterns, amount of exercise, and lifestyle. Creating such an aggregated dataset could help flag those who are at a higher risk of serious health issues based purely on lifestyle. When aggregated with a national healthcare database however, such data could act as an initial flag for screening, which then starts a process of treatment super-charged by the clinical, R&D, and cost data that was mentioned earlier.

3 Modern Methods of Data Aggregation

3.1 NoSQL and RDBMS

NoSQL and RDBMS (Relational Database Management Systems) are modern solutions in the field of Big Data Technologies. While they are used to accomplish similar objectives there are some important differences between what exactly they are suited for.

NoSQL is often used for large volumes of unstructured and semi-structured data. These databases can accommodate changing data structures without requiring the usual migration or schema alterations common in SQL databases. The flexibility and scalability of such a system is also quite important to consider, since a national healthcare dataset would be quite large. Since adding a new node to a NoSQL database cluster is often quite easy, it means the never-ending stream of data coming from every aspect of the American Healthcare System could be handled without significant processing delays, (GeeksforGeeks, n.d.), (MarkLogic, n.d.), (Kotsilieris, 2021), (Lonti, n.d.).

RDBMSs however, require structured data with well defined relations between different entities. This requirement means that RDBMSs are less flexible and scalable, but they are ACID (atomicity, consistency, isolation, and durability) compliant. For this reason, RDBMSs are, in a sense, more reliable than their NoSQL counterparts, but they are more brittle and require schema changes if a particular data structure needs to change (Dremio, n.d.), (Javatpoint, n.d.).

3.2 Knowledge Graphs and Large Language Models

Knowledge graphs are a type of database which allow for heterogeneous data to be combined and comprehended. In general, an entry into a knowledge graph looks something like this: (Bob, is friends with, Alice). In this way, the knowledge graph has stored that concept and it may also contain an entry like (Bob, grew up with, Alice). By adding more and more entity relationships, a full knowledge graph emerges which can store complex concepts as simple vertices and edges. If a standardized ontology and lexicon were introduced specific to medicine and the healthcare system, these graphs could be highly regular without compromising the complexity of the concepts it stores. Additionally, knowledge graphs can be added to vector-stores, which embed these concepts in a way that allows for highly efficient querying from an Large Language Model (LLM).

Modern LLMs struggle when it comes to hallucinations and making mistakes. This problem can be partially addressed through fine-tuning of a model, but the models still suffer from the fact that they are ignorant to anything outside the original training dataset. With modern breakthroughs in Retrieval-Augmented Generation however, an LLM can effectively act as a grounded "expert" of a given knowledge graph by summarizing and contextualizing any of the concepts stored in the graph. Today, inference time poses a significant problem when using LLMs for such operations; however given the intense competition in the field it is a safe bet to assume that LLMs will continue to improve for at least the next few years, (Brown *et al.*, 2020).

There are many concerns regarding HIPAA when combining an LLM and patient data. Medical companies today which want to use ChatGPT for example need to be careful to anonymize any data which is sent to the OpenAI servers, or risk violating HIPAA. This can be circumvented by hosting a local open-source LLM (such as the Llama model from Meta) through a service such as Ollama or LLMStudio. Doing so would mean that the data never leaves the HIPAA approved servers and thus does not pose any legal problems.

3.3 Foundations of a National Healthcare Database

In order to create a National Aggregated Healthcare Database (NAHD), both NoSQL Databases and RDBMSs would need to be employed in harmony to capture the structured and unstructured data-sets present across the whole fragmented industry.

To begin, a NoSQL data-lake which ingests all the data in its raw form could be implemented to allow for scalable and continuous data-ingestion. This way clinical, R&D, cost, and patient sentiment data will all begin in the same part of the NAHD and would always be accessible there in their original form.

From there, the more structured datasets (like cost analysis and structured experimental R&D data) could adopt the same schemas from which they originated. In this way, a system could be set up which first identifies a new piece of data as being important for an existing RDBMS via an LLM process, and then could be automatically added in the appropriate way to this RDBMS. A fine tuned LLM could be implemented to help facilitate the cleaning of particular data-dumps which may not neatly fit into the existing RDBMS schemas. The remaining data, would need to be stored in smaller and more specific NoSQL pools to accommodate the unstructured nature of the data. For example, one such pool could be related to Cancer and could contain all the unstructured relevant R&D, clinical, and patient sentiment data pertaining to that disease. That way individuals could query based on keys such as a specific cancer, Patient ID, outcome, pathologies, treatment pathways, particular drugs, etc. and retrieve all the information relevant to their particular query.

The final step in setting up such a database would include a unified query layer, capable of pulling from the appropriate RDBMSs and NoSQL databases. Accomplishing such a unified query layer would be quite difficult however, given the different inherent natures of RDBMSs and NoSQL databases. Modern Knowledge Graphs and Large Language Models could potentially solve this problem.

4 Systems Made Possible by a National Aggregated Healthcare Database

4.1 Data-Driven Healthcare Professional Assistant

Consider a particular problem which needs to be addressed with a curated dataset. Perhaps a healthcare professional wants to understand what the best path for treatment is for a new patient who has been taking a certain prescription and who is presenting with certain symptoms. An LLM could be tasked with examining all the names and descriptions of the different RDBMSs, selecting the most appropriate tables, and writing relevant queries for such a table. Modern LLMs may have slow inference times and limited context windows; however by breaking down the problem into atomized chunks through use of another LLM it could be expected to accomplish these smaller atomized tasks. In the example mentioned earlier, the first LLM would be tasked with atomizing the problem into smaller queries like this:

- What diseases could be causing these symptoms?
- What side-effects does their specific prescription cause?
- What data is available on this particular patient's behavior and lifestyle?
- What are the clinical treatment pathways taken by other doctors presented with a similar case?
- Which treatments would be most cost effective?

Assuming the NAHD is organized in a meaningful hierarchical manner, an LLM could traverse the NAHD and find the appropriate data pools and tables which would help answer the question. Then the LLM could write queries in the appropriate query language to pull that information from these data pools and tables. A final LLM call could then work through this pulled data and extract the entity relationships in order to curate a personalized Knowledge Graph for this individual patient and their case.

If the Knowledge Graph is further embedded in a vector-store, an LLM could act as an expert on the case by performing Retrieval-Augmented Generation (RAG) with the Maximum Marginal Relevance (MMR) algorithm. There are additional methods by which an LLM can crawl through the knowledge graph to clean up repeated relationships and further clarify other relationships; resulting in a clean, well-structured, and sensible knowledge graph. In theory, since the knowledge graph is populated with all the appropriate data from the LLM's database queries, this expert LLM should be able to answer all the original atomized queries laid out above. Additional algorithms could be run across the whole of the Knowledge Graph to try and identify specific nuances of the user's case which may not be easily thought of by the given healthcare professional. An advantage to this approach is that since it is ultimately data-driven, the final answer could be traced all the way back to the original documents which were inserted into NAHB and the knowledge graph, and which ultimately influenced the LLM's response– yielding a degree of transparency that other AI systems often lack. Such a system would undoubtedly be a great tool for healthcare professionals in every sector of the industry.

4.2 Preventative Health Care System

Given that the U.S. is severely lacking in a serious preventative health care system and culture, one major advantage of having a NAHD would be identifying where exactly a preventative healthcare system would be most effective both in cost and outcome. In this way, the United States could begin quickly catching up to other modern countries in the most efficient manner possible. Specifically, a NAHD would enable policy makers and R&D specialists to identify which problems are causing the most egregious inefficiencies and could begin taking steps to counteract these problems at the source. They could answer questions such as:

- What medical interventions could help individuals earlier?
- What specific shortcomings of the education system are yielding serious health issues later on in American's lives?
- What states / cities are worse off than others in preventative care?

Generally, preventative systems attempt to stop a medical problem before it happens and achieves this through policy and cultural pressures. These systems operate at the scope of communities, municipalities, and states and therefore do not directly impact individuals. To clarify, instead of a policy-maker saying "Hey Joe, you drink too much soda so I'm limiting the size of soda bottles which can be served to you", they enact a policy which says "Hey New York City, a significant amount of you are drinking too much soda, so I'm limiting the size of soda bottles which can be served to all of you." This is the fundamental difference between a preventative healthcare system and a personal predictive health care system.

4.3 Personal Predictive Health Care System

Big data and machine learning often go hand-in-hand given that, in general, a larger dataset translates to improved performance in a model. With an implemented NAHD, the possibilities for predictive health care systems becomes practically endless. Rather than storing the data retrieved from the unified query layer in a knowledge graph, a data-scientist could use these curated and aggregated datasets to train highly effective machine learning models. Imagine a world where a symptom suddenly crops up in an individual's life, and instead of asking WebMD, that individual asks the Personal Predictive Health Care System.

This system would contain a large number of specifically trained models which helps to direct the patient to the proper care and treatment. Additionally, such a system could predict that an individual is in need of some medical intervention if the user is steaming their own personal health information through a device similar to a FitBit. During training, these screening models would be exposed to other patients with similar lifestyles to the imagined individual and would be able to predict and point to the next appropriate models which could ultimately predict the most cost effective and highest utility treatment plan for the user. In this way, the United States could enact the world's first personal predictive healthcare system which intervenes on the individual level to get care to those who need it; potentially before they even know they need it.

5 Leapfrogging Technologies

5.1 Historical Examples of Leapfrogging Technologies

The term "leapfrogging technology" applies to a technology which has been introduced to a country before its legacy version was widely adopted across the country. In that way, the country can "leapfrog" other countries and catapult themselves into the future.

Perhaps the most well-known example of a leapfrogging technology is the mobile phone when it was introduced to countries in Africa such as Kenya and Ghana. These countries had not built the infrastructure for landlines by the time the mobile phone was available and, as a consequence, they did not have to retrofit a legacy telecommunication infrastructure for the modern mobile phone.

This shortcut allowed for mass adoption of the mobile phone far faster than many other developed countries.

Another similar leapfrogging technology was the introduction of renewable energy to rural areas all around the world. In remote, agrarian pockets of the world the challenge of running a power line to the main grid was simply insurmountable for many farmers. In today's world they can effectively set up their own power grid with solar panels, hydroelectric turbines, and wind turbines. Since these grids were not based on fossil fuels, more attention to renewable-energy specific problems (such as energy storage) could be more completely considered when designing these green grids.

5.2 Ingredients for Leapfrogging

Countries which want to adopt a leapfrogging technology must meet a handful of requirements before they can achieve a successful upgrade.

First of all, it requires the absence of a legacy system. This absence creates a vacuum for innovation to fill, like in the case of mobile phones and renewable energy. It also requires the technological capacity and the educated populace to roll out such an upgrade. Finally, there needs to be a federal policy ecosystem capable of enacting such a change.

5.3 American Healthcare's Leapfrogging Event

Given that the U.S. lacks a universal health care system and a robust preventative healthcare System, the nation lacks what could be considered a legacy system to a predictive healthcare system. The U.S. also certainly has the technological and educational capacity to implement such a system. The final hurdle, which the U.S. fails to pass at present, is the federal motivation to enact policy to take full advantage of the vacuum. That said, the increasing demand for a functional national healthcare system continues to be a talking point of modern political campaigns. Additionally if an economic case were made that demonstrated the amount of money being left on the table, political and corporate entities may change course and adopt a predictive healthcare system.

6 Conclusion

The power of big data is only just beginning to show itself. The modern age of machine learning and computation has unlocked a number of opportunities that was once thought impossible to humans. Predictive systems have already begun revolutionizing industries across the economy, allowing for efficient upgrades that save both time and money.

The American Healthcare System, in particular, is an overloaded, inefficient behemoth of a system. As the industry continues to modernize in the twenty-first century, the need for more comprehensive data will only increase. A National Aggregated Healthcare System would supercharge this modernization. Allowing data-scientists across the country to create predictive systems and likely capitalize on the shortcomings of the healthcare system. Many of the more practical problems, like access to care, cost-effective utilization of treatment, drug-development, etc. would also benefit from automated systems which more efficiently distill the overwhelming amount of data into a useful, human-readable format.

It is easy to forget when examining this information that the dollar signs and percent symbols are all representative of one thing: human lives. A more efficient healthcare system means the people who need the care can actually get it and at a reasonable price. People in the United States are dying today because they do not have access to proper care and or the funds necessary to pay for the proper care. It is negligent and irresponsible to not build the absolute best healthcare system possible in the wealthiest country the world has ever seen. The greed and political lethargy which has delayed a Universal Healthcare System and a National Aggregated Healthcare Database, while inexcusable, has provided the exact environment required for a leap-frogging technology if only a proper policy could be enacted. The backbone of such a NAHD which was laid out above and which depends on RDBMSs and NoSQL databases realistically could have been constructed soon after these technologies were fully available and computationally viable in the early 2000s.

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