



Scenario Planning in Healthcare Development in the VUCA World

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Abstract. VUCA is an acronym that stands for Volatility, Uncertainty, Complexity and Ambiguity. This VUCA classification encourages creating new strategies according to unknown situations, rather than copying traditional patterns from good practices. Firstly, in order to respond to rapid changes, it is necessary for everyone to make quick decisions. To do that, a vision is required in terms of environmental volatility. Secondly, since success means continuing until achieved, which means being sustainable. Therefore, to stay successful, choose affordable losses within tolerance, rather than maximizing profits. Modeling simplifies complex phenomena. It is possible to understand complicated phenomena as they are. Lastly, if the object is not visible, it is possible that an obstacle is blocking your view. Switching perspectives, looking for the object from a different view-point may work. After analyzing the situation, design thinking is effective at the stage of creating a concrete solution. And in the current complex societies, causal loop diagram is a particularly effective method to explore a vision for sustainable business ecosystems.

Keywords: VUCA · Healthcare data science · Future design

1 In the World of VUCA

1.1 What is VUCA

The world is undergoing rapid structural changes as it faces various challenges from the COVID-19 pandemic declared by WHO on March 11, 2020. Structural change is often sparked by technological innovation, new economic developments, global shifts in the pools of capital and labor, changes in resource availability, changes in supply and demand of resources, and changes in the political landscape. Unfortunately, however, many structural changes are being caused by unknown viruses this time.

The battle between humans and viruses has been repeated over the years. Since the virus is carried by humans, the development of transportation is accelerating the spread of the virus. It can be said that structural changes have occurred in the tactics against viruses. Fighting unknown enemies requires a new method of situational judgment. One of the methods is VUCA [1], which is an acronym that stands for Volatility, Uncertainty, Complexity and Ambiguity as shown in Fig. 1. In this context, volatility refers to the volatility of the environment.

1.2 How to Get Through the VUCA

General Approach to Volatility. In order to respond to rapid changes, it is necessary for everyone to make quick decisions. To do that, a vision is required to choose the adequate action for changes in environment [1]. By presenting the vision to all members, each of them will be able to clarify their own objectives and act autonomously. Without enough time to communicate, visioning is more flexible and agile than creating rules. To achieve this, source credibility, discussion transparency, information sharing, and a short message of vision are important.

General Approach to Uncertain. Causal models focus on maximizing returns by selecting optimal strategies. In general, the higher the expectations, the higher the risk. However, the risk should not be a fatal loss to stop all actions because success means continuing until achieved, which means being sustainable. Unfortunately, if you encounter a fatal failure, the path to success is cut off. Therefore, unsustainable failures should be avoided anyway. Given some options, you need to determine if the loss is acceptable, rather than expecting a profit. To stay successful, first choose affordable losses within tolerance, rather than maximizing profits [2]. Further development of this perspective will lead to an ecosystem for sustainability. This is the royal road to success and avoiding uncertain.

General Approach to Complexity. Modeling simplifies complex phenomena. In addition to modelling, modularization is to make a model divided into units that can be driven independently with minimal association with others. Modularization narrows down factors to consider and makes problem solving easier. By utilizing the modularization, it would be possible to understand complicated phenomena as they are.

General Approach to Ambiguity. If an object is not visible, it is possible that an obstacle is blocking your view. In order to solve this problem, one way to solve this problem is to switch perspectives and look at them from different perspectives. Factor analysis is a method of analyzing emotional value using different perspectives. In the analysis, the emotional value is measured as the length of the shadow projected on the axis of a certain interest. Since vector cosine is defined as the cosine of the angle between the vector and the axis, the length of the shadow on the axis is also defined as the cosine of the value vector. Therefore, the cosine of the new angle vector can be defined as a new viewpoint in factor analysis. The image of factor loading plot in Fig. 2 shows a factor loading plot in terms of power generation efficiency. The vertical axis shows the value of power generation efficiency. The horizontal axis shows the value of eco-friendly.

Figure 2 shows four vectors, which are Nuclear power generation before and after the accident, thermal-power generation, wind-power generation. Each vector component shows the characteristics in the power generation methods. Wind power is eco-friendly, but the efficiency is poor. Thermal power generation is more efficient than wind power generation, but it is not eco-friendly. On the other hand, in the nuclear power generation, the efficiency before and after the accident is the same, however it seems that there looks a significant change from eco-friendly to not eco-friendly. In this way, each axis component defined as the cosine of the value vector is compared to understand the characteristics of each vector.

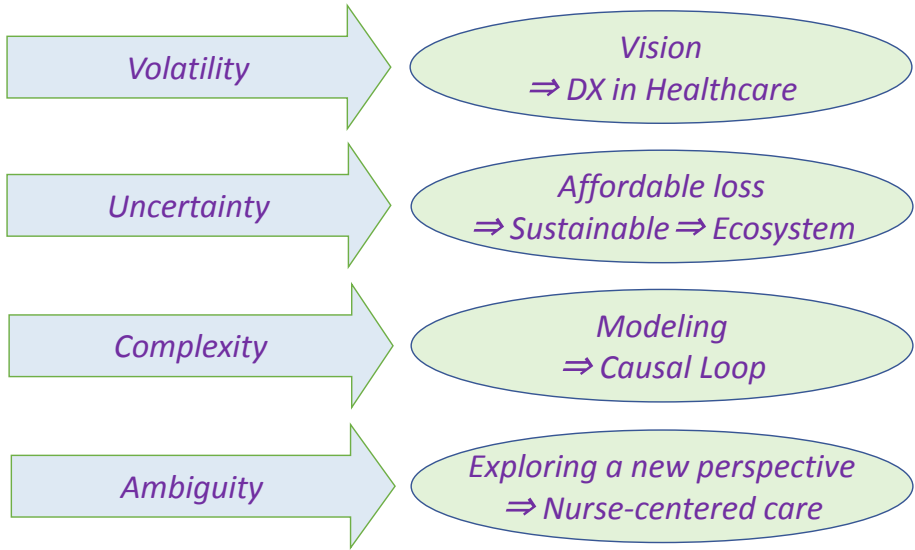


Fig. 1. How to get through the VUCA

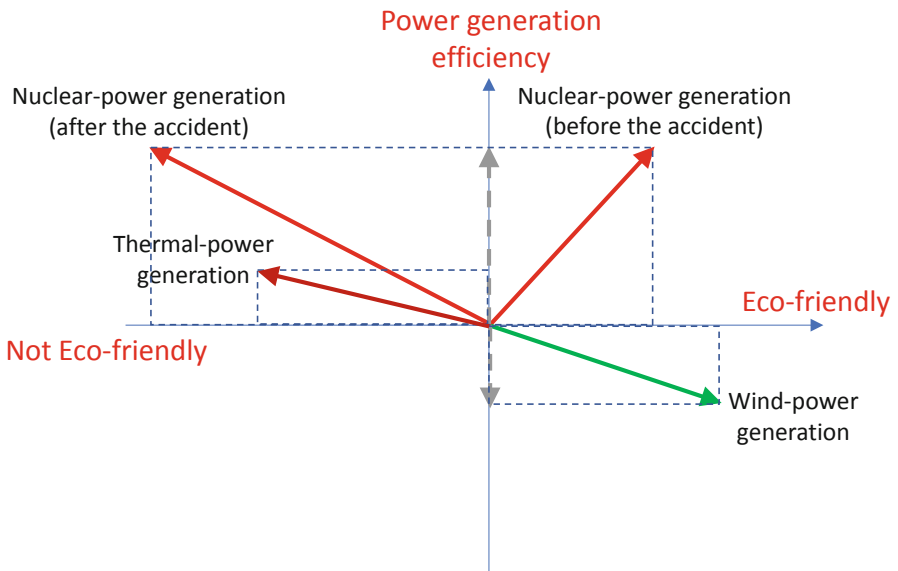


Fig. 2. Illustration of factor loading plot in terms of power generation efficiency

As shown in, Fig. 3 economic parameters are closely related to economic profit, so they are along the axis of economic profit. For this reason, factor analysis uses this phenomenon to explore the axis that maximizes the component variance. In exact terms, this variance is called the covariance. The larger the variance, the larger the difference,

which means the axis that makes it easier to distinguish the data. It is the axis that characterizes the data. In other words, the axis extends in the direction to represent the characteristics of the data. In this way, factor analysis provides a new axis as a new perspective, even if there is no suitable existing perspective.

In order to solve the ambiguous situation, one way is to switch perspectives and look at them from different perspectives. And factor analysis can be also used to find new perspectives.

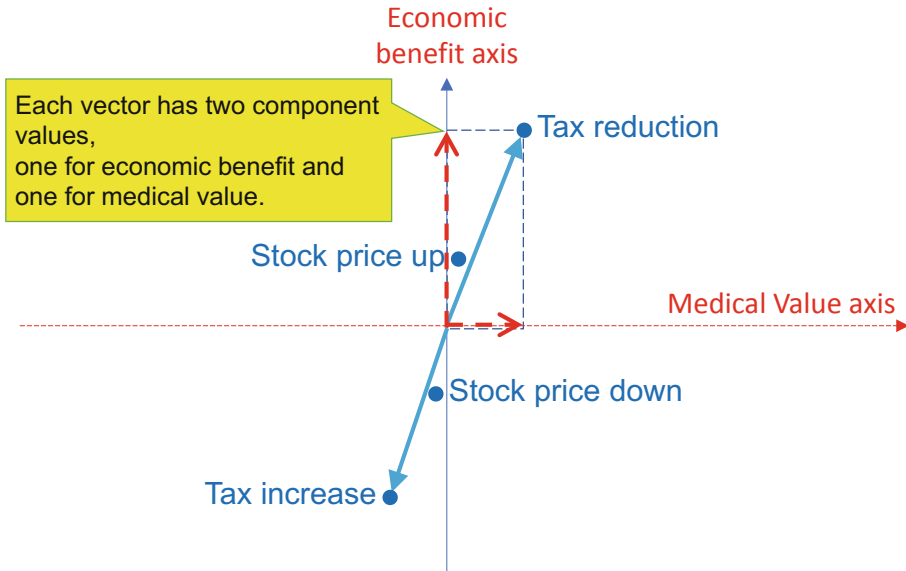


Fig. 3. Illustration of factor loading plot in terms of economic parameters

2 Backcasting from the Future 10 years Ahead in the Healthcare Development

2.1 Game Changer in the Healthcare Development

Our future is unpredictable, but signs of change can be detected. We will identify significant changes and envision the scenarios. The scenario analysis is not for future prediction, but it is for discussing how to deal with various structural changes. Since one of the ideal solutions is to create an autonomous virtuous cycle, we use a causal loop diagram to explore the ideal business ecosystem.

Standing 10 years in the future, backcasting [3] the current turmoil as follows:

Figure 4 shows the causal loop of healthcare development with an ecosystem. As shown in the diagram, rapid aging was a fundamental problem in Japan. In addition, the COVID-19 pandemic caused a lot of confusion. There was a growing need for

telemedicine to resolve them. Nurse-centered care was important for the realization of telemedicine. With the promotion of home medical care, the development of home medical devices has progressed. The development of home medical devices is ahead of drug development due to lower development costs and reduced health risks. And more home medical devices were used for lifelong data and disease analysis.

Many personal health records (PHRs) are stored on the device and merged with electronic medical records (EMRs) into big data. This data is used in precision medicine and contributes to extending the healthy life expectancy of people. Finally, the promotion of National Health Insurance has continuously reduced medical costs.

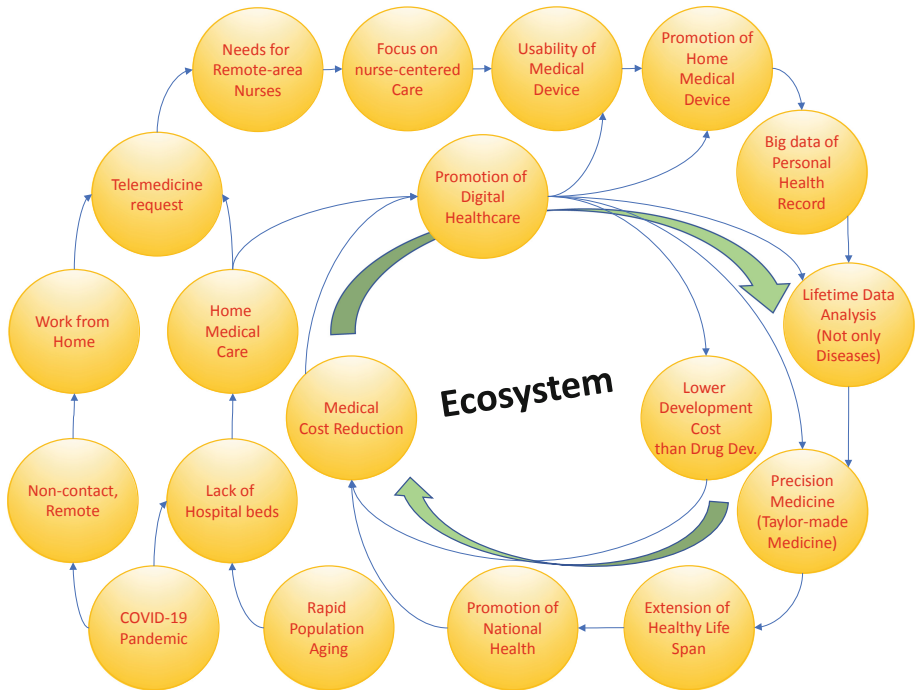


Fig. 4. Causal loop of healthcare development

2.2 Nurse-Centered Care

Figure 5 shows the case of telemedicine without a remote-area nurse to support home medical care on the patient side. In this case, there was concern that the medical treatment will not go smoothly, including administrative issues, such as online connection. One of the best solutions was to assign remote-area nurses to the patient side, as shown in Fig. 6. The nurses were able to provide a variety of care, including ECG, vital signs, intravenous injections, and blood collection. The mobile medical devices for nurses have been replaced by personal home medical devices for daily measurements.

This success has promoted nurse-centered care. Improvements in the hospital were made from the nurses' perspective, on behalf of patients who could not speak well of their demands. The nurses' working environment was improved, work efficiency increased, and patient satisfaction increased. As shown in Fig. 7, by focusing on the new perspective of nurse-centered care, issues that had not been noticed before were clarified. The importance of the third perspective, following the physician's and patient's perspectives, was recognized. ICT-related developments, such as the application of wearable devices and robotics, were further promoted. Big data on personal health records generated through the network.

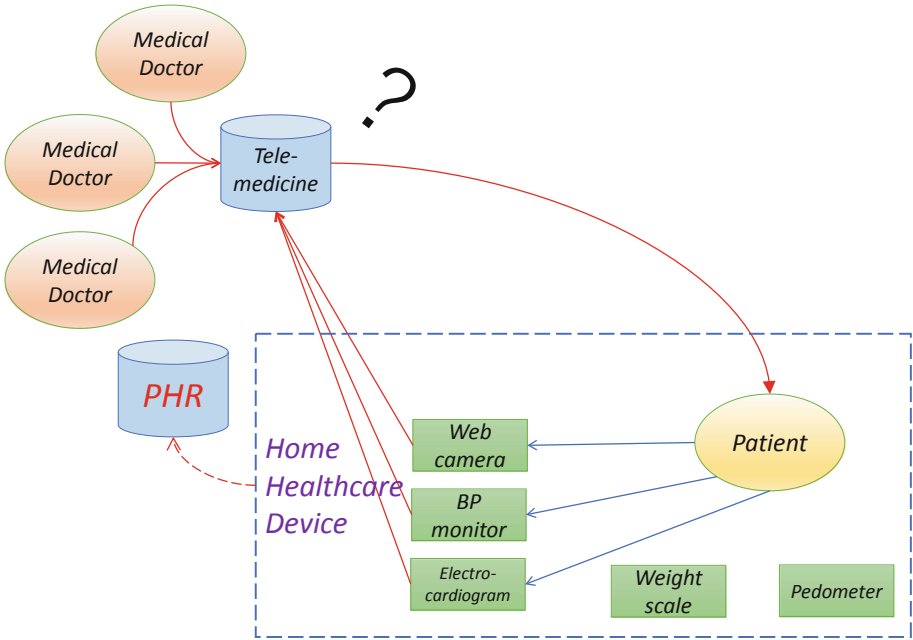


Fig. 5. Telemedicine without remote-area nurses

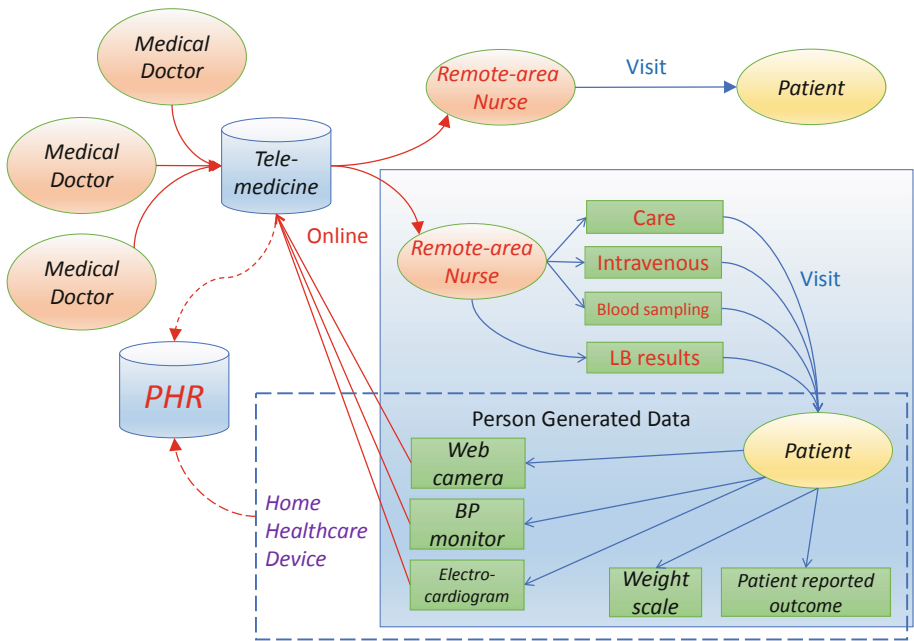
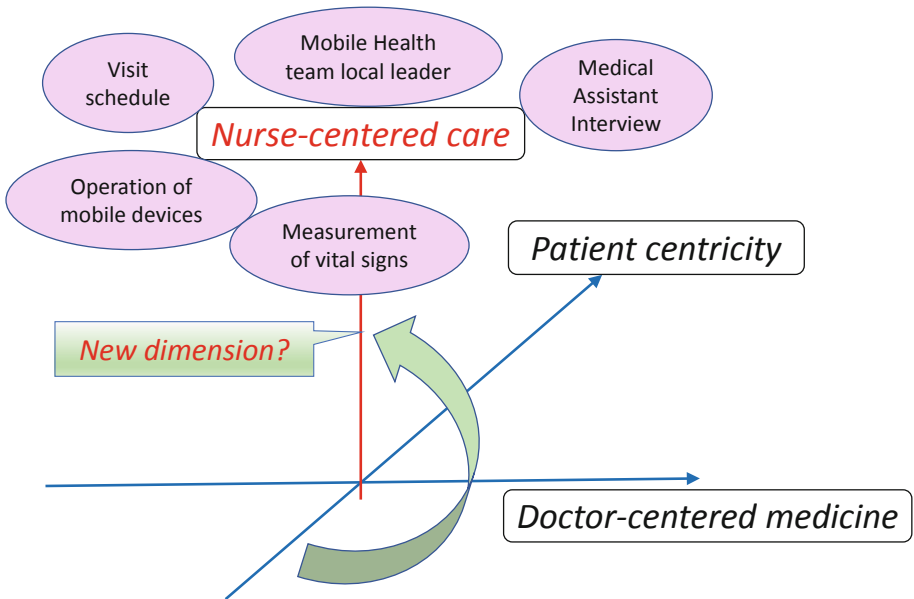


Fig. 6. Active telemedicine with remote-area nurses



Meme's Diagram

Fig. 7. Nurse-centered care in telemedicine

2.3 Algorithm-Driven Data Analysis

Limitation of Clinical Trial Utilizing Real-World Data (RWD). Figure 8 shows the overview of clinical development process and clinical trial design utilizing real-world data (RWD). RWD is patient health data collected from routine medical care. The opposite is clinical research data that derives clinical evidence from unrealistic and ideal research environments such as a placebo group. Therefore, daily medical data is called real-world data.

Comparative studies with placebo group as a control group are common to establish evidence. However, patients in the placebo group are not treated. On the other hand, a study design with a historical control group of data extracted from electronic medical record (EMR) had the advantage that patients in both groups were treated equally, although the differences between old and new.

However, contrary to what everyone expected, the EMR could not be used to predict disease. This is because the EMR had no pre-disease data, and no individual differences because it followed a standardized clinical pathway to simplify receipt calculations. The next expectation was the personal health record (PHR). It was daily health big data measured by home medical devices, not only during hospital visits.

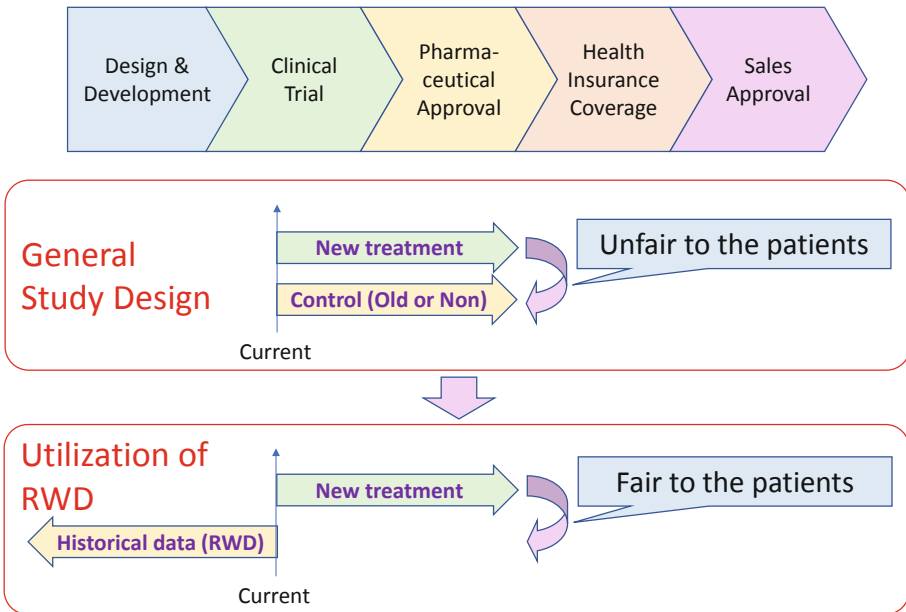


Fig. 8. Potentials for clinical trial utilizing real-world data (RWD)

Growth of PHR (Personal Health Record) into Big Data. Figure 9 shows the PHRs (Personal Health Records) positioning around 2020 in Japan and Fig. 10 shows the PHRs (Personal Health Records) positioning around 2030 in Japan. The horizontal axis indicates whether source of data is medical data or personal generated data. The vertical axis

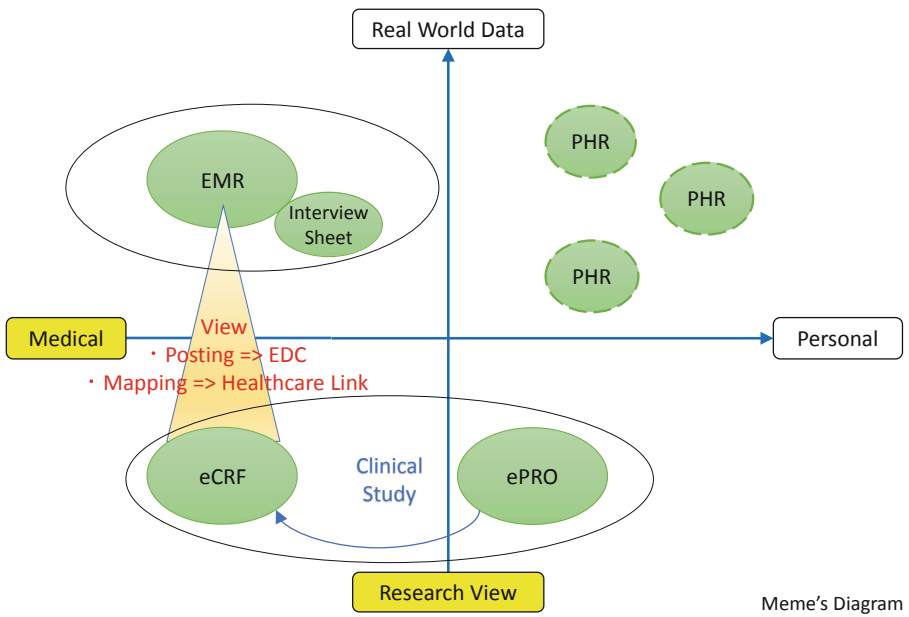


Fig. 9. PHR (Personal Health Record) positioning around 2020 in Japan

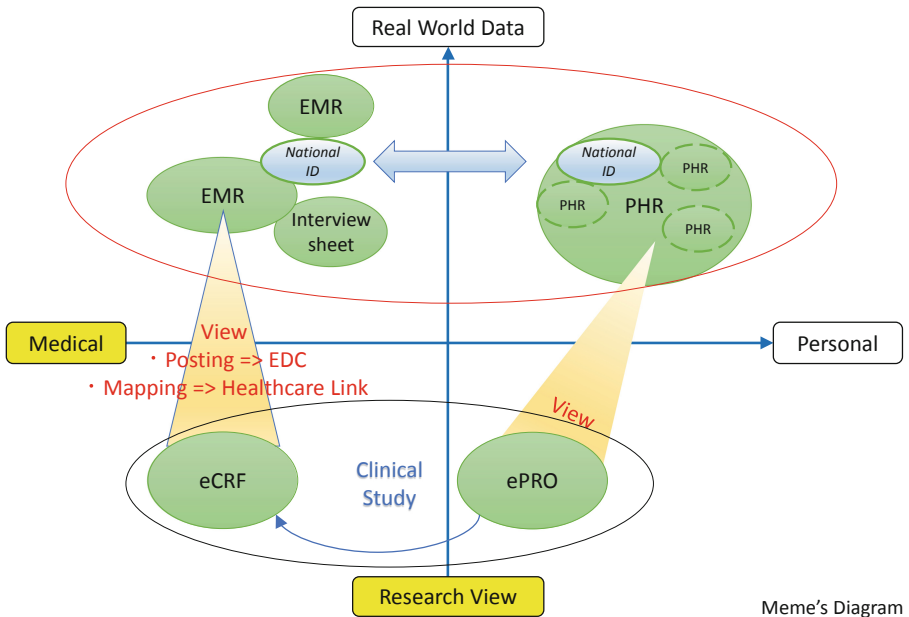


Fig. 10. PHR (Personal Health Record) positioning around 2030 in Japan

indicates whether daily observational data, defined as real-world data, or interventional data for clinical research.

PHRs around 2020 were scattered as small data and had low interoperability. For this reason, the data transcribed from EMR was mainly used as data for clinical research, which was called eCRF (electronic Case Report Form) and was collected by the EDC (Electronic Data Capture) system. In order to reduce the transcription work, the goal of development was an automatic direct mapping between EMR and eCRF called Health-care Link. For lifestyle-related diseases, ePRO (electronic Patient Outcome) records, such as patient diaries collected on tablet devices, were used as supplementary clinical research data. A view is defined as a table with information selected to make a decision. Therefore, eCRF can be defined as a view extracted from EMR for clinical research. And ePRO can be configured as a view extracted from general person generated data for clinical research, but around 2020 it was still undeveloped.

Around 2030, scattered PHRs were integrated on the basis of EMR, and highly useful big data was formed in Japan due to advances in online access, acceleration of e-government development, and the introduction of national IDs in Japan. The ePRO was developed as a view extracted from general person generated data for clinical research. The patient big data enabled lifetime analysis, improved medical treatment outcomes, promoted preventive care, and resulted in reduced medical costs.

Lifetime Analysis Utilizing Personal Health Records. Figure 11 shows the causal loop of the business ecosystem brought about by lifetime analysis utilizing personal health records. Around 2030, PHR was actively used as real-world evidence (RWE),

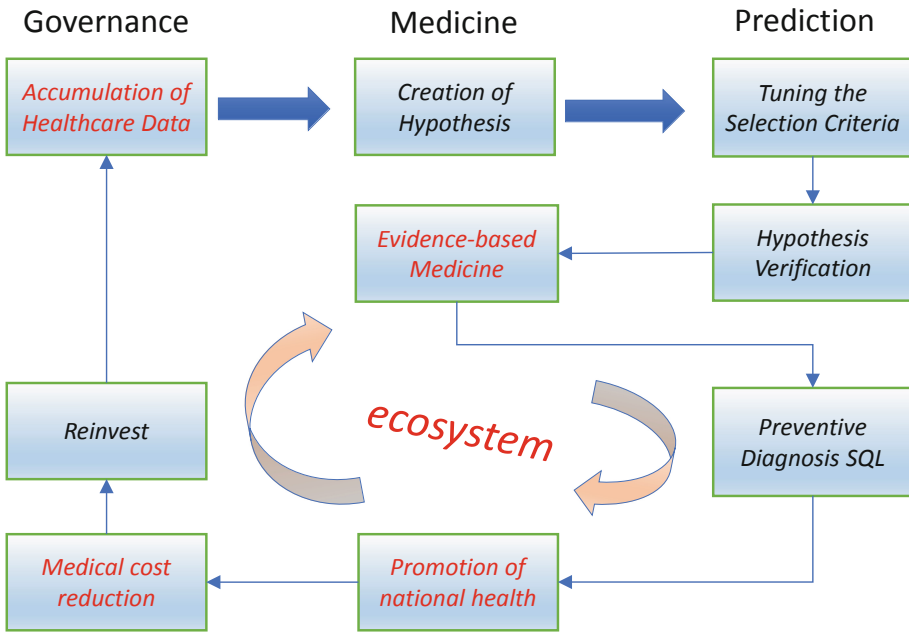


Fig. 11. Lifetime analysis utilizing personal health records

patient selection criteria were used in SQL were applied for preventive medicine, national health was promoted, and medical costs were reduced as a result.

Deep Neural Network (DNN). On the other hand, structural changes have also progressed in the method of analyzing clinical research data. The application of AI in the healthcare field has advanced. Figure 12 shows the illustration of three typical types of deep neural network. One is a CNN (Convolutional Neural Network), which is a neural network suitable for analyzing visual images. This corresponds to human visual function. Another is RNN (Recurrent Neural Network), a neural network suitable for analyzing audio time series data. This corresponds to human auditory function. The last one is a neural network used for multivariate analysis. It is classified as applied mathematics.

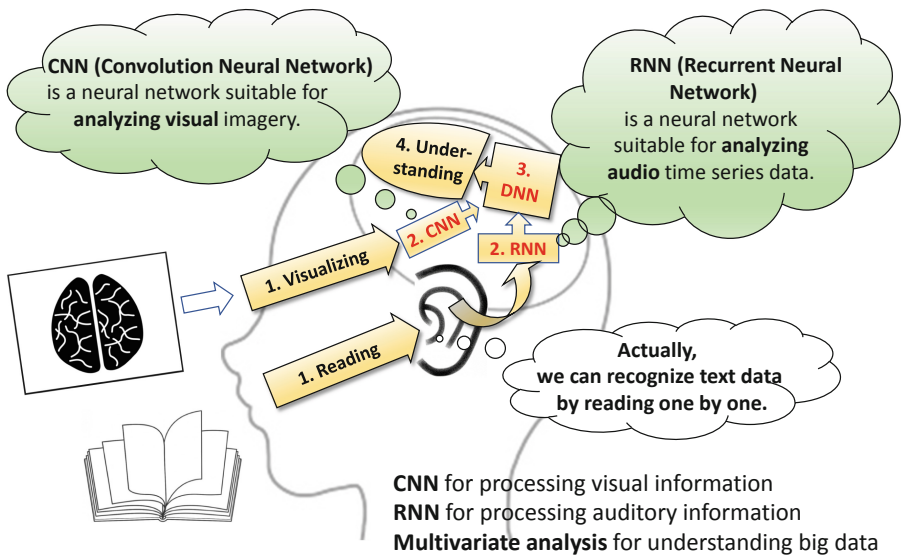


Fig. 12. Illustration of three typical types of Deep Neural Network

Lifetime Analysis Utilizing Personal Health Records. Figure 13 shows a movement of statistical methods, starting with model-driven, data-driven, and algorithm-driven approaches. In a sense, the mainstream of clinical statistics was a model-driven approach that utilizes probability distribution models such as the normal distribution. Since Statistical thinking is based on methodological discipline, wrong hypotheses are rejected and correct hypotheses are uniquely obtained. The next mainstream was data-driven methodology based on deep neural networks to find one of the better solutions in its walking domain to explore it. It was classified as applied mathematics rather than statistics, because the solution changes depending on the given data, such as Taylor series model with numerical derivatives for initial value problem.

Finally, a new perspective on clinical statistics focuses on algorithm-driven approach. In a sense, deep neural networks can be defined as big data analysis, but as an evolution,

sparse analysis, which derives hypotheses from a small amount of data, is attracting attention. The algorithm-driven approach has been found to lead to different results, even if the initial values are the same, such as lasso regression and ridge regression.

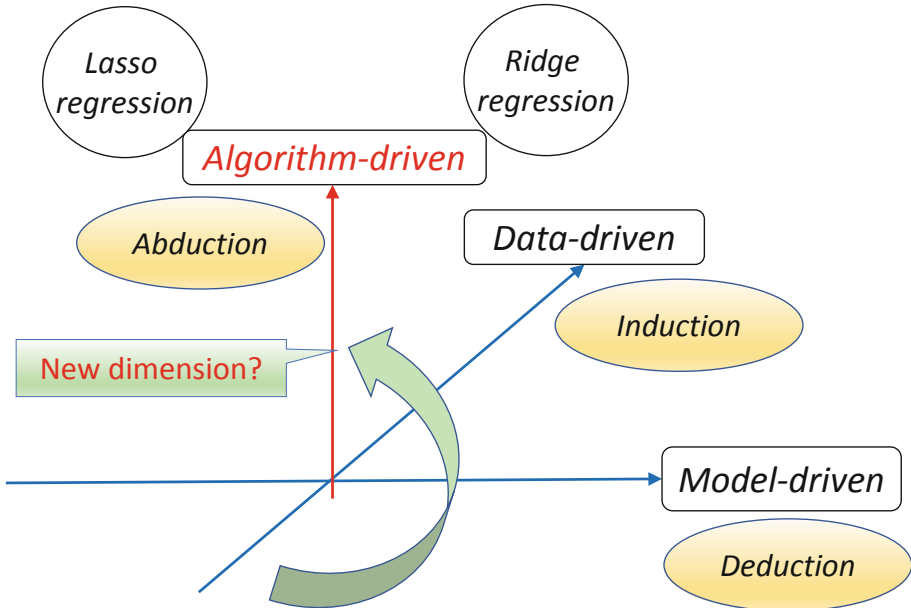


Fig. 13. Algorithm-driven as a new perspective on clinical statistics

Algorithm Difference Between L1-Norm and L2-Norm.

Figure 14 shows the method of Lagrange multiplier with L2-norm (Ridge regression). The solution obtained is indicated by the contact point between the limited distance (L2 norm), which is indicated by the Pythagorean theorem, and the log-likelihood function, which is the solution of the generalized linear model. When the probability distribution of the log-likelihood function is changed in order to find the optimal solution, the contact point moves in the same way. This means that the solution of the ridge regression is unstable, and the simulation is a time-consuming algorithm.

On the other hand, Fig. 15 shows the method of Lagrange multiplier with L1 norm (Lasso regression). The solution obtained is indicated by the contact point between the limited distance (L1 norm), which is indicated by the Manhattan distance, and the log-likelihood function, which is the solution of the generalized linear model. Even if the probability distribution of the log-likelihood function is changed in order to find the optimal solution, the contact point does not move in the contrary. This means that the solution of the lasso regression is stable, and the simulation is a time-efficient algorithm.

In this way, from the new perspective of the algorithm-driven approach, ridge regression when precision is required and lasso regression when speed is required can be used appropriately according to the clinical research design.

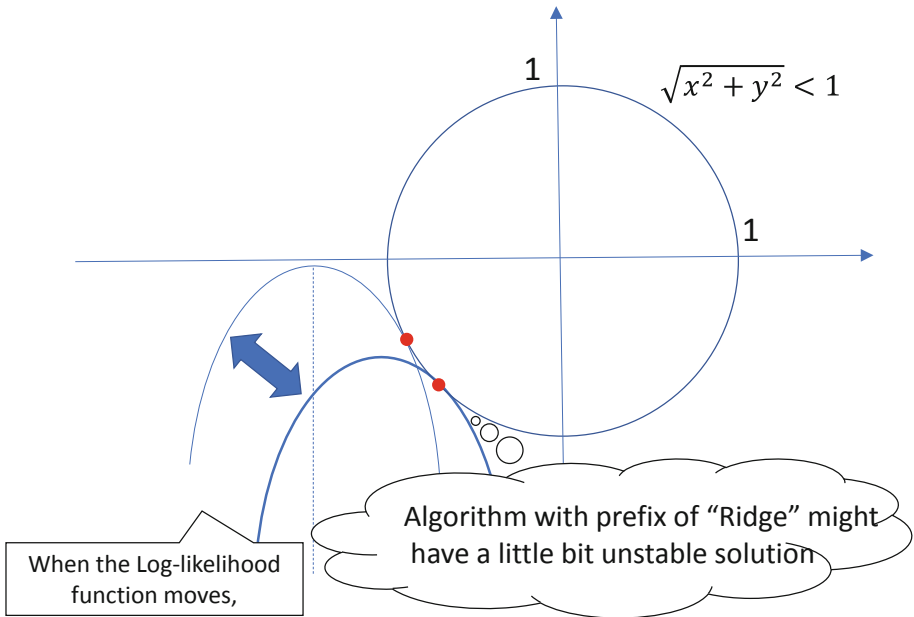


Fig. 14. The method of Lagrange multiplier with L2 norm (Ridge regression)

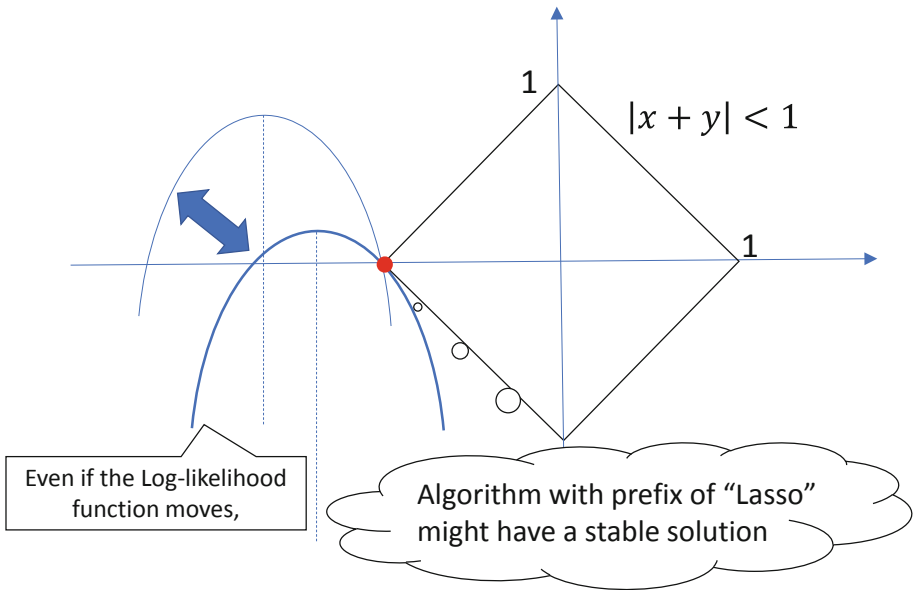


Fig. 15. The method of Lagrange multiplier with L1 norm (Lasso regression)

Design Thinking Tools in Healthcare Data Science. After the situation analysis, it is necessary create a concrete solution and introduce it appropriately. Figure 16 shows an

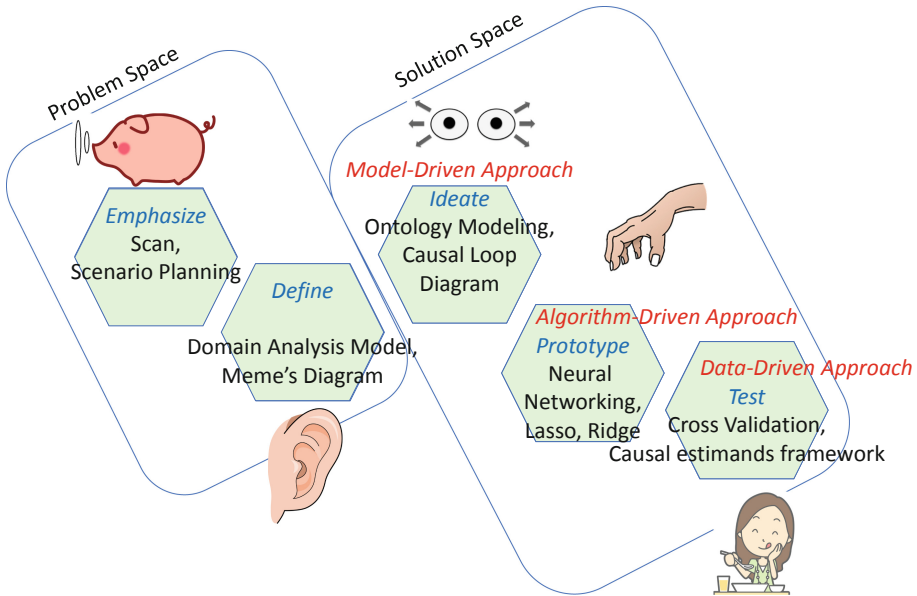


Fig. 16. Illustration of design thinking tools for healthcare data science.

illustration of design thinking [5] tools for healthcare data science. In the case of the five human senses, the five stages of design thinking could correspond to the sense of smell, hearing, sight, touch, and taste, respectively. The first stage in design thinking, “empathy”, is likened to the sense of smell to detect risk. The sense of smell is the most dominant of the five senses, as it has evolved as the first function in detecting danger in the evolutionary history of animals. Therefore, to avoid ingestion of toxic substances, about 90% of our taste is determined by the sense of smell, not the tongue. This is the reason why we cannot taste food when we have a cold.

In the first stage of design thinking, leading tools for empathy include Scan [4] and scenario planning. Before starting with scenario planning in order to make a strategic long-term planning, we have to scan for signs of change. The Scan cannot accurately predict the future, but it can help us find signs of change that will follow in the future. Next, combine the signs of change and create a scenario, which is intended to discuss how to handle structural change, the title is never good or bad scenario. The purpose of scenario planning is to create enough options to discuss various structural changes for the unpredictable future.

The second stage of design thinking, “definition,” is likened to hearing, listening to a problem. In the second stage of design thinking as a stage of “define”, leading tools for defining problems includes domain analysis model [6] and Meme’s diagram [7]. Both “empathy” and “define” stages are classified into problem space.

The solution space includes “ideate” to visualize the solution, “prototype” to create a prototype model that the sense of touch can recognize it, and “test” to finally verify like “tasting”. The leading tools of “ideate” are the ontology modelling [8] and causal loop diagram mentioned above, which are classified in model-driven approach. And the

leading tools of “prototype” are neural networking, lasso regression, and ridge regression mentioned above, which are classified in algorithm-driven approach. And the leading tools for deep learning “test” include cross validation and causal estimands framework [9], which are classified in data-driven approach. In particular, the causal estimands framework consider that normal health conditions create null values because no need for blood tests, and uses all observational data (FAS: complete analysis set) including null values, and efficient analysis is possible without dropout records.

3 Conclusion

As described above, the “VUCA” is highly likely to be the practical situational judgment method in clinical data science. This VUCA classification encourages creating new strategies according to unknown situations, rather than copying traditional patterns from good practices. After analyzing the situation, design thinking is effective at the stage of creating a concrete solution. In the current complex societies, causal loop diagram is a particularly effective method to explore a vision for sustainable business ecosystems.

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