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Faculty of Informatics and Management

Master Thesis

Advanced Computer Systems For Decision Support In Healthcare

Final Thesis

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Declaration:

I declare that I have prepared myself this diploma thesis independently with using the mentioned literatures.

handwritten signature

In Hradec Králové on 15.8.2022 Ratheesh Thaliyadath

Acknowledgments:

I would like to express my sincere gratitude to my supervisor and mentor Ing. Karel Mls, Ph.D. in the Department of Information Technologies, I am really grateful for the support guidance and encouragement throughout this master thesis work.

And I would like to thank prof. MUDr. Jan Pirk, DrSc., the former Director of the Cardiovascular Surgery Department at the Institute for Clinical and Experimental Medicine in Prague (IKEM) for finding time for an interview to provide practical insight and advices from personal experiences in the healthcare sector.

Abstract

Title: Advanced computer systems for decision support in healthcare

This work is focused on the potentials of advanced computer systems in healthcare and the steps for adapting advanced computer systems to the current state of the healthcare domain. Finally, it proposes two potential practical usages in the Czech Republic.

The aim is to identify the proven methods used for data collection and analysis, and the available type of tools for the formation of an advanced computer system which could be utilized to support healthcare professionals across the country to make better decisions for their patients and to help to save lives with reduced risks.

Part of this work´s intent is the analysis of logical components used in advanced computer systems in general and the raw data availability in the healthcare domain. This work includes some practical advice through an interview with professor Pirk, who is the former Director of the Cardiovascular Surgery Department at the Institute for Clinical and Experimental Medicine in Prague (IKEM). Throughout this work, the terms 'Advanced Computer systems and Expert systems' are interchangeably used.

KEYWORDS

Advanced computer systems, Expert systems, Data collection, Data analysis and usage, Decision making, Decision support, Knowledge data base

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1. Introduction

"Medicine is in-between science and art, it's a mixture of both. Patients are unique human beings; they are not an engine. Each and every good and qualified doctor understands how much medicine is required for their patient, that means, if the textbook guidelines suggest giving a certain quantity, still the doctor can decide whether to add or reduce the quantity of medicine for his patient, and these changes of applied quantity need to be recorded with relevant explanation and justification in the journals for future references", as stated by professor Pirk, during the interview.

There are plenty of data available in different forms in the healthcare domain. Due to the complexity of healthcare domain these data are stored in different places in different forms such as different types of scanning results, X-ray results, printed reports from clinics and labs, and many more. Each sample of these data is highly vital and useful for research as these kinds of medical records with relevant justification are required to be stored for over 50 years, even after the death of the patient.

Recently the world has begun to experience a very sophisticated way of data presentation to show the impact and spread of pandemic. This work is a theoretical approach to examine the concept of healthcare data, its collection and usage in advanced computer systems in the domain, with a proposal to consider about organizing this data in a centralized way and to utilize the expert systems and data mining to improve the patient care in the industry. Along with reducing the operational cost for generating paper records, storage of physical records and as such.

2. Purpose of this work

The purpose of this work is analyzing the high-level data collection and analysis process, alongside with usage of expert systems in healthcare domain, to find out how to increase the efficiency in healthcare domain by using these available modern technologies, and how to improve the whole process flow in healthcare domain in the country.

Furthermore, this work aims to analyse the usage of qualitative data collection and data mining techniques to be applied for extracting useful information to build a strong knowledge database, and to support healthcare professional to connect with a suitable expert system or advanced computer system to use this knowledge database on the healthcare domain for their decision-making process.

As in the old saying "To err is human", it is important to contemplate that not all errors have an extenuation or any easy mitigation to fix. As we know some errors are at high risk, so it would be better to consider the digitization of healthcare industry to make the use of the vast data compatible with suitable expert systems to support professionals in their efforts to make better decisions for the population. The benefit is not only for the current generation but also for the next generation to improve and advance from the current stage.

3. Processing method

The foundation and motivation of this work originated with the support of my supervisor Ing. Karel Mls, Ph.D, and the logic and knowledge I gained through the subject KSPM1 (Systémy pro podporu managementu I), and influence of decision support systems, and their impact to the corresponding domain.

In order to get a real-world approach, I have conducted a personal interview with prof. MUDr. Jan Pirk, DrSc. at IKEM. This interview was highly valuable as anyone from outside of the healthcare sector does not have an insight and full understanding of the potential usage of systems in healthcare domain. So, the primary data collection was done by using direct personal interview method.

According to the statement from prof. Pirk, a human doctor can look at their patients and assess patient’s condition and decide how much dose of a medicine is required, but if we depend on the expert systems, the system will give the same dose as mentioned in the data base. Because the tool is missing the human way of seeing and adapting the current state of the patient.

Even though there is a vast amount of information available on the internet and specialized databases, the attempt is to adapt the core methodologies from two modules, KSPM1 (Systémy pro podporu managementu I) and KSTMO (Statistické modely a data) to this work.

4. Advanced computer system or expert system

An advanced computer system or expert system is an innovative computer application that is implemented for the purpose of providing solutions to complex problems. These problems typically require intelligence and human decisions, which take considerable time to evaluate. Expert systems use pre-defined rules to determine behaviors or outcomes of specific events. These rules are not constant, if required; rules could be changed to adapt upcoming deviations due to unforeseen scenarios. As stated by Anjaneyulu (1998), "Sometimes the knowledge which is expressed in the form of rules is not known with certainty (for example our flu rule is not absolutely certain). In such cases, typically, a degree of certainty is attached to the rules" (p.49) [1].

Expert systems are mostly used in complicated business domains and are considered as widely utilizing for alternative searching for solutions that require the deep understanding of explicit human expertise. The expert system is also able to justify its provided solutions based on the knowledge input and data upload from previous users. According to Anjaneyulu (1998), "Depending on the complexity of the domain, knowledge engineering could take anywhere from a few days to a few years. Expert system tools have been created which provide support in the creation of this knowledge and carry out checks on the completeness and correctness of the knowledge represented in the system" (p.57) [1].

Examples of expert system domains and usages are:

- Banking – processing of mortgage requests
- Weather forecasting – processing of projecting potential weather patterns on given geographical areas
- Logistic management – finding the next best route, due to unexpected incidents (such as natural disasters or accidents or wars)
- Medicine – research and development of cures for diseases, helps to develop faster efficient treatments

4.1. History of advanced computer systems

Some of the most notable advanced systems are listed in this section, it is also significant to mention the origin of the term "robot" in this context. Amongst in the listed, there are, Dendral, MYCIN, MOLGEN, and CADUCEUS from the medical science domain. The rest are from different domains, such as PROSPECTOR from geological domain, XCON from commercial domain, and STEAMER from industrial.

4.1.1 Hello world from Czech (1920)

It was the famous Czech writer Karel Čapek, who introduced the word "robot" to this world through one of his famous dramas R.U.R. (Rossum's Universal Robots), published in November 1920 [2]. The premiere was performed in Hradec Kralové. Since then, the world adapted the word robot as a universal term for mechanical devices which are automated or operate by remote controls, and for artificial-intelligence machines. More often these devices are designed to look anthropomorphic.

4.1.2. Early stages of development

In the late 1950s, some researchers started experimenting with the potential for using computer-based technology to match human decision-making. For example, biomedical researchers started creating computer-aided systems for diagnostic applications in medicine and science. These systems were often described as the initial forms of expert systems.

4.1.3. Dendral (1965-70)

Dendral [3] was a venture in artificial intelligence, which started in the 1960s, and got named after the expert system which this project produced. The name Dendral refers to the acronym of the term "Dendritic Algorithm". Its primary aim was to study hypothesis formation and discovery in science, mainly for chemistry area.

Dendral was developed in Stanford University collaborated by Edward Feigenbaum, Bruce G. Buchanan, Joshua Lederberg, and Carl Djerassi.

The software program Dendral is considered as the very first expert system because it automated the decision-making process and problem-solving behavior of organic chemists. The project involved the research of two core programs, such as Heuristic Dendral and Meta-Dendral [3] and various sub-programs. It was written in the Lisp programming language. Several related systems were originated from Dendral, such as MYCIN, MOLGEN, PROSPECTOR, XCON, and STEAMER.

4.1.4. MYCIN (1970-75)

MYCIN [4] was developed in the early 1970s at Stanford University. It was an initial expert system that used AI to detect bacteria causing dangerous infections, such as bacteremia and meningitis, and to recommend antibiotics, with the dosage adjusted for patient's body weight. MYCIN was written on the Lisp [5] computer language.

MYCIN is based on the Backward chaining (or backward reasoning) [6], which is an inference method described colloquially as working backward from the goal. It is used in computerized hypothesis provers, inference engines, proof assistants, and other AI applications.

Backward chaining begins with a list of objectives (or an assumption) and runs backwards from the result to the beginning to see if any existing data support any of the listed conclusions. An extrapolation engine uses backward chaining to search the implication rules until it finds one with a consequent (“Then” clause) that matches a desired goal. If the predecessor step (“If” clause) of that rule is known to be true, then it is attached to the list of available goals. This means that one's goal is added to the list only with supporting data that confirms the new goal.

4.1.5. MOLGEN (1975)

MOLGEN [7] is an expert system that is used for reasoning in designing molecular genetics experiments. MOLGEN'S organization is involved in four features. These are: interactions between nearly independent subproblems, which are represented as constraints, interactions between subproblems, which are discovered via constraint propagation, use of explicit problem-solving operators to reason with constraints, and use of alternates between least-commitment and heuristic strategies in problem-solving.

In the minimum assurance strategy, MOLGEN creates one choice only when its available restraints adequately limit its alternatives. Its problem-solving operators are capable of being terminated so that a decision can be postponed. Constraint propagation is the method for transferring information among subproblems. It enables MOLGEN to utilize the combined effect between decisions in several subproblems.

4.1.6. PROSPECTOR (1970-75)

PROSPECTOR [8] is an expert system used for valuation of the mineral potential in a geological site or region. The system is based on multi-disciplinary decision-making. PROSPECTOR deals with geologic setting, structural controls, kinds of rocks, minerals, and alteration products present or suspected.

4.1.7. CADUCEUS (1975-80)

CADUCEUS [9] was a medical expert system that emerged during in 1980s, with a motivation for improve MYCIN to focus on more comprehensive issues than a narrow field like blood poisoning.

CADUCEUS ultimately could analyze up to 1000 different diseases. While CADUCEUS worked using an inference engine like MYCIN's, it made several changes in dealing with the additional complexity of internal disease - there can be several simultaneous diseases and data is generally flawed and scarce.

4.1.8. XCON (1978 -80)

The R1 (internally called XCON, for eXpert CONfigurer) [10] expert system was a production-rule-based system written in OPS5 [11] by John P. McDermott in 1978 to support the ordering of DEC's VAX computer systems through automated selection of the computer system parts based on the customer's requests.

OPS5 is programmed for constructing production rules (modules) in the form of “IF...THEN...” arguments, where the “IF” part, or left-hand side (LHS), states a set of data forms which must be reliably paired with the portion of the actual data set that exists in the "working memory". Consequently, the “THEN” portion, or right-hand side (RHS), specifies the set of schedules to be carried out when the LHS is matched. Usually, the RHS procedures make or eliminate data aspects in working memory and start off I/O with the operator or files and execute essential computations via peripheral calls.

4.1.9. STEAMER (1980)

The Steamer Project [12] was an attempt to use state-of-the-art AI software and hardware to implement an intelligent computer centered training system. The Steamer project is a research attempt, focused on discovering the use of AI systems and hardware in the execution of intelligent computer-based training systems. Moreover, the STEAMER project also focuses on the research issues of how individuals identify the complex dynamic systems to the use of intelligent graphical interfaces, with emphasis on the construction of a system to assist in propulsion engineering instructions.

4.1.10. Other systems from 1990 to present

In the early 1990s, the focus of research and development of expert systems shifted to intelligent agents, and how they can be used: chat bots, news retrieval, online shopping, and browsing the world wide web. Intelligent agents are also sometimes called agents or bots. With the use of vast data from internet and using the Big Data processing programs, they have gradually evolved into personal digital assistants, or virtual assistants.

At present, the market leading tech giants [13] such as Google, Facebook, Amazon, and Microsoft are researching several Artificial Intelligence projects, including virtual assistants. All these companies are aiming to create a perfect virtual assistant for the human user. Examples of such assistants are Google assistant, Cortana from Microsoft, Apple's Siri, or Alexa from Amazon.

The use of Big Data has allowed AI to take the next evolutionary step. Now, the goals are further moved over to develop software programs capable of speaking in a natural language, like English, and to act as virtual assistants. These virtual assistants signify the future of AI research and may indicate the shape of robots for various uses, such as tangible help, storage in laptops or mobiles, help in making business decisions, or they may be integrated into a business's customer service program and answer the phone. As mentioned above, most of the companies have chat-bots to service their customers using the company knowledge database for FAQs. One of the recent examples which can be pointed out is the virtual nurse Anežka [14], introduced by Czech ministry of healthcare to support people during the global Covid-19 pandemic.

One of the important aspects to consider is that the impact of AI oriented approach is sometimes crossing the lines of privacy of the user. In any business environment, which is a Microsoft cloud-based, technology-controlled business environment, the AI and Machine learning are used to study the behavior of workers, which is generated by the data constructed from the user's interaction with various Microsoft applications. The job security of the employees is always insecure because these collected data can also be used to keep or layoff the employee. Since the curiosity of humanity never sleeps, the Artificial Intelligence keeps advancing and discovering new horizons.

4.2. Characteristics of an Expert System

An expert system usually possesses knowledge from many experts across a specific domain, hence finding the solutions for different scenarios is more effective and efficient. The system uses knowledge base and interpretation engine so that it decreases the cost of consulting an expert for various domains such as in medical diagnosis. It provides efficiency, accuracy and inventive problem-solving. Expert Systems can interact in a very reasonable time with the end user. This approach always takes less time than one based on consultation with a human expert to get an accurate solution for the same problem. As mentioned by Anjaneyulu (1998), "Knowledge engineering or acquisition is the process of extracting knowledge about the domain in which the expert system is being created. Typically, this knowledge is obtained from a human expert in the domain. This knowledge is normally in the form of heuristic knowledge (rules of thumb) which the expert gains through experience over a period of time." (p.55) [1] .

An expert system is capable of handling challenging decision problems and delivering solutions. This means that the system can solve complex problems by understanding new challenges through existing patterns in the knowledge base, implicitly following the "if-then" rules rather than through predictable methods. Above all when a living expert (human) dies, the knowledge, experiences, and knowhow die with that person, but the knowledge base in the expert system is unperishable and can be copied from one device to another or stored in cloud to share with multiple systems. Anjaneyulu (1998) explains that "During knowledge engineering, the doctor would be interviewed and posed representative cases. Based on his responses, the knowledge he is applying needs to be understood and encoded in the form of the knowledge representation used. The expert would then need to examine the behavior of the system to see if the knowledge has been encoded properly.” (p.55) [1].

As shown in Figure 1, the expert systems can be described as a knowledge-based information system that uses its database about a specific field or domain to search through by following ‘what if’ analysis and to act as an expert consultant to the end users for that specific industry. The database with qualitative information is the main component or the core of its activity, the database is called the knowledge base for the specific subject area. The other component is the interface engine or the program refining the database and responding to user queries.

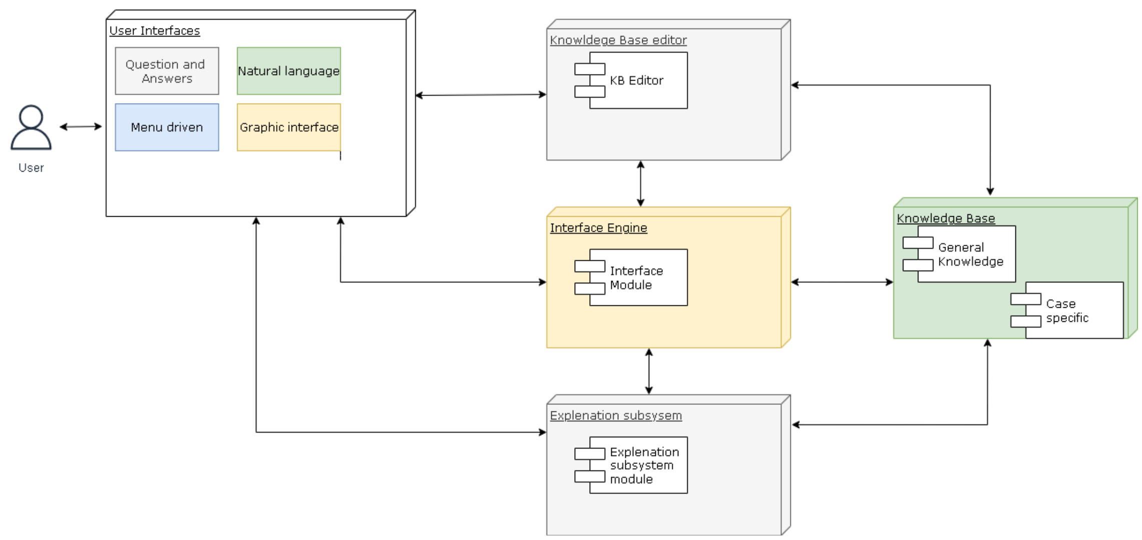

Figure 1: Components in Expert system
Source: my own work
Inspiration: Abuel-ReeshSamy, J. Y., & Abu-Naser, S. S. (2017). The main components of typical expert system [15]

5. Decision Support System

A decision support system (DSS) [16] is a computer system used to support business during uncertain problem scenarios and select decisions to support the strategies of action in corresponding domains.

The advantage of DSS is that the system sifts through and analyzes massive amounts of data to construct broad information, which is used to solve a given problem in the domain for decision-making. The ideal system analyzes information and proposes decisions for the user. Most importantly they allow human users to make more informed decisions at a quicker pace.

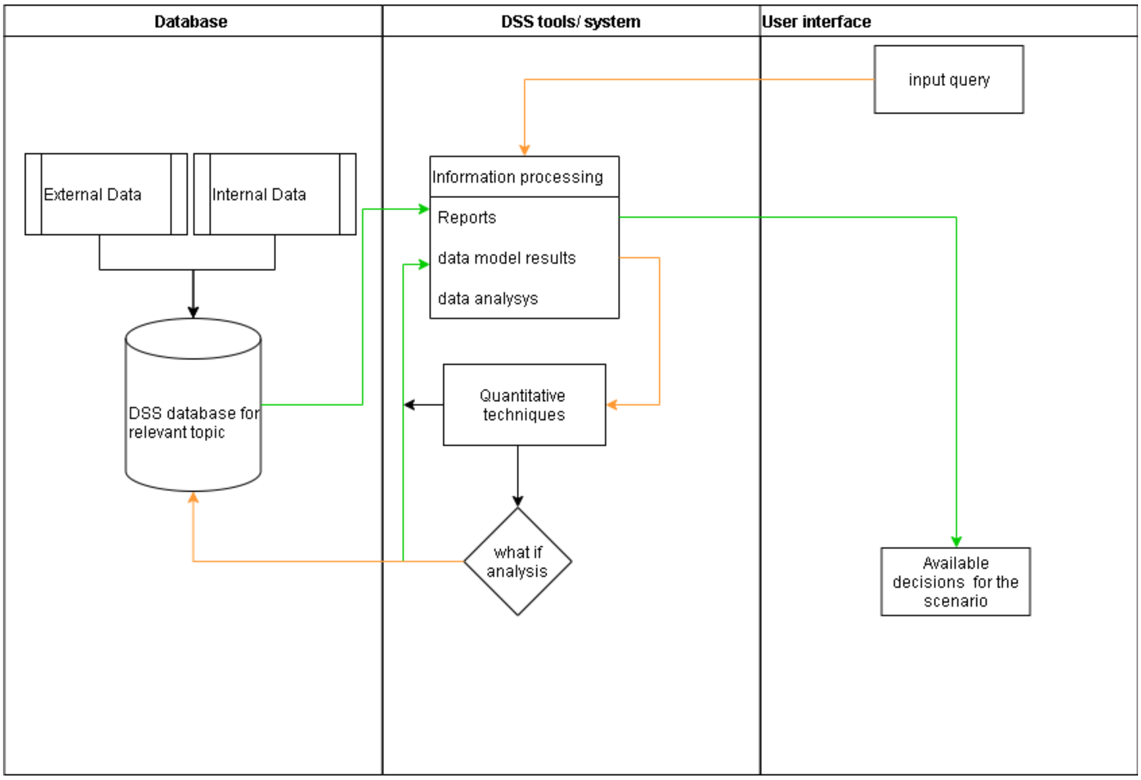

Figure 2: Components of a DSS.
Source: my own work.
Inspiration: Mukhlash, I., & Maulidiyah, R. (2017). The components of DSS [17].

As showed in Figure 2, the most important factor is that decision support systems do not replace the human role in the execution part, whereas the DSS is like a guidance tool or compass to direct in which direction to proceed according to the data available for the tool to process. As a matter of fact, some of the stakeholders use their gut feeling along with the guidance from DSS; this approach corresponds with the statement from Prof. Pirk.

5.1. Benefits of a Decision Support System

In general, DSS software helps in making more informed decisions. Frequently used in top and mid-level management, decision support systems are used to make decisions to execute, or to list many potential consequences based on present and past business data. Besides that, the decision support systems can create detailed view for the stakeholders, which are easily understandable without deep technical awareness in the corresponding domain. Fortunately, DSS configurations are highly flexible, so the configurations are easily adjustable based on changing business needs.

5.2. Characteristics of a Decision Support System

The main purpose of using a DSS is to support decision making processes of its user by visualizing the information in an easy-to-grasp way. The added value in DSS systems is that the tool can be adjusted to produce many types of reports, based on the customer specifications. For example, a DSS reporting capability can be used to combine available data to any kind of report and transform its information graphically, such as a graphical bar chart that represents projections for given scenarios. For example, as shown in Figure 3, which illustrates the comparison of five types of decision-making methods based on the given weights for each. The result in this example is very clear; the method with more weights is the preferred one for the given scenarios.

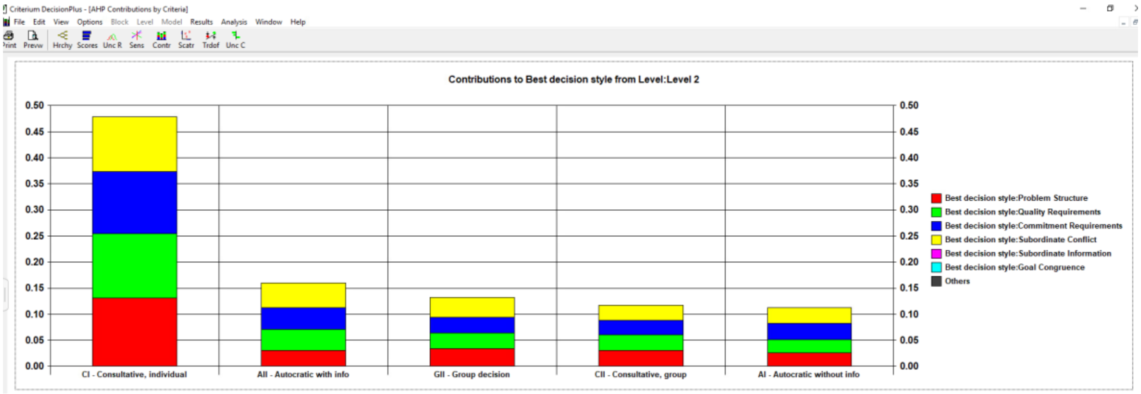

Figure 3: Example of output visualization of DSS.
Source: my own work in Criterium Decision plus.

As the technology continues to advance, data analysis tasks are no longer limited to large, massive mainframe computers. Since a DSS is essentially an application, it can be easily added or installed to most computer systems, whether on desktops or laptops. Certain DSS applications are also available through tablet or mobile devices.

5.3. Differences between Decision Support Systems and Expert Systems

Table 1: Comparison DSS and ES

DSS	Expert Systems
• A computer-based system that aids the process of decision making. • It is an interactive, flexible, and adaptable computer system. • It is mainly built for finding a solution for an unstructured business problem for enhanced decision making. • DSS is in general a specialized class of computerized information systems that enables supports to business domains and their organizational decision-making activities.	• A computer program that is intended to simulate the decision-making capability of its user. • It consolidates a collection of information about a specific domain or subject. This information includes the facts and judgmental knowledge which offers the system the capacity to speculate like a person. • There are set of rules on which it makes decisions using if-else structure.

	• The inference engine does reason by manipulating the knowledge base. The user interface represents questions and information to the operator and receives answers from the operator.
• Enables decision making • Decision environment is unstructured • Extracts knowledge from relevant database • Uses goals and data to establish alternatives and outcomes – for good decision making	• Computerizes decision making • Decision environment is structured • Inject expert knowledge into a computer program • The system can eventually replace the decision maker

Note: Nelson Ford, F. (1985). Decision support systems and expert systems: A comparison. Information & Management[18].

6. Artificial Intelligence

Artificial Intelligence (AI) is the ability of a computer program to grasp, adapt and process information. It is a branch in modern technological science and progressive engineering that focus on making intelligent machines, or intelligent computer programs. AI is quickly changing our world. Remarkable surges in AI capabilities have led to a wide range of innovations including autonomous vehicles and connected Internet of Things devices in modern homes. “One of the goals of Artificial Intelligence is to develop systems which exhibit 'intelligent' human-like behavior. Initial attempts in the field (in the 1960s) like the General Problem Solver created by Allen Newell and Herbert Simon from Carnegie Mellon University were to create general purpose intelligent systems which could handle tasks in a variety of domains.” explains Anjaneyulu (1998) in their work, (p.46) [1].

AI is even adding to the expansion of a brain-controlled robotic body-parts that can improve the quality of life of any paralyzed person, by connecting through complicated human-brain and microchip interfaces. These progressive AI-aided systems are transforming all aspects of our daily lives.

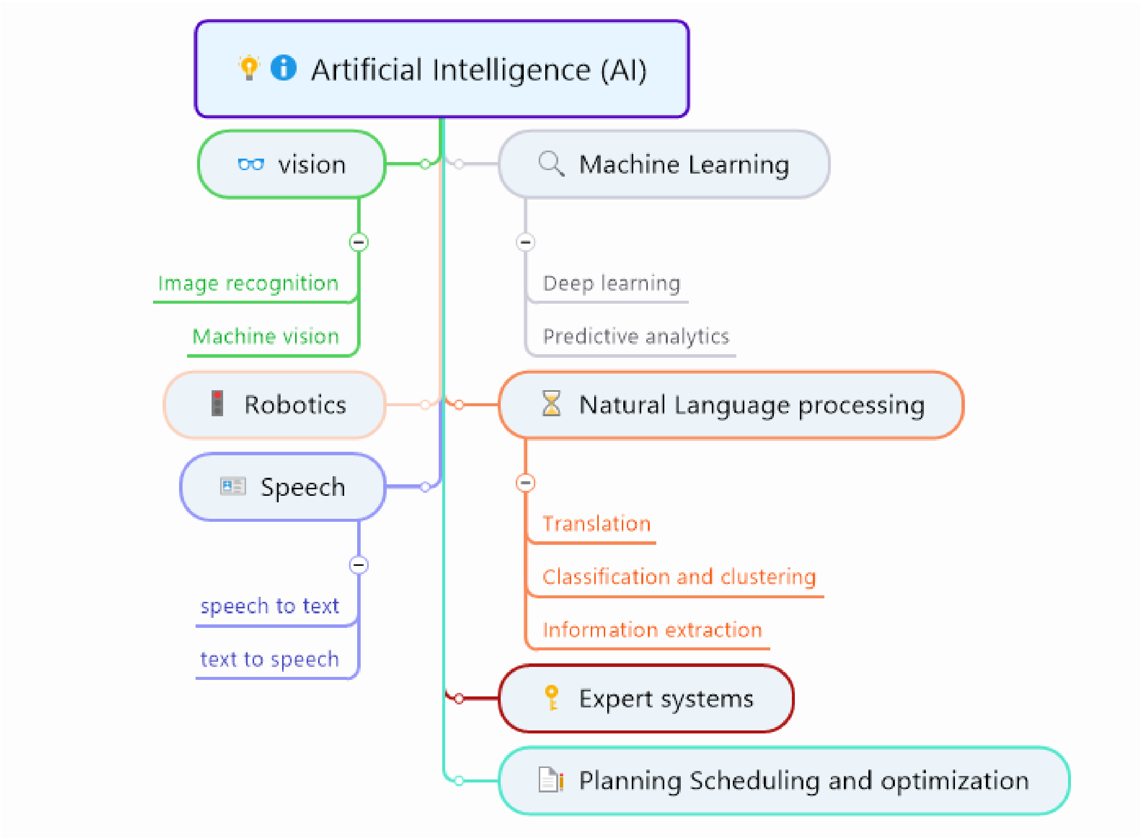

Figure 4: Subfield in an AI.
Source: my own work.
Inspiration: Regona, M., & Yigitcanlar, T. (2022). Components types and subfield of AI [19].

As illustrated in Figure 4, AI system, like a smart highway interconnect all its interfaces to exchange and process data to learn, process, decide and react almost like a human. The components in AI and their assembling [20] are be listed below,

- AI Applications: Packaged applications (expert system) that solve a business problem (i.e., virtual agents, financial planning)
- Data Preparation and Cleansing: preparation of data ready for AI to be used
- Model, Build, Train and Run: A data science developed for personal and team use, trains and operates models (machine learning)
- Consumer Features: Communication, pictures, and vision, primarily used in business use cases
- Natural Language Processing: The core system of enterprise AI

- Lifecycle Management: Managing the complete lifecycle of AI models to observe its performance and evolution

6.1. Difference between Artificial Intelligence and Expert Systems

Table 2: Comparison of AI and ES

Artificial Intelligence	Expert Systems
AI is the ability of a machine or a computer program to think, work, learn and react like normal human beings.	ES represent the most successful demonstration of the skills of AI.
AI includes the use of techniques based on the rational behavior of humans to analyze and solve complex problems.	ES are computer programs designed to solve complex decision problems.
Components: • Natural Language Processing (NLP) [21] • Knowledge representation • Reasoning • Problem solving • Machine learning	Components: • Inference engine • Knowledge data base • User interface • Knowledge collection module

Note: Benfer, R. A., Brent Jr, E. E., & Furbee, L. (1991). Artificial Intelligence and Expert Systems. [22]

7. Healthcare

As we look in the history of healthcare innovations and advancement, the methods of healthcare professionals to adapt a technology need to go through digitization, interference, and transformation. Digitization is the process of setting up digital abilities that support everyday healthcare processes and services such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) scans. These examples prove digitization has transformed healthcare services. Other digital tools like electronic medical prescriptions have changed manual administrative processes. As a result, digitization has made it easier for data to be saved, retrieved, and distributed. “Digitalization is defined as the concept of “going paperless”—the technical process of transforming analog information or physical products into digital form”, stated by Moro Visconti, R., & Morea, D. (2020) (p.17) [21].

Interference stage is the transition period to fully reach digitization. There are some areas digitalized, but the users are yet to be confident to use these tools in order to complete the process. Finally, transformation is the stage where the healthcare domain or a healthcare service is completely blended into digitization; its services and all activities are running through technology services with a 100% utilization of information technology in the area, including automation or robotics.

Around the world digital revolutions are rapidly helping global industries to transform to meet the growing needs of civilization. The industries that are willing to adapt to the new trends tend to be very successful in the long run. In healthcare domain the service providers like hospitals, health-systems manufacturers, and pharmaceutical companies apply these trends to improve the medical care of populations, decrease the costs and enhance the result.

Healthcare providers now have more technology alternatives to support evidence-based care, and they can implement and control new systems of engagement to improve treatment experiences for patients and providers. As the modern technological advancement is part of an evolution in the healthcare industry, which is moving forward for a better incorporation and collaboration between healthcare disciplines as well as value-adding care. Moro Visconti, R., & Morea, D. (2020) explain that "What is still controversial is the effective impact of digitalization, due to the lack of a sufficient track record and to the intrinsic difficulty of forecasting the effect of technological innovation." (p.16) [21].

The potential of healthcare is to focus on using quality data for patient centered care models to maximize the output. The trend is showing that the focus of healthcare service delivery is shifting from quantity to a value-added care that provides motivations for good health outcomes for the customers.

Healthcare business domains require to adapt a better data management, increased inter-connectivity between different systems, and improved ways to record the outcomes. As a result, healthcare cost can be rapidly reduced by identifying breakthroughs to improve and shape the industry that delivers a high-quality experience for the people it serves.

7.1. IBM Watson Health

IBM Watson Health [23] is a digital system created by one of the divisions of the International Business Machines Corporation (IBM). After development the system IBM Watson was introduced to the public in 2011 through a TV show. IBM Watson Health (Watson) supports healthcare users to simplify medical and clinical research, and provide healthcare guidance, using its AI driven data analytics, cloud computing, and other advanced information technology components.

In healthcare domain, Watson was introduced with its ability of natural language processing, hypothesis creation, and evidence-based learning competences. Watson tends to aid medical doctors in the treatment of their patients, as the doctor has to submit a query to the system with details of symptoms and other related aspects. Watson initially parses the input data from the doctor to categorize the most significant bits of information; then it extracts patient data to find evidences corresponding to the patient's medical and genetic data; then it scrutinizes available data sources to formulate and test hypotheses; then finally it delivers a list of personalized, high-scored references. According to Strickland, E. (2019) “Watson learned fairly quickly how to scan articles about clinical studies and determine the basic outcomes. But it proved impossible to teach Watson to read the articles the way a doctor would.” (p.30) [24].

The sources of data that Watson uses for analysis are derived from medical treatment guidelines, collections of electronic medical record, reports from healthcare providers, research items, clinical studies, journal articles and patient data.

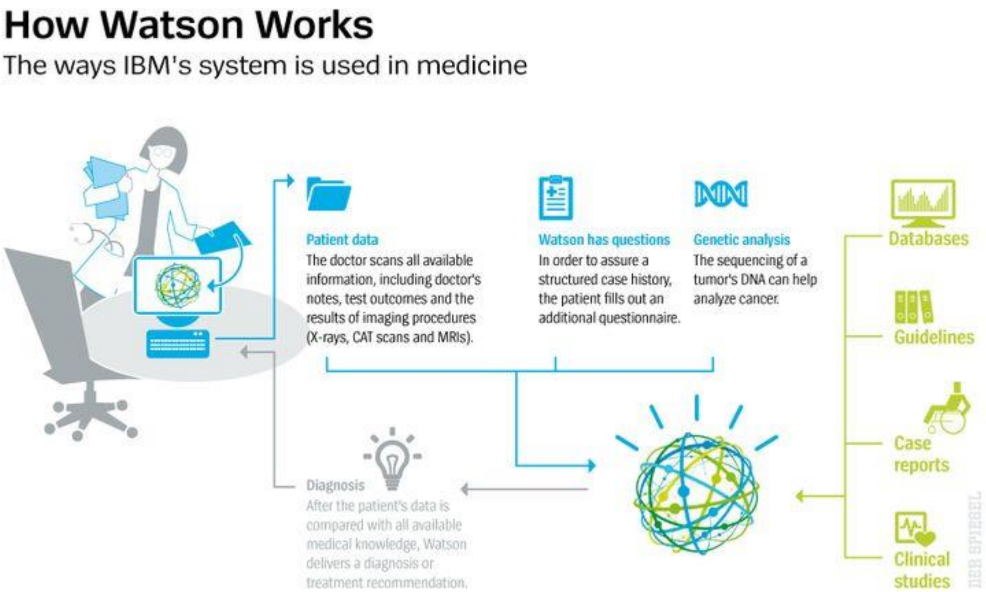

Figure 5: IBM Watson health method
Source: Müller, M. U. (2018). Medical Applications Expose Current Limits of AI [25].

From the Figure 5 it’s been evident that Watson has access to unusual collection of patient indication records. As a result, this system can produce a useful list of probable diagnoses, each marked with Watson's assurance level and connections to supporting medical literature found in the collection.

One of the crucial things is that, regardless of being built and promoted as a ‘diagnosis and treatment advisor’, Watson has never been allowed to contribute to the medical treatment activity, rather being used only to assist with finding treatment options for patients who have already been diagnosed. “Watson has a relatively easy time with genetic information, which is presented in structured files and has no ambiguity—either a mutation is there, or it’s not. The tool doesn’t employ NLP to mine medical records, instead using it only to search textbooks, journal articles, drug approvals, and clinical trial announcements, where it looks for very specific statements” stated by Strickland, E. (2019) (p.31) [24].

This method is showing one of the clear approaches in the domain stated by Prof. Pirk, in that current technology advancements and innovative movements are just tools which healthcare professionals can use, but these tools are not the replacement for the professionals.

7.2. Zlatokop in Institute for Clinical and Experimental Medicine

In the Institute for Clinical and Experimental Medicine (IKEM) Prague, their healthcare professionals are using the internal system called Zlatokop [26] (“Gold digger” in English). This system is an inhouse designed and developed system. That means this tool was developed by one of the doctors in the faculty. The Zlatokop system was introduced to the faculty directly by its creator, MUDr. David Hačkajl, who outlined the basic concept of the tool in IKEM.

Zlatokop software is an example for the importance of domain knowledge for system design. As stated, the domain knowledge is vital to understand user requirements from any domain to design and develop a tool that can fully be utilized by all of its user community. Zlatokop was designed and developed by a doctor. This is crucial since a doctor knows what makes tools more perfect or helpful on their daily duties with patients. This means the more one is involved into relevant domain the better for them to understands the requirements to design a tool to assist to solve the problem.

Zlatokop is built as a user portal for the needs of doctors or nurses to search for card data according to two main criteria. The first criteria are querying according to the personal data of patients - in this way it is feasible to obtain specific diagnoses, survey results and image data related to the selected patient. The second option is to query in the opposite direction, that means according to the type of diagnosis, the possibility of search according to the items of regulations. Other possibilities of refining the search options of the system are also considered.

Figure 6: Screenshot of a heart of a patient record in Zlatokop
Source: Prof. Pirk

7.2.1. Characteristics of ZLATOKOP

ZLATOKOP – is an influential clinical information system of its own attribution and is becoming one of the main sources in IKEM for analytical data transfer to Enterprise Resource Planning system (ERP) from clinical practices.

Some of its core characteristics are as follows,

• This system is developed on a modern platform enabling future enhancement, user-friendly environment, fast responses, and high variability for all solutions

• The system is capable to work with both object-oriented data and structured data

• Data suitable for processing in the economic system are usually stored in structured way in the system

• IKEM inhouse development team guarantees a reasonable response to the requirements of users in both the clinical and economic areas

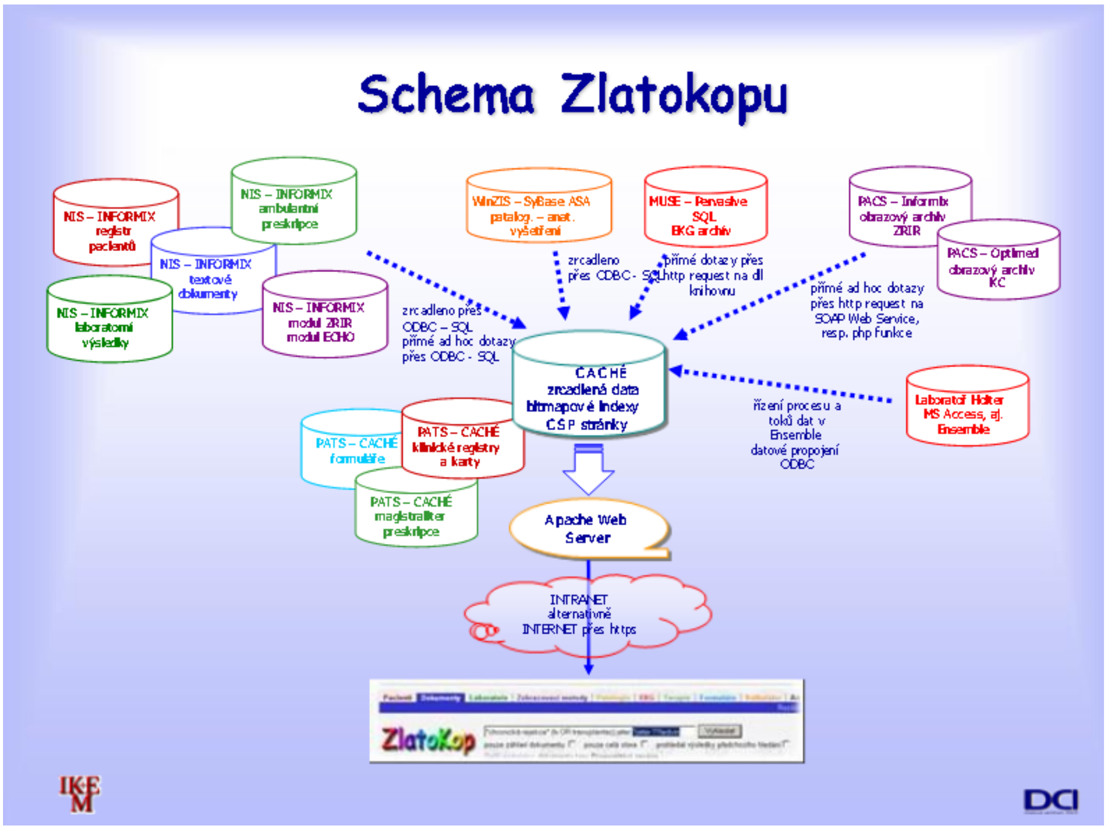

Figure 7: Zlatokop architecture as it was in the year 2005.
Source: MUDr. David Hačkajlo Datové Centrum IKEM, ÚIK (2006) [27].

8. Methods for collecting qualitative data

Data collection is a continual systematic process of collecting, analyzing, categorizing, and interpreting various types of information from different data sources. One of the main purposes of data collection is to understand the full picture of a domain of interest and to build a standard for decision-making or forecasting. As mentioned by Sapsford, R., & Jupp, V. (1996): "As research progresses, theoretical ideas develop in conjunction with data collection. More specific research questions, propositions and hypothesis emerge from an examination and analysis of initial data. These then form the basis of, and provide focus for, future data collection." (p.79) [28].

8.1. The data

There are many definitions for the term data, however in this context data are facts or figures to be processed. These factors or figures are evidence, records, statistics, and so on from which conclusions can be inferred. In other words, facts which can be analyzed, used to gain knowledge or to make decisions.

8.2. Importance of data

The quality of any decision has a direct relation with the quality of underlying data that support the decisions.

Some reasons for the importance of data are as follows.

- Data is vital to make better decisions.
- Data can be used to solve problems by finding the root cause.
- Data is useful for performance evaluation over a period.
- Data facilitates to improve processes.
- Data helps to understand the domain trend.
- Data helps comparison easier.

8.3. Types of data

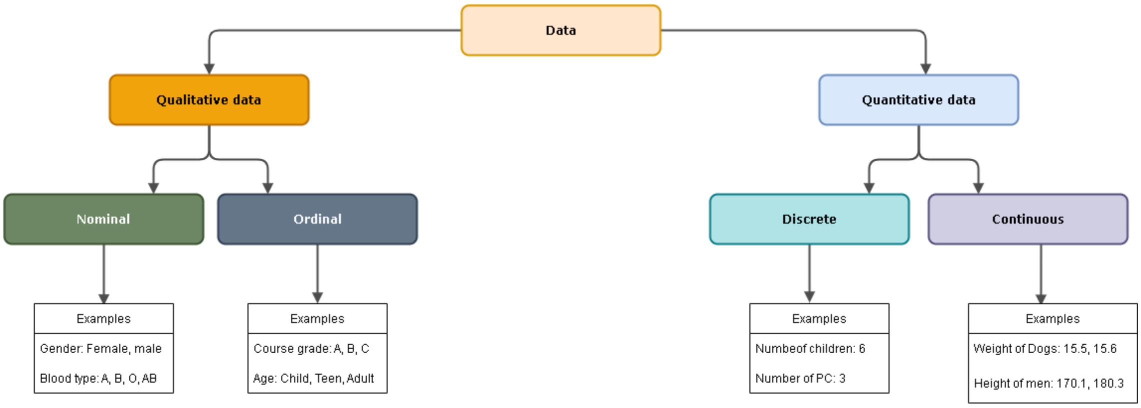

Figure 8: Types of data
Source: my own work
Inspiration: Abuel-ReeshSamy, J. Y., & Abu-Naser, S. S. (2017). The main components of typical expert system [Illustration][29].

As shown in Figure 8, data are divided into two main categories and further into four subcategories. They are as follows:

- Qualitative Data type
  - Associated with facts or details
  - Collected data cannot be evaluated
- Quantitative Data type
  - Associated with numbers
  - Collected data can statistically analyzed

8.3.1. Qualitative data type

Qualitative data type refers to the consideration that uses a finite set of discrete classes. It means that this type of data can't be counted or measured easily using numbers and therefore divided into two subcategories as below. These types of data are usually extracted from audio, images, or text.

- Nominal: these data types are the set of values that don't possess a natural ordering
- Ordinal: these data types of values have a real ordering while maintaining their set of values.

8.3.2. Quantitative data type

Quantitative data type aims to quantify factors, and it does so by using the numerical values that make it enumerable in nature. The important note is that there could be an infinite number of values, which can be included

- Discrete: The numerical values which fall under this category are whole numbers.
- Continuous: The fractional numbers are considered as continuous values and as information that could be meaningfully divided into smaller levels.

8.4. Stages in data collection

Since data plays a vital part in decision making, the planning of data collection is highly crucial. The stages prior to the collection are:

1. The purpose of data collection
2. The kind of data that is meeting the purpose of collection
3. The adequate process and methods to collect, store and process the required data

In general, there are two methods to collect the data: primary and secondary data collection

8.5. Primary data collection

Primary data is the collected raw data taken directly from the targeted sources. This method is potentially time-consuming and expensive because the data collection could be in face to face or phone interviews, surveys sent out to the audience, and so on. The data collectors themselves are the first to deal with the primary data and take conclusions from the data. Primary data is usually collected for a specific purpose, but it is a challenging process for the data collectors to interpret. That's because the raw data is unstructured and needs to be arranged systematically to allows to make meaningful decisions.

8.6. Secondary data collection

Secondary data are second-hand data collected by other parties for other purposes that have already undergone statistical analysis. Secondary data is easier and cheaper to obtain than primary data, but secondary information does not guarantee the accuracy and authenticity. Quantitative data constitutes most of the secondary data.

Some of the data collection techniques and their characteristics are listed in Table 3

Table 3: Data collection techniques

Method	Advantages	Disadvantages
Interviews	• Possibility to use different mediums, such as face-to-face, through phone or online meetings • Possibility to get additional information • Can build a trust with the participants to gather connected information	• Time consuming • Depending on the medium the cost varies from expensive to low • Interviewer's approach and attitude directly impact the responses
Close-ended surveys	• Low cost and can be sent out to many participants in parallel • Participants can answer anonymously • Processing of the data collected is easy, as the system will do the work	• Response rate could be lower • Unable to ask clarifying questions • No guarantee of the completion of the entire survey
Open-ended surveys	• Potentials to get insights • Can be used to explore different aspects of a given problem • Cost effective	• More difficult to analyze • Not able to ask clarifying questions • Responses may be unorganized and hard to categorize
Observational data collection	• Widely accepted technique • Possibility to apply in multiple situations	• Difficult to stay objective

	• Relatively easy to set up and conduct	• Certain things cannot be observed by the data collector
Research or reported data collection	• Faster than interviews or any other above methods • Flexibility to use multiple data sources together to get the big holistic picture	• Quality of the data is not guaranteed • Hard to get the data which is directly required by the target topic
Online analytic tools	• Ability to understand participants' interaction on certain targeted areas • Easy to create tests and hypotheses to improve the results	• No room for the interaction with participants • The data is limited and there is no room for reasoning

Note: Partington, S. N., Papakroni, V., & Menzies, T. (2014). Optimizing data collection for public health decisions: a data mining approach. BMC Public Health, 14(1) [30].

9. Data in healthcare

The current trend shows that the amount of data generated under healthcare domain increases rapidly, demonstrating the era of an exponential increase in patient health data. One of the recent examples the world has been observing is the translation of the pandemic into numbers or percentages to show the stages of impact. Such as where we were in the past, where we are now and where we will be. According to Shilo et. al (2020) “Analyses of large-scale medical data have the potential to identify new and unknown associations, patterns and trends in the data that may pave the way to scientific discoveries in pathogenesis, classification, diagnosis, treatment and progression of disease.” (p.29) [31].

It’s been estimated that a single patient generates nearly 80 megabytes of data each year in tomography and electronic medical records [32] data. According to 2017 estimates, based on these assumptions some of the experts estimate that by 2025, the mixture of annual growth rate of data in healthcare will reach about 36%. This projection of growth rate is remarkably faster than estimated for many other major industries, including manufacturing, financial services, and media and entertainment. In 2018 Statista [33] estimated that as many as 2,314 exabytes of new data could be generated worldwide in 2020. That means healthcare industry was expected to produce 2,314 exabytes before the pandemic appeared on the list of one of the triggers for the data generation on a global scale.

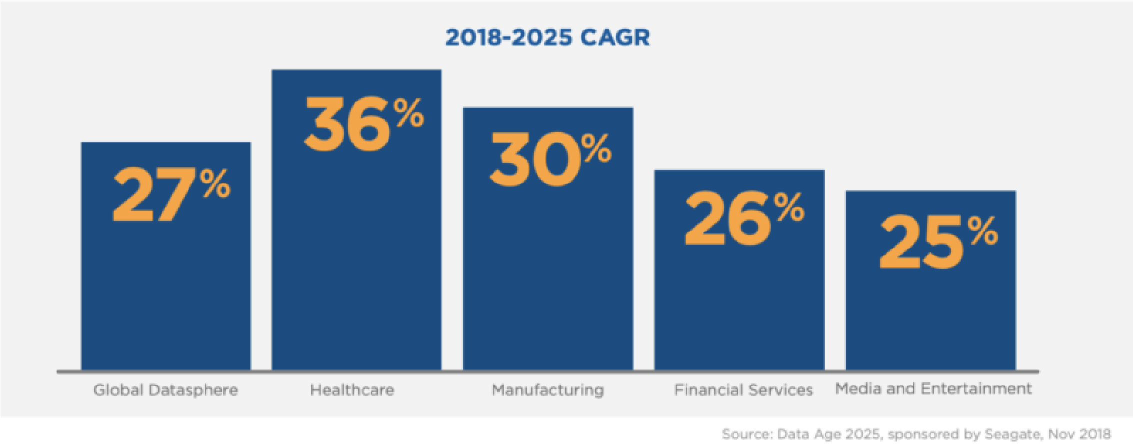

Figure 9: Data growth trend in different domains
Source: Reinsel, D., Gantz, J., & Rydning, J. (2018). Comparing Industry Datasphere Growth Rates [Graphic] [34]

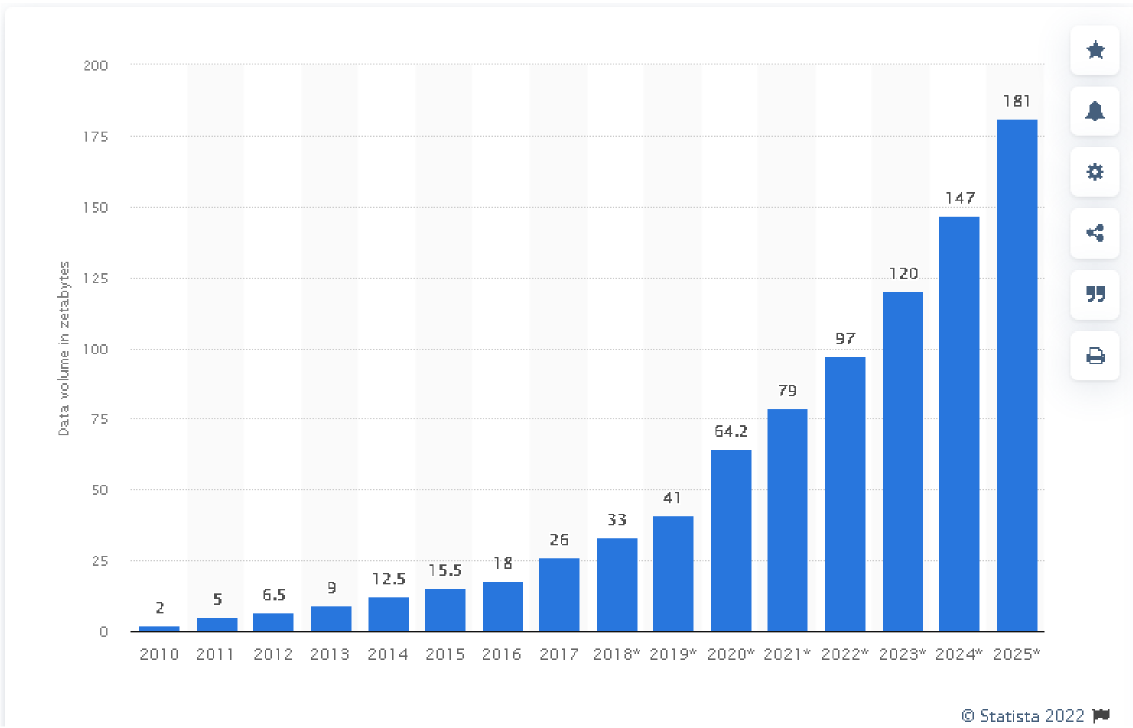

Figure 10: Expected data trend in zettabytes for 2010 -2025
Source: Statista.com. (2021), Volume of data/information created, captured, copied, and consumed worldwide from 2010 to 2025 [33]

The illustration shown in Figure 10, demonstrates the volume of data/information created, captured, copied, and consumed worldwide from 2010 to 2025 (in zettabytes). If 2010 is considered as a base, the jump from 41 to 64.2 (hike from

2019 to 2020) zettabytes sums up around the total of growth between 2017 to 2019. By looking at the figures there might be a potential risk of medical data pollution on the horizon, such as that the useful or meaningful lifesaving data are getting dumped in the mix of other data.

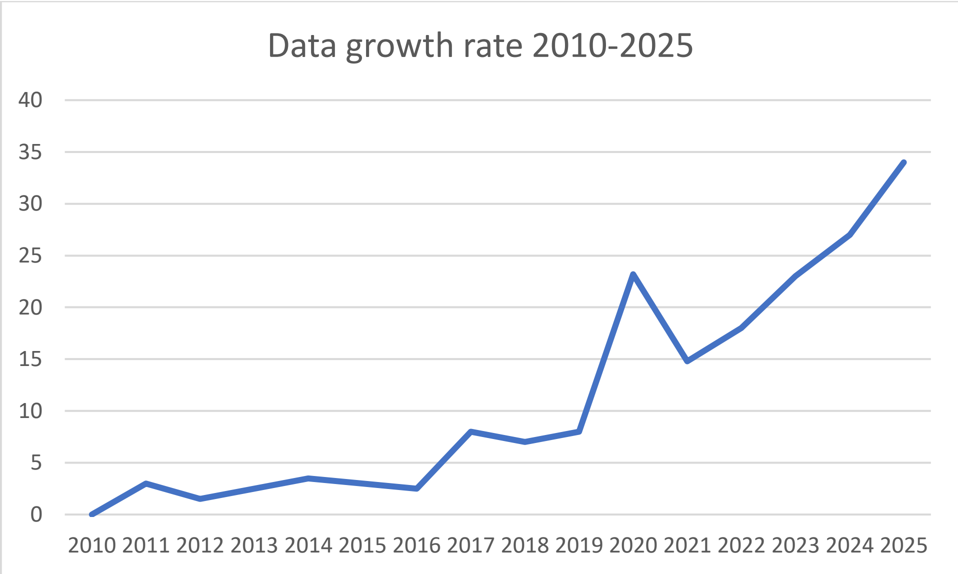

Figure 11: Data growth rate
Source: my own work
Inspiration: Statista.com. (2021). Volume of data/information created, captured, copied, and consumed worldwide from 2010 to 2025 [33].

The purpose of analyzing the growth rate as shown in Figure 11 is to visualize the assumption of Covid-19 pandemic impact in the data sector on the global level. Since the internet enabled most of the working population and academic institutions to operate remotely, this assumption is considered to be valid.

10. Data Mining

Through the Data mining process, large amount of data can be analyzed to find patterns, correlation, and anomalies. Data mining helps the analytics to find the patterns in the data to predict an outcome and helps to contribute to the decision-making process. Through this entire process the business risk is highly reduced. As mentioned by Franklin, J. (2005), “Data mining, with its roots in the neural networks and decision trees developed by computer scientists in the 1980s, is a collection of methods aiming to understand and make money from the massive data sets being collected by supermarket scanners, weather buoys, intelligence satellites, and so on.” (p.84)[35].

The **Cr**oss-**I**ndustry **S**tandard **P**rocessing[36] for data mining is called **CRISP** methodology. The six steps in the CRISP methodology are as follows in the illustration Figure 12 with detailed explanation in the sections 10.1 to 10.6

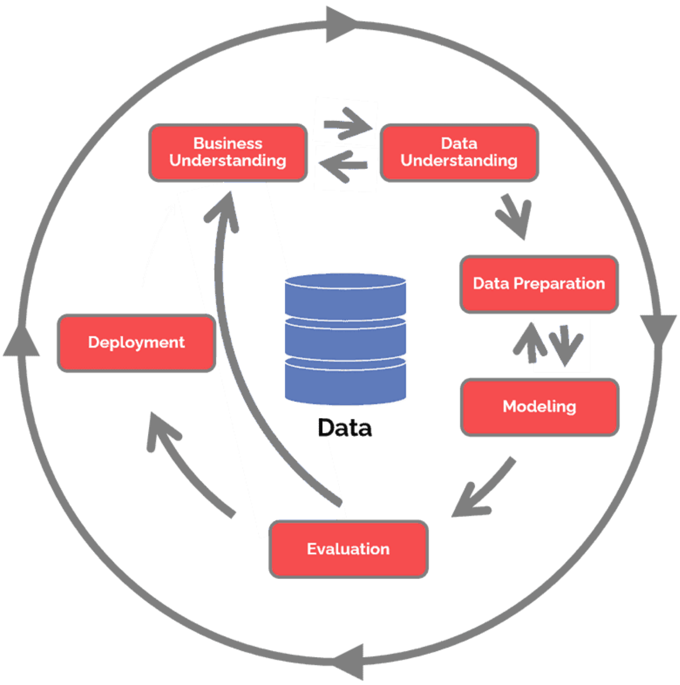

Figure 12: CRISP methodology

Source: HOTZ, N. I. C. K. (2018). CRISP-DM diagram [37]

10.1. Business understanding

The very first phase is to establish the business objectives and scope, then recognize the questions or problems business stakeholders want to solve. The basic question to address in this phase is "what are the given demands of business condition to extract from the available data?". Sub-tasks under the business understanding are,

- ✓ Determine business objectives: it's mandatory to absolutely understand the requirements from the business perspective such as what the business/customer really wants to accomplish, and to define the customer success criteria based on the business requirements.
- ✓ Assess situation: overall assessment against the business requirements and data requirements that includes the availability of resources, project requirements, risk assessments and contingencies, and performing cost-benefit analysis.
- ✓ Determine the data mining goals: along with defining the business requirements or objectives, it is vital to define the successful completion from the technical data mining perceptiveness. It helps to identify the deviations to be addressed
- ✓ Project plan creation: in the business understanding phase, the last process is to identify the technologies, and tools to be used for the data mining process and to define the detailed plans for the rest of the upcoming phases.

10.2. Data understanding

This phase is identifying the collected data, which is relevant to the question or problem being solved for the business. The very basic question addressed in this phase is, "what data are required to address all the requirements or demands from the business, and are all of these collected-data usable to address the requirements?" Sub tasks under the data understanding phase are:

- ✓ Collection of initial data: Acquire the required data, which meet the business requirements and if needed, load the data into the data analysis tool, which was selected during the project plan.
- ✓ Describe data: Analyze the collected data, verify, and document their external properties such as data format, number of records, or field identifiers.
- ✓ Data exploration: Examine deeper into the collected data. Query the data, visualize, and identify relationships among the data. In general, there are statistical and non-statistical methods that are involved to explore the data.
- ✓ Data quality verification: validate the cleanliness such as accuracy of the data, completeness, and consistency along with the believability and interpretability, and document any deviation from the required quality.

10.3. Data preparation

This phase goes through the preparation of the final dataset and identifies its dimensions and variables intending to be explored within the collected data. The question being focused on this phase is "what are the best options available to organize the collected data for modeling?". Subtasks under the data preparation phase are:

- ✓ Select the data: Define the data sets which will be used and record the justification for exclusion or inclusion of the data sets.
- ✓ Clean the data: One of the time-consuming tasks. The cleaning process helps to reduce the data garbage-in and garbage-out. General procedure during performing this task is to rectify, assign, or eliminate the inaccurate data values.
- ✓ Data construction: Develop new properties which are going to be helpful for the data preparation.
- ✓ Integrate the data: Creation of new data sets through combining the collected data from various data sources.
- ✓ Format data: Format or re-format the data as needed to achieve the business requirement.

10.4. Modeling

Select the appropriate modeling technique for the collected data. This could be moving back to the very first phase to reassure whether the model needs to be expanded in its dimensions or variables or in the scope of gathering data from different sources. The focus on this phase is "what is the suitable data modeling technique required to be applied on these collected data?". Sub tasks under the modeling phase are:

- ✓ Select the data modeling techniques: Establish which algorithms to be used, such as regression, or linear regression, or decision tree regression
- ✓ Generate test design: Divide the collected data into training data collection, test data collection, and data collection for validation.
- ✓ Build model: Create a model (ideally to the training data collections) with the data. This could be performing a small line of code
- ✓ Assess model: Usually, various data models are challenging each other. During this phase, it's vital to use the business knowledge to interpret the outcome of the model. Usually, this step validates the pre-defined accomplishment criteria and evaluates the design.

10.5. Evaluation

This stage tests and measures the success of the chosen data model at answering the problems identified in the very first phase. This could be something like stepping back to the previous phases in case the data modeling is not meeting business goals. In this phase the focus is on "How do the business stakeholders access the outcome?" Sub tasks under the evaluation phase are,

- ✓ Evaluate results: Compare the data models against the business success validation criteria and choose the best one for the business requirements

- ✓ Review process: Review the data model and its successful result. Evaluate the stages and compare the tasks in each stage, ensure all the recorded tasks are properly executed. Document all the findings and mitigate anything if necessary.
- ✓ Determine next steps: according to the above three sub tasks in this phase, finalize whether to continue to deploy or repeat the evaluation phase, or to move back to the very first phase called business understanding.

10.6. Deployment

Once these results are accurate, reliable, and meeting the business requirements, then findings can be shared with stakeholders with an easy-to-understand structure and put into place. Sub tasks under the deployment phase are:

- ✓ Plan deployment: Create a detailed deployment plan and review the pre-requests and risks with the business stakeholders for deploying the model.
- ✓ Plan monitoring and maintenance: Develop an operational plan for monitoring and maintenance to face and prevent issues during the operational phase of the model.
- ✓ Creation of final report: Documentation of the summary of all of the above phases including the final result of the data mining.
- ✓ Review project: Documentation of the lesson learned in conducting a retrospective review about what went well, what could have been improved, and how to improve in the future.

As stated by Caetano et.al (2015), [38]: "Due to advances in Information Technology, hospitals are collecting vast amounts of data related with their clinical information systems. All this data can hold valuable knowledge. The development of the Data Mining (DM) field has created new exciting possibilities for extracting such clinical knowledge, in what is known as medical data mining".

11. Analysis and management of data

There are mainly two ways of data analysis: qualitative and quantitative analysis. One of the interesting facts about these two types of analysis is that both are interconnected, as stated by KAPLAN et.al (2005), [39]: "the qualitative data enabled the researchers to make sense of their quantitative findings. The qualitative data helped to explain why the quantitative results were as they were." That means the hypothesis or assumptions are derived from the quantitative side of the data analysis are justified by the qualitative analysis in order to show how the accuracy or the deviation from the hypothesis got originally created.

11.1. Qualitative data analysis

"A strategy for empirical research that is conducted in natural settings, that uses data in the form of words (generally, though pictures, artifacts, and other non-quantitative data may be used) rather than numbers, that inductively develops categories and hypotheses, and that seeks to understand the perspectives of the participants in the setting studied, the context of that setting, and the events and processes that are taking place there.", [39] KAPLAN et. al (2005) stated.

As stated above, qualitative analysis is beyond the numerical or statistical information. In qualitative data the information is spread on descriptive nature; the quality of information consists in words, pictures, objects and so on. The collected information cannot be quantified using the numbers. The process of gathering knowledge from any such kind of type is a perplexed activity. For example, there are multiple ways to discover a specific trend on the printed material, and one of the globally accepted strategies is to instate a word-based scheme to find the patterns. In the past qualitative data analysis was conducted manually, fortunately in this era, there are Natural Language Understanding [40]systems.

11.1.1. Natural Language Understanding

Natural Language Understanding (NLU) means that the computer understands the written language and its meaning. NLU is the sub area of Natural Language Processing (NLP) [41], which recognizes the part of the text or the speech. Some examples for the success in this area are IBM Watson [23], Deepmind [42] from Alphabet Inc. (former Google), and PyText or MUSE [43] from Meta (former Facebook).

11.2. Steps in qualitative data analysis

In general, the steps for qualitative data analyzing are listed below,

- Identify the need for quantitative analysis
- Follow the corresponding data collection methods (such as interviews, open-ended surveys, texts and documents, observational notes, and so on)
- Select most appropriate method for qualitative analysis based on the collected data (such as, narrative analysis, content analysis, thematic analysis, discourse analysis and grounded theory)
- Structure and organize the collected data
- Label and organize the structured data
- Analyze the labeled data to find the insights from the collected data
- Generate reports which contains the findings and insights (this can lead to further discussion or to find the correct action)

The Figure 13 shows a high-level overview of these steps, which are starting from the stakeholder needs of identifying qualitative data analysis.

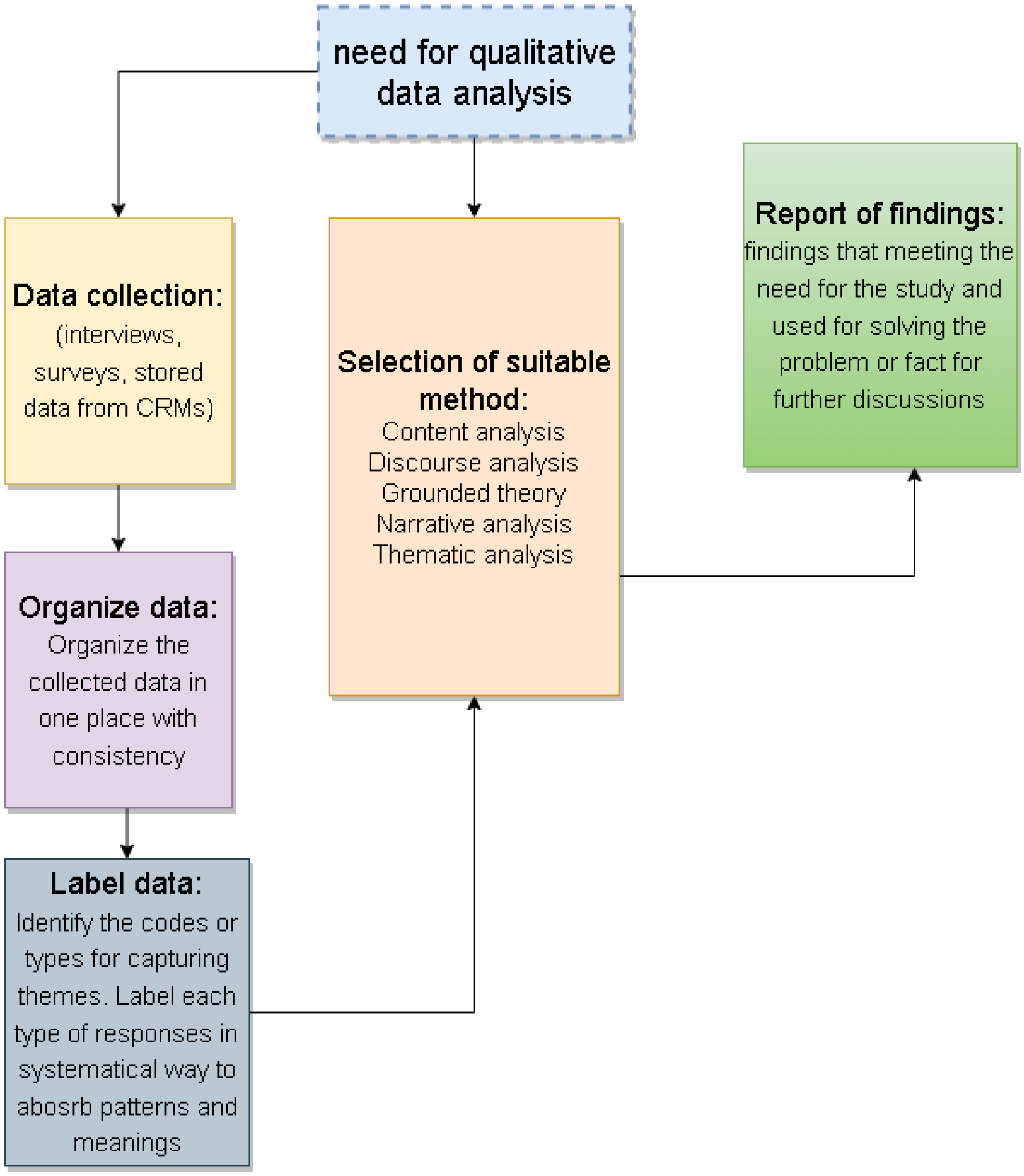

Figure 13: High-level overview of the qualitative data analysis flow
Source: my own work
Inspiration: Ismail, F., & Maryama Daud, D. (2021). Procedure of qualitative data analysis [44].

11.3. Quantitative data analysis

This type of data analysis is a descriptive type and is essential for calculations and additional statistical analysis. Like the qualitative data the outcome of the quantitative analysis can be used for decision making or problem solving. Examples of quantitative data collection question could be the responses from participants for “how many times they went for the Polymerase Chain Reaction test?” The responses are always mathematical figures or numbers, and there is no further explanation from the respondents. And it is easy to identify the quantitative data collection questions, as they are usually “how-many”, “how-much”, and “how-often”, and so on. Applications like Excel and PowerBI or other relevant applications have support to visualize the quantitative data analysis. According to Dhall (2019): “In any kind of research, the measure objective is to analyze the data, to have meaningful information which will enable the researcher to undertake actionable managerial decisions, for the problems defined before the research is undertaken.”, (p.109) [45].

12. Usage of data in decision making

Data driven decision making is one of the safest decision-making approaches in any domain. As the fact is hardcoded in the data, it is easier to use the fact to face the problems in the future. One of the simple examples is Google showing certain advertisement within the search result. The decision to show a specific advertisement on the page is not a random choice, as the Google's algorithm uses the facts from the data and displays it on the closest product advertisement as a recommendation.

12.1. Decision making process

In general, decision-making is the process of selecting one of the alternatives from the group of available choices. That means that the decision-making process is a cognitive process of selecting one of the suitable choices from many, based on the preferences, experiences, values, and emotional state of the decision maker. The outcome of every decision-making is the selection of a final choice for the given problem.

Decision making could be an intuitive (unconscious) process or rational (analytical) process. The intuitive decision-making process is the quickest and easiest way to get to a most suitable solution for a given problem. The risk is very high in the intuitive decision-making process as the decision maker is blending their gut-feeling, experiences and emotions while making the decision or selecting the best alternative.

On the other hand, in the analytical decision-making the decision maker is considering all the available facts, research findings, and expert consultation to find the best suitable alternatives. Besides the advantage of very low risk, one of the drawbacks of analytical decision-making is its time-consuming side. Since the backbone of analytical decision-making process is fact-based, the collection of quality data and its related data-mining methods are the essential step to achieve the best anticipated result. As stated by Dwivedi et.al (2021) that, "Although we do not believe that machines will replace human physicians in the foreseeable future, AI can nevertheless help physicians make better clinical decisions and possibly even replace human judgment in healthcare-specific functional areas." (p.3) [46].

Each business domain requires decision-making by its stakeholders, either individual or by group. Two of the pioneers in implementing quality decision-making are Victor Vroom and Phillip Yetton. Vroom-Yetton decision model was originally introduced in 1973 by Victor Vroom and Phillip Yetton and in 1988 the decision model was expanded by Arthur Jago. Now it is widely known as the Vroom-Yetton-Jago decision model [47].

Vroom-Yetton-Jago decision model consists of five styles of decision-making, ranging from autocratic to consultative to group-based, based on the Yes or No answers to 8 sequential queries.

Table 4: Vroom-Yetton-Jago model

8 Sequential questions in order		**Styles of decision making**
Questions	**Options**	I.Autocratic l (Al) II.Autocratic ll (All) III.Consultative l (Cl) IV.Consultative ll (Cll) V.Group ll (Gll)
1. Quality Requirement (QR)	High / Low	
2. Commitment Requirement (CR)	High / Low	
3. Leader's Information (LI)	Yes / No	
4. Problem Structure (ST)	Yes / No	
5. Commitment Probability (CP)	Yes / No	
6. Goal Congruence (GC)	Yes / No	
7. Subordinate conflict (CO)	Yes / No	
8. Subordinate information (SI)	Yes / No	

Note: Vroom, V. H., & Jago, A. G. (1988) Vroom-Yetton-Jago Normative Decision Model [47].

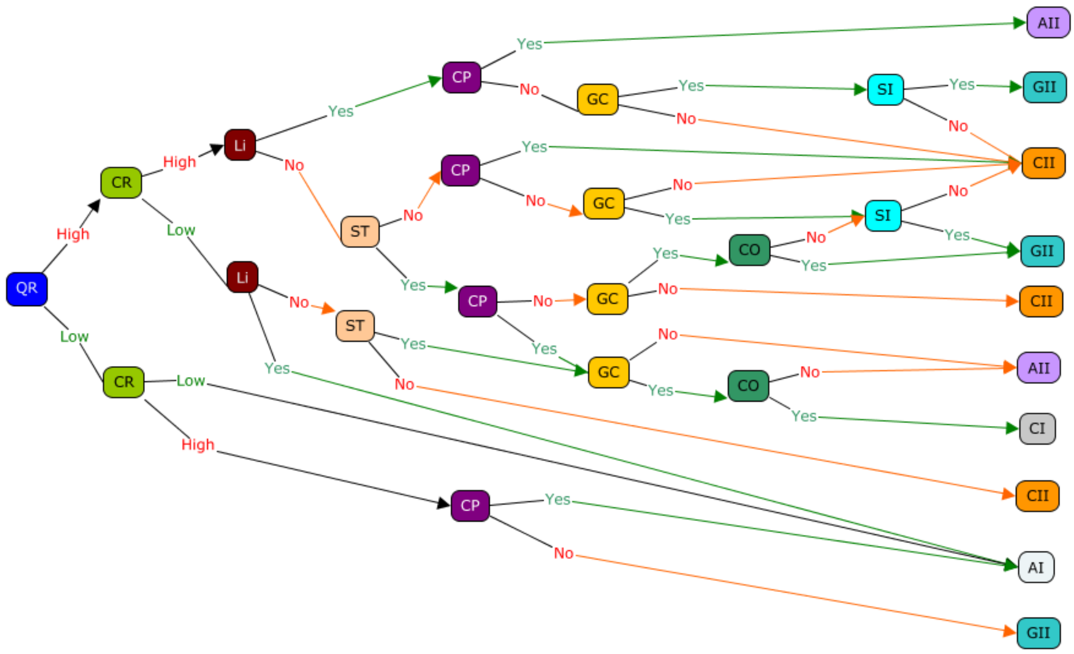

Figure 14 : Map view of the Vroom-Yetton-Jago decision tree
Source: my own work
Inspiration: Vroom, V. H., & Jago, A. G. (1988) Vroom-Yetton-Jago Normative Decision Model [47].

The Table 4 and its correlated Figure 14 shows a path of suitable decision-making model based on the requirements. It is evident that quality decision making is a long process, which requires quality data for support.

One of the biggest challenges faced by the healthcare personals is the time window for making decisions. For example: in general, facing an unexpected scenario during the surgery forces the surgeon to decide based on gut feelings and experiences, as the situation is completely new for everyone present in the surgery room. Or handling patient outside of the clinic due to unexpected scenarios on the road or in the plane. So, if healthcare staff needs to make decisions during these kinds of extreme scenarios with time constraints, the best way is to use intuitive thinking and improvise according to the availability of tools and help that the healthcare personal can get on the scene to save lives.

12.2. Rule based decision making

As the name implies, rule based decision-making process [48] is based on the predefined rules. The easy way to explain this type is to visualize the whole process like a tree with interconnected branches. The path to each branch is based on rules. That means following the rule led to the end of the corresponding branch. In the programming world, it tends to be syntax-ed as "if, then", and, "if then", which varies depending on the programming language. As demonstrated by Anjaneyulu (1998), "For instance, to represent the knowledge that if a person has a runny nose, a high temperature and bloodshot eyes, then one has a flu, we could have the following rule:

rl: If is(nose, runny)and is(temperature, high) and is(eyes, bloodshot)
then disease is flu "(p.48-49) [1].

One of the drawbacks is that in rule-based decision making these rules will not work on the new scenarios happening in real life. For example, considering the behavior of newly discovered SARS-CoV-2 virus, where some symptoms are common for one section of population, but for others such as a population of a different age, different health conditions, the symptoms vary greatly in the progression of the disease. So, rule-based decisions are very suitable for the routine activities.

12.3. Decision making in healthcare

Healthcare decisions are constructed on the evidence-based approach, meaning that the decision-making process is strongly backed by the best available facts and research evidence. Thus, the outcome is not based on the intuitive thinking or gut feeling of the decisionmaker; in fact, the decision relies on the qualitative data analysis and facts.

The expected ways of utility of an expert system or decision-making system in the domains are:

- Assists healthcare professionals in their clinical decision making
- Enhances the ability of healthcare professionals to provide consistent and appropriate care for their patients

- Improves care and outcomes for patients while reducing the risk of clinical adverse events

According to BLOXHAM, et. al (2013) [49], each decision-making process has its own advantages and disadvantages. These advantages and disadvantages help the decision-maker to use either analytical, automatic, or rule-based decision-making based on the scenarios. Table 5-7 listing the advantages and disadvantages from the perception of the healthcare domain.

Table 5: Advantages and disadvantages of analytical decision making

Advantages	**Disadvantages**
▪ Uses all the evidence	▪ Slow and expensive
▪ Fully compares the alternatives	▪ Breaks down under pressure
▪ Uses expertise of others	▪ Unsuited to noisy, distracting, and dysfunctional environments
▪ Most likely to produce an optimal solution (when long on time and short ▪ on information)	▪ Affected by stress and fatigue
▪ Can be justified	▪ May produce overload and stall the decision maker
▪ Can be audited	▪ May ignore local good practice
▪ Many techniques available (e.g., from business)	

Note: BLOXHAM, et.al (2013). Safer Care—Human Factors in Healthcare: Trainer's Manual [49].

Table 6: Advantages and disadvantages of automatic decisions

Advantages	Disadvantages
▪ Very fast	▪ Requires experience
▪ Robust (most of the time)	▪ Often is (or becomes) unconscious
▪ Useful in routine situations	▪ Does not deal well with the unfamiliar
▪ Little conscious thought required	▪ May not prompt a situation awareness check when things change or should be reviewed
▪ Overloaded less easily than other modes	▪ Hard to explain or justify later
	▪ Prone to the limitations of heuristics

Note: BLOXHAM, et.al (2013). Safer Care—Human Factors in Healthcare: Trainer's Manual [49].

Table 7: Advantages and disadvantages of rule-based decision-making

Advantages	Disadvantages
▪ Good for novices	▪ May not suit new situations
▪ No need to understand reasoning behind each step	▪ There is not a rule for every situation
▪ Rapid, (if the rule is known)	▪ A rule that does exist may not be known or not be found
▪ Course of action has expert backing	▪ If interrupted, may miss a vital step
▪ Uses available evidence of good practice	▪ May not understand reasoning, leading to risk of wrong procedure being selected
▪ Produces consistency	▪ Can produce unthinking compliance
▪ Easy to justify	▪ May stifle creativity
▪ Allows managerial control and audit	▪ Can be time-consuming
▪ Many good decisions come from following rules	

Note: BLOXHAM, et.al (2013). Safer Care—Human Factors in Healthcare: Trainer's Manual [49].

In order to get a high-level overview, these advantages and disadvantages are further distributed on the Table 8 with three different properties.

Table 8: Comparison of analytical, automatic, and rule-based decision making

Properties	**Analytical decision making**	**Automatic decision making**	**Rule-based decision making**
Availability of decision support systems	High	Null	High
Conscious process	High	Low	Medium
Consistency result	High	Low	High
Control and audit	High	Null	High
Easy to adapt	medium	High	Low
Evidence-based	High	Null	High
Expensive	High	Low	High
Experience required	Medium	High	Medium
Group based	High	Null	Null
Handles time constraints	Null	High	Null
Optimal output	High	Medium	High
Risk	Low	High	Low
Routine work	Null	High	Null
Suitable for new and unexpected scenarios	Low	High	Null
Time consuming	High	Low	High

Note: Note: BLOXHAM, et.al (2013). Safer Care—Human Factors in Healthcare: Trainer's Manual [49].

The Table 8 demonstrates the importance of data presentation. The data presentation helps users to easily grasp the information embedded in it. This same example is demonstrated through a graphical comparison of the properties by supplying values for High=5, Medium=3, Low=1 and Null=0 as is shown in the Figure 17.

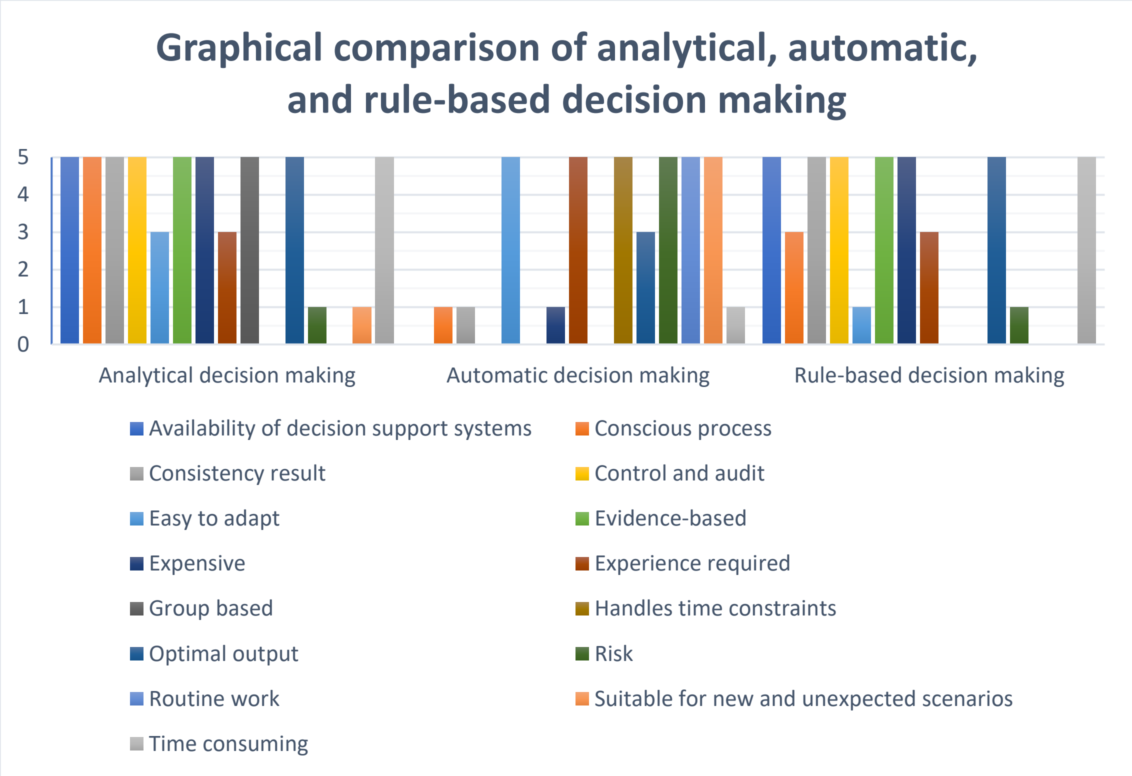

Figure 15: Graphical comparison of analytical, automatic, and rule-based decision making.
Source: my own work
Inspiration: Note: Note: BLOXHAM, et.al (2013). Safer Care—Human Factors in Healthcare: Trainer's Manual [49].

The purpose of this illustration in Figure 15 is to present the facts by highlighting three properties from Table 8. Both analytical and rule-based decision-making processes are fully depending on evidence-based property, whereas experience requirement property is a medium for both. Even though with the support of high experience property, the risk is also high on automatic decision making. The assumption which could be reached is that use of knowledge base can rapidly reduce the risk in healthcare.

One of the key characteristics in specialized service industries like healthcare is that the professionals are deeply engaged and blended in their environment which requires high qualification. So, the doctors or any of the healthcare professionals are not required to know information-technological developments, which occur outside of their domain, as data collection, processing and analyzing the data are not part of the job for healthcare professionals. In fact, they are the end users who make the use of structured data for their decision making. However, healthcare professionals can contribute to the data collations, hence they are the primary contact with the patients or patients' close relations.

As mentioned by Tao et. al (2019) "In smart healthcare applications, IoT sensors/devices are introduced to patients in aspects. The patients' health information (data) are collected from ECG, fetal monitors, temperature or blood glucose levels and safety of this data is crucial regarding patients' lives. Computer science and IoT community, and healthcare providers have been struggling secure each and every sensor/device in the IoT network with the integrity of its data." (p.1) [50]. By considering the knowledge-data base aspect, it is the healthcare professionals' responsibility to collect and record the knowledge and update the knowledge based on the new findings. Technically the healthcare professionals do not require to do it on their own, but they can supply these details to relevant knowledge editors or use the tools they are using for their daily job.

In healthcare, the complete decision-making process can be summarized as collecting the data, analyzing the data, taking the evidence, evaluating the evidence, implementing this evidence into practice, and evaluating it whether all of these processes are making a transformation.

13. Proposals for implementation

Since the framework of healthcare system and its related activities are very vast, complex, and impacting the whole population in the country, this is a theoretical proposal without considering any practical feasibility through user requirement specification, functionality and design specifications, configuration specification, or logical and technical system architecture designs.

According to the Czech Republic Supreme Audit Authority (NKU) report [51] the country had spent around 75 billion Czech Crowns during 2012-2018 for digitization public services, which includes electronic ID. By considering that fact that there are two options or proposals to be suggested, one proposal is a fully independent project, and as matter of fact needs to consider investing more funds as new capital investment to transform the plastic health insurance card into a smart health card. The second proposal is to eliminate the plastic card for health insurance and utilize the electronic ID interface and adapt medical data along with other existing services to the electronic ID.

Based on European commission's eGovernment benchmark 2021 report [52] these are the results for the current stage of the Czech digitization trend in the public service sector:

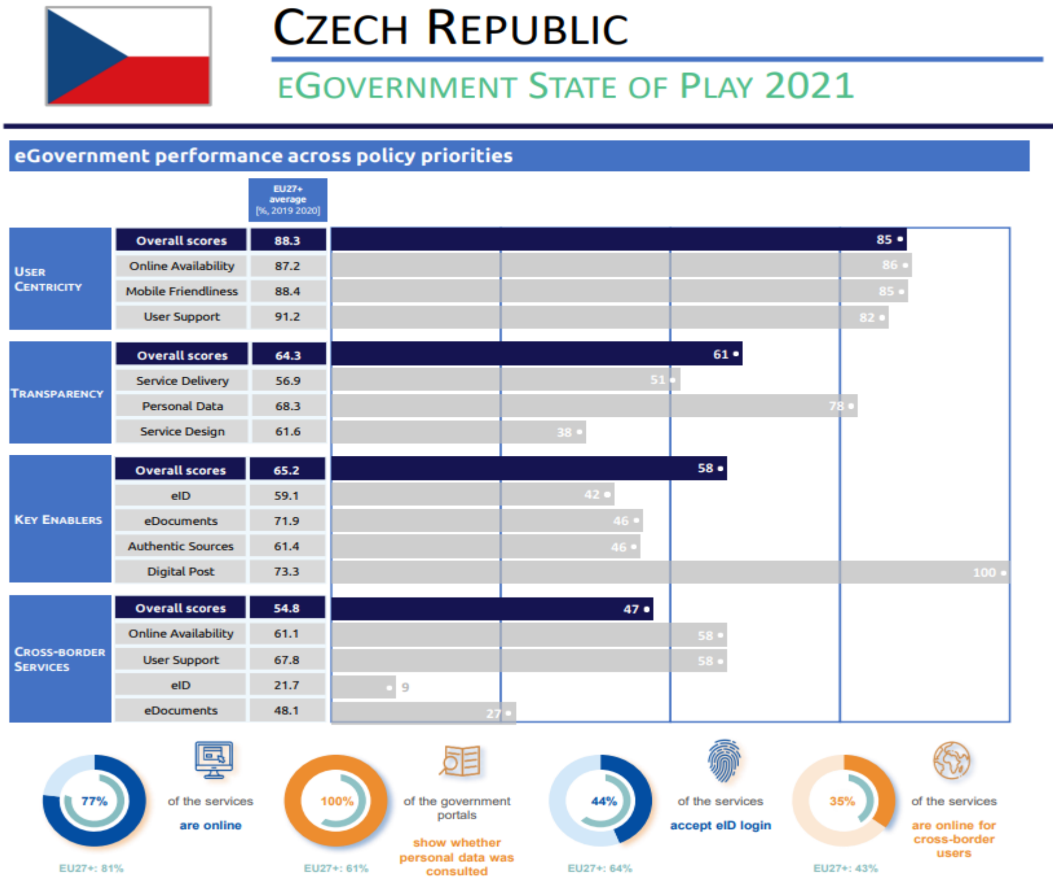

Figure 16: Digitization performance in 2021
Source: eGovernment benchmark 2021. (2021). Shaping Europe's Digital Future [52].

The Figure 16 shows the effectiveness of usage and service delivery in the public service sector. As can be seen, the User Centricity overall score of 88.3 % includes the 87.2% of Online Availability of services and related information online for the public. Besides that, over 91.2% of User Support shows the interactive feedback functionalities which are available for its users.

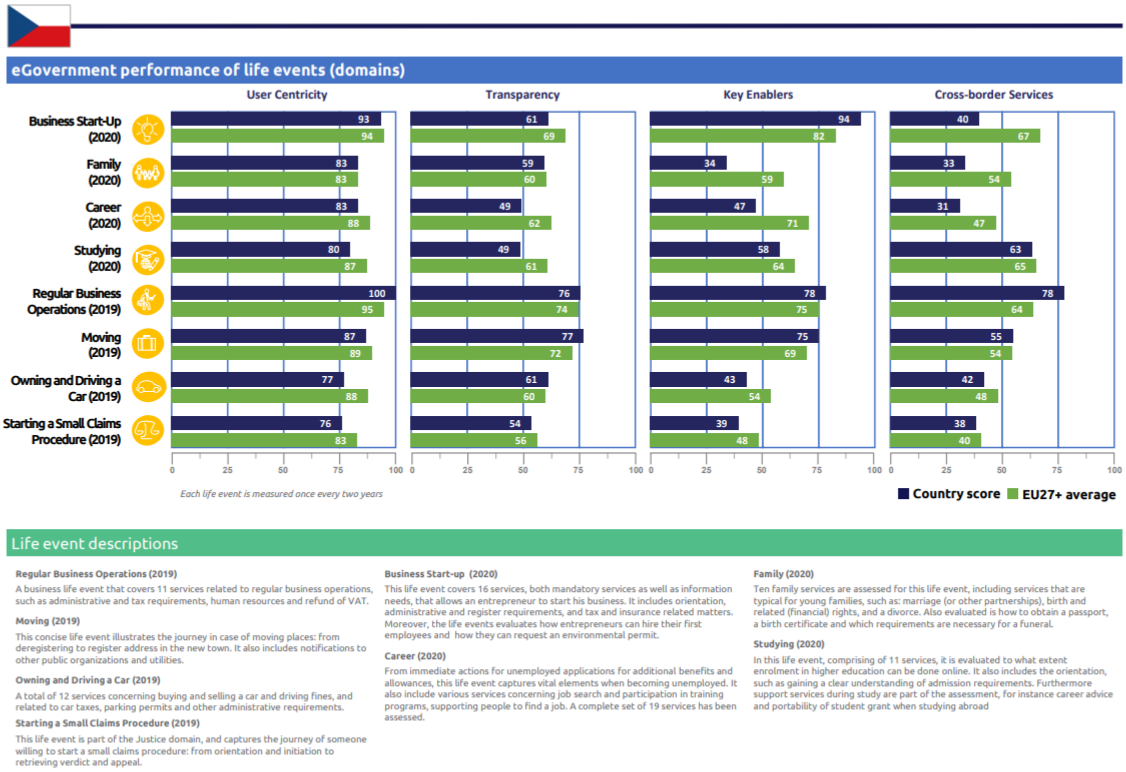

Figure 17: Domains in digitization
Source: eGovernment benchmark 2021. (2021). Shaping Europe's Digital Future [52].

The Figure 17 shows that most of the domains are effective over the European Union average. Since healthcare is one of most the complex and biggest service industries with lots of opportunities, it is still unknown if the European Union is yet to initiate the complete digitization in the healthcare domain across the EU. Healthcare is missing in the eGoverment domain of the Czech Republic, even though one of the recent proven milestones achieved in Czech healthcare sector is achieved through Electronic Receipt [53].

13.1. Proposal for transforming European Health Insurance Card to smartcard

These proposals are purely based on a theoretical approach. They could be potentially challenged by the feasibility of the perception of data protection and privacy Law, or technical infrastructure perception or investment or political perception. Otherwise, this can be considered as a starting point for further discussion and research.

13.1.1.European Health Insurance Card

The European Health Insurance Card is a proof that a person is an ‘insured person’ (or covered by the state social security scheme) within the denotation of Regulation (EC) No 883/2004 and permits [54] the card holder to get same treatment on similar terms as other individuals insured within the public health system of the Member State of stay. At the same time, it is for Member States to define what charges, if any, to enforce for healthcare service. EU law does not limit Member States in that respect, other than the prerequisite that all persons covered by the Law are treated equally. This signifies that if nationals must pay, the individual seeking treatment with the EHIC will have to pay as well; and if the nationals receive compensation, patients having shown an EHIC can be compensated as well. In certain circumstances where the national healthcare systems need payment for medical care which can later be refunded by the health insurers, the persons using an EHIC can claim refund either in the country through which they are transiting or which they are visiting while they are, or when they go back to the country where they are insured.

Figure 18: Specimen of health insuarnce card
Source: EHIC (2004) [55].

13.1.2.Vision

Since every individual in the country is required to carry the EHIC physically for getting the medical care, the vision is to create a utility to the card by implementing a microchip in it to connect to a centralized medical records database. The chip is a unique identification and authentication method. With the help of a card reader the microchip communicates with the cardholder's medical database and pulls out the details through an application interface (the approach is same as eObčanka or electronic ID). This proposal is an ambitious move to revolutionize healthcare sector and associated industries, without looking into the technological requirement.

As a result, through this longer vision investment the Ministry of Healthcare's expenses will be reduced for the coming years and moving forward. This proposal enables easy collection, management, and organization of medical records and healthcare related activities for the population. In addition to that, the Ministry of Healthcare will be able to use trend analysis for the population's health condition and identify where to focus for providing best healthcare service for the population.

Medical practitioners and healthcare associated staff's day to day service activities and redundant tasks will be reduced as the complete data for any patient is available anywhere using the centralized database with the authentication. Research and development related activities can be done more efficiently.

13.1.3. Value adding return from the proposal

- This proposal is aiming to add values and effectiveness to the centralized medical database for the population, which can be used for effective service in the healthcare domain.
- Patients' records can be retrieved at any time anywhere using the application interface or the card reader, and in future the data accessibility can be externed to the entire EU or to the rest of the world, where the country has bilateral agreement.
- Records are not getting lost in terms of any kind of disaster affecting any healthcare service centres.
- Using Natural Language Processing or Artificial Intelligence can contribute to the progressive research and development in life science industry in the Czech Republic.

- The data sharing with pharmaceutical companies can help to easily identify the impact of medicines to be recalled and to track the side effects, as well as to look for innovation of new medicines.
- Blood banks and organ transplantations can be performing their jobs easier as the whole country's medical history and records are available in the database.
- Potentials for early identification of pandemic trends or highly spreading diseases.
- Records can be used to create models and data simulations for deep analysis
- Human error can be reduced – since the medical records and history are available, medical practitioners will be able to avoid prescribing such medicines, which are causing side-effects or allergies to the patients.
- Based on the family root of medical history the medical experts can identify early stages of Oncological symptoms.

13.1.4.High-level overview

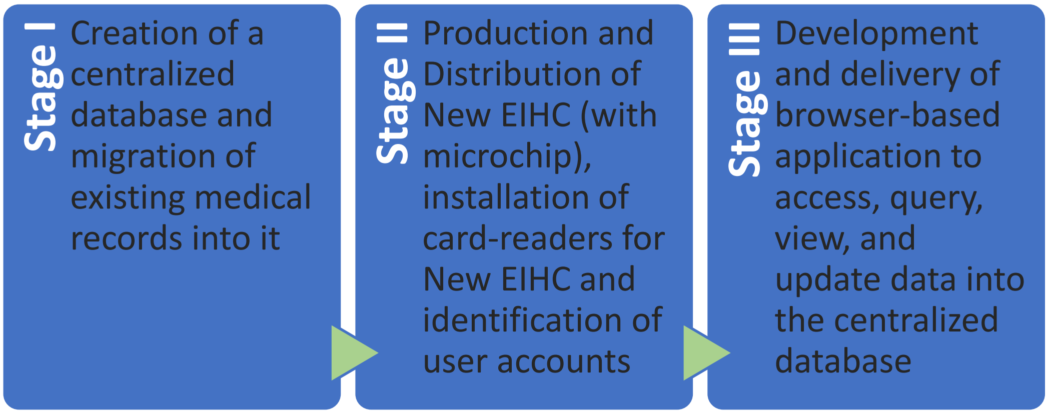

Figure 19: Overview of realization stages
Source: my own work

13.1.5.Stage I

Centralized database

Consists of assessment and creation of stable infrastructure services for creating a datacentre to store the current and future medical records in a centralized database. Existing government datacentres can be a potential choice for expansion to host the medical records, or conversely, entirely new datacentres can be created. These excising or newly created datacentres are required to meet all the requirements to store medical data for current and future population.

Record Migration

Migration can be started with mass scanning of paper medical records from all healthcare service centres across the country, including records from doctors. As a suggestion, birth number can be used as a unique identifier for holding medical records, where all birth numbers are considered as a bucket for these initial phases of migration process. Once the scanning is completed, the system extracts texts from the scanned copy of records and moves to the database. At the end of this stage, each bucket from different healthcare service centre with same birth number is merged and the data are aligned in order.

Data export from different live systems

This is a part of migration approach where different systems are used across the country and the data export is done in batches. Data export starts from the batch of least used systems and continues to largely use systems. After export, these data are imported to the interim database and distributed in corresponding buckets based on the birth numbers.

Least used systems can be deactivated after completing the data export. Users are instructed to use predefined excel templates during the interim period. In the meantime, the widely used systems are still in use with limited capabilities.

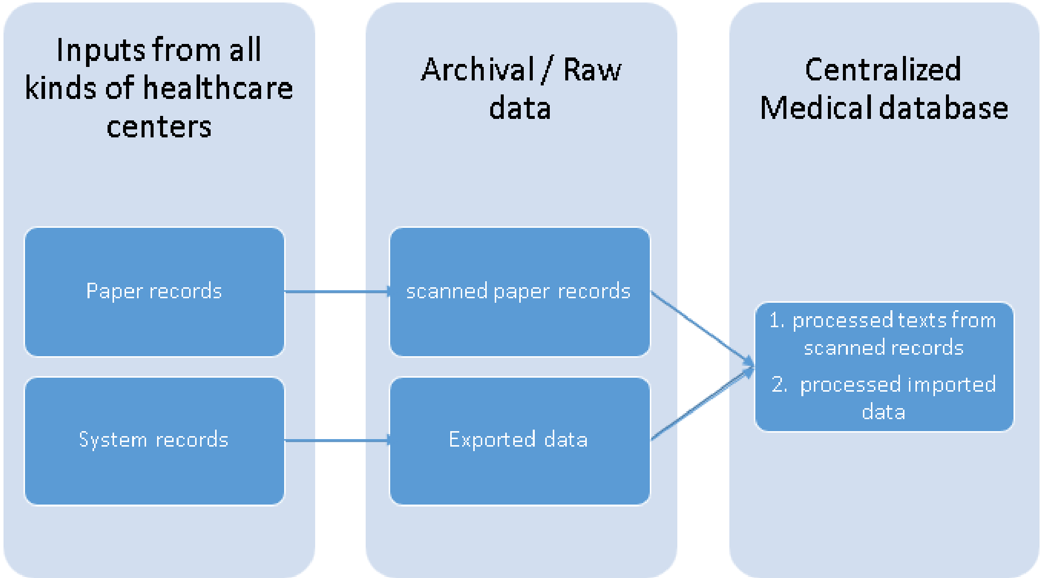

Figure 20: Overview data collection and storage
Source: my own work
Inspiration: Saha, D. (2021) Entity framework core5.0 [56].

As shown in Figure 20, Archival/Raw data section stores the scanned medical records and imported raw data in a separate database for processing and later for archival. Deceased patient's records, which appear over 50 years after the death will stay in the Archival area without moving to the centralized medical database. These archival data will be contributing to research and development purposes.

13.1.6.Stage II

New card manufacturing and installation of card readers

In this stage the card manufacturing and the card reader installation are able to run in parallel with the stage I, as these are independent activities the initiation for producing new EHIC cards with chips and also the card reader production, distribution, and installation of card reader terminals in healthcare service areas for pilot run can be started.

Examples of two card reader models are shown in the Figures 21 and 22. The card reader in Figure 21 is suitable for ambulance service or paramedic team.

Figure 21: Miniature USB contact ID card reader
Source: Axagon.eu[57].

Figure 22:Universal desktop USB contact Smart / ID and SD / microSD / SIM card reader.
Source: Axagon.eu[58].

The card reader in Figure 22 is suitable for inhouse healthcare professionals.

13.1.7.Stage III

Application development

Application development can be started in parallel, but the testing and validation will be conducted, once the migration of certain percentage of data has been completed. These early migrated data can be used for testing purposes to review the business requirements and validate the systems' functional requirements.

13.2. Proposal for adding healthcare domain to electronic ID

With this proposal, the country's healthcare sector can make use of the existing infrastructure, with an assumption that this existing infrastructure for the public services can accommodate the healthcare domain with capability of handling expansion.

With this approach numerous of overheads and capital investment can be saved. As was stated, Stage II can be eliminated from the previous proposal. In addition to that there is no need to produce any more plastic EHIC cards and some additional card reader terminals are required to operate for some extended period.

13.2.1.Potentials

One of the potentials is that the success of this approach may lead to move the driving licenses to the electronic ID, which means that the driving license database and data property can also be transferred to the electronic identity. And one of the added values is the quick detection of health state of the driver in extreme scenarios, which can be used to save lives.

13.2.2.Risks or dependencies

Table 9: Comparison of risks or dependencies in proposals

Risks or dependencies	Proposal I	Proposal II
Project cost covered by Insurance companies	High	Low
Project Cost covered by Government	Low	High
Passing Law to classify medical records and its handling	High	High
Issuing eID for children	N/A	High
Recognition of eID as EHIC in member states	N/A	High
Impact of Cybercrime or hacking or ransomware attack	High	High

Note: Risk based on current political and economic awareness

As listed in the Table 9 the dependences for the cost bearing for the project by insurance companies are higher in the proposal one. As these expenses are impacting the economic profit of the insurance companies, there is high chance to get it rejected by some of the insurance companies.

The government needs to pass a Rule/Law to eliminate the EHIC cards and consider exceptions for children, as the adults are generally getting citizen IDs in the country. As in democracy not everyone appreciates everything, even technological potentials in healthcare, and people have a unique approach for everything; it would be hard to pass this kind of Law by the Parliament.

If there is an issue, which could potentially cause interruption on other services linked in the eID services. Since the healthcare services have direct impact on the lives and wellbeing of the population, assigning priority on the service availability is crucial.

Cybercrime or hacker attacks can create a nation-wide impact, rather than the individual attacks on healthcare centers. Continued education of users is essential to protect the data.

14. Summary of results

Every life matters on the planet, either humans or animals, as this topic is about the expert systems and their usage in healthcare. The history of almost all medicines and their research is originated from experimenting on animals, and after passing the high-risk of fatal stage, the phases of testing in human patients start. The advancement in information technologies enable new approaches in research and development of medicines and in treatment methods, as a result the sophisticated computer systems are able to simulate the traditional lengthy process in very short period of time. As an example, the world was able to witness the big leap through an unpleasant experience of pandemic, surprisingly a handful of pharmaceutical companies were able to produce vaccines in a short period of time. And as a matter of fact, these changes or advancements are far more from traditional way, which produces the consequence of acceptance variation in the society.

According to professor Pirk, who compared the present era and 1970-80s, the computer systems helped and contributed to the healthcare and had especially a big impact at IKEM for scientific research and developments. In order to progress further and utilize the progressive technological advancements to prevent epidemics or pandemics during the early stages, and as well as finding better cure for oncological based issues, the government needs to consider investing into healthcare sector.

With the vision of centralized medical records, the research communities and pharmaceutical companies in the country can utilize the properly handled (anonymized) data to create hypothesis and conduct deep analysis. The research findings or medical records can be shared or compared with other geographical areas to make combined effort.

At present the data is stored and distributed in different places in different forms. It would be better to come up with a plan to centralize the data and through that, individual administrative overhead and operation cost in each healthcare center can be reduced. And the importance of classifying medical records under the Law of government or Ministry of Healthcare is to be responsible for the medical data and the processing of the medical data of the population.

15. Conclusion and recommendations

This work concludes that medical science or healthcare is not isolated from other branches of studies like Managerial decision making or Statistical data modeling. Data collection and processing, generating hypothesis about a concrete thing, use of qualitative analysis to prove or discard the hypothesis, all of these activities are not certainly directly connected with patient care, but these are the paths to improve the healthcare services.

Everyone in healthcare plays equally important role for data primary collection, as the doctors or nurses or the medical devices operators are directly involved in the active participation with patients, these healthcare personals are a good source of data collection and to feed the data into the database.

As the healthcare system is one of the examples of man-made complex system, it is not very easy to understand it and make changes to its setup. With sufficient understanding and investments, a country's healthcare sector can be improved. The importance of centralized medical record database is vital for the progress of research and development.

It is vital to utilize the expert systems, automation, and robotics in healthcare for improvement. Since this work is not covering the technological competency area for migrating medical records, creation of datacenter infrastructure, application development, and the proposal of new legislation for querying and displaying the medical records. All these non-covered areas require a feasibility study to challenge or accept the proposals for implementation.

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Příloha č. 1

Oskenované zadání práce

UNIVERZITA HRADEC KRÁLOVÉ
Fakulta informatiky a managementu
Akademický rok: 2020/2021

Studijní program: Informační management
Forma studia: Kombinovaná
Specializace/kombinace: Informační management (im2-k)

Podklad pro zadání DIPLOMOVÉ práce studenta

Jméno a příjmení:	**Ratheesh Thaliyadath Bc.**
Osobní číslo:	**I2000802**
Adresa:	V Lázních 358, Jesenice, 25242 Jesenice u Prahy, Česká republika
Téma práce:	Pokročilé počítačové systémy pro podporu rozhodování ve zdravotnictví
Téma práce anglicky:	Advanced computer systems for decision support in healthcare
Vedoucí práce:	Ing. Karel Mls, Ph.D. Katedra informačních technologií

Zásady pro vypracování:

Cíl: Analýza metod počítačového zpracování kvalitativních dat ve zdravotnictví.
Osnova:
Metody získávání kvalitativních dat
Analýza a řízení dat
Využití dat při rozhodování
Návrh na využití systémů kvalitativních dat ve zdravotnictví

Seznam doporučené literatury:

KAPLAN, Bonnie; MAXWELL, Joseph A. Qualitative research methods for evaluating computer information systems. In: *Evaluating the organizational impact of healthcare information systems*. Springer, New York, NY, 2005. p. 30-55.
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Podpis studenta: Datum:

Podpis vedoucího práce: Datum: