Chapter 2

Electronic Health Records: A Survey

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2.1 Introduction

An Electronic Health Record (EHR) is a digital version of a patient's medical history. It is a longitudinal record of patient health information generated by one or several encounters in any healthcare providing setting. The term is often used interchangeably with EMR (Electronic Medical Record) and CPR (Computer-based Patient Record). It encompasses a full range of data relevant to a patient's care such as demographics, problems, medications, physician's observations, vital signs, medical history, immunizations, laboratory data, radiology reports, personal statistics, progress notes, and billing data. The EHR system automates the data management process of complex clinical environments and has the potential to streamline the clinician's workflow. It can generate a complete record of a patient's clinical encounter, and support other care-related activities such as evidence-based decision support, quality management, and outcomes reporting. An EHR system integrates data for different purposes. It enables the administrator to utilize the data for billing purposes, the physician to analyze patient diagnostics information and treatment effectiveness, the nurse to report adverse conditions, and the researcher to discover new knowledge.

EHR has several advantages over paper-based systems. Storage and retrieval of data is obviously more efficient using EHRs. It helps to improve quality and convenience of patient care, increase patient participation in the healthcare process, improve accuracy of diagnoses and health outcomes, and improve care coordination. It also reduces cost by eliminating the need for paper and other storage media. It provides the opportunity for research in different disciplines. In 2011, 54% of physicians had adopted an EHR system, and about three-quarters of adopters reported that using an EHR system resulted in enhanced patient care [1].

Usually, EHR is maintained within an institution, such as a hospital, clinic, or physician's office. An institution will contain the longitudinal records of a particular patient that have been collected at their end. The institution will not contain the records of all the care provided to the patient at other venues. Information regarding the general population may be kept in a nationwide or regional health information system. Depending on the goal, service, venue, and role of the user, EHR can have different data formats, presentations, and level of detail.

The remainder of this chapter is organized as follows. Section 2.2 discusses a brief history of EHR development and Section 2.3 provides the components of EHRs. Section 2.4 presents a comprehensive review of existing coding systems in EHR. The benefits of using EHRs are explained in more detail in Section 2.5, while the barriers for the widespread adoption of EHRs are discussed in Section 2.6. Section 2.7 briefly explains some of the challenges of using EHR data. The prominent phenotyping algorithms are described in Section 2.8 and our discussion is concluded in Section 2.9.

2.2 History of EHR

The first known medical record can be traced back to the fifth century B.C. when Hippocrates prescribed two goals for medical records [2]:

- A medical record should accurately reflect the course of disease.
- A medical record should indicate the probable cause of disease.

Although these two goals are still appropriate, EHR has a lot more to offer. Modern EHR can provide additional functionalities that could not be performed using paper-based systems.

Modern-day EHR first began to appear in the 1960s. Early EHRs were developed due to physicians' concerns about the increasing complexity and size of medical data. Data retrieval was much faster using digital format. In 1967, Latter Day Saints Hospitals in Utah started using Health Evaluation through Logical Programming (HELP) software. HELP is notable for its pioneering logical decision support features. In 1969, Harvard Medical School developed its own software Computer Stored Ambulatory Record (COASTER) and Duke University began to develop The Medical Record (TMR).

In 1970, Lockheed unveiled the Technicon Medical Information Management System/ Technicon Data System (TDS). It was implemented at El Camion Hospital in California. It came with a groundbreaking Computer Provided Order Entry (CPOE) system. In 1979, Judith Faulkner, a computer programmer established Human Services Computing Inc., which developed the Chronicles data repository. The company later became Epic Systems. It was initially based on a single longitudinal patient record and designed to handle enterprise-wide data from inpatient, ambulatory, and payer environments.

In 1985, The Department of Veterans Affairs launched the automated data processing system, Decentralized Hospital Computer Program (DHCP), which includes extensive clinical and administrative capabilities within its medical facilities. It received the Smithsonian Award for best use of Information Technology in Medicine in 1995. The current variant of DHCP is VistA (Veterans Health Information Systems and Technology Architecture). By providing care to over 8 million veterans operating in 163 hospitals, 800 clinics, and 135 nursing homes, VistA manages one of the largest medical system in the United States [4]. In 1983, Epic Systems launched a patient scheduling software program called Cadence. This application helped clients to improve resource utilization and manage patient access. In 1988, Science Application International Corporation (SAIC) secured a $1.02 billion dollar contract from the U.S. Government to develop a composite healthcare system. In 1992, Epic Systems introduced the first Windows-based EHR software named EpicCare. Allscripts released the first software with an electronic prescribing solution for physicians in 1998.

From 2000 and beyond, EHR software has been increasingly trying to incorporate other functionalities to become an interactive companion for physicians and professionals. In January 2004, President George W. Bush launched an initiative for the widespread adaptation of EHRs within the next 10 years. He said in his State of the Union Address, "By computerizing health records, we can avoid dangerous medical mistakes, reduce costs, and improve care" [5]. In January 2009, in a speech at George Mason University, President Barack Obama said "[EHRs] will cut waste, eliminate red tape, and reduce the need to repeat expensive medical tests. It just won't save billions of dollars and thousands of jobs – it will save lives by reducing the deadly but preventable medical errors that pervade our health care system" [6]. The data from a National Ambulatory Medical Care Survey (NAMCS) and Physicians Workflow mail survey shows that in the year 2011, 54% of the physicians had adopted an EHR system. About three-quarters of the adopters reported that their system meets the federal "meaningful use" criteria. Almost half (47%) of the physicians said they were somewhat satisfied, and 38% reported being very satisfied with their system. About three-quarters of the adopters reported that EHR has resulted in enhanced patient care. Nearly one-half of physicians without an EHR system at the time of the survey said they had plans for purchasing one within the next year [1].

2.3 Components of EHR

The main purpose of EHR is to support clinical care and billing. This also includes other functionalities, such as improving the quality and convenience of patient care, improving the accuracy of diagnoses and health outcomes, improving care coordination and patient participation, improving cost savings, and finally, improving the general health of the population. Most modern EHR systems are designed to integrate data from different components such as administrative, nursing, pharmacy, laboratory, radiology, and physician' entries, etc. Electronic records may be generated from any department. Hospitals and clinics may have a number of different ancillary system providers; in that case, these systems are not necessarily integrated to the main EHR system. It is possible that these systems are stand-alone, and different standards of vocabularies have been used. If appropriate interfaces are provided, data from these systems can be incorporated in a consolidated fashion; otherwise a clinician has to open and log into a series of applications to get the complete patient record. The number of components present may also vary depending on the service provided. Figure 2.1 shows different components of an EHR system.

2.3.1 Administrative System Components

Administrative data such as patient registration, admission, discharge, and transfer data are key components of the EHR. It also includes name, demographics, employer history, chief compliant, patient disposition, etc., along with the patient billing information. Social history data such as marital status, home environment, daily routine, dietary patterns, sleep patterns, exercise patterns, tobacco use, alcohol use, drug use and family history data such as personal health history, hereditary diseases, father, mother and sibling(s) health status, age, and cause of death can also be a part of it. Apart from the fields like "comments" or "description," these data generally contain <name-value> pairs. This information is used to identify and assess a patient, and for all other administrative purposes. During the registration process, a patient is generally assigned a unique identification key comprising of a numeric or alphanumeric sequence. This key helps to link all the components across different platforms. For example, lab test data can create an electronic record; and another record is created from radiology results. Both records will have the same identifier key to represent a single patient. Records of a previous encounter are also pulled up using this key. It is often referred to as the medical record number or master patient index (MPI). Administrative data allows the aggregation of a person's health information for clinical analysis and research.

2.3.2 Laboratory System Components & Vital Signs

Generally, laboratory systems are stand-alone systems that are interfaced to the central EHR system. It is a structured data that can be expressed using standard terminology and stored in the form of a name-value pair. Lab data plays an extremely important part in the clinical care process, providing professionals the information needed for prevention, diagnosis, treatment, and health management. About 60% to 70% of medical decisions are based on laboratory test results [7]. Electronic lab data has several benefits including improved presentation and reduction of error due to manual data entry. A physician can easily compare the results from previous tests. If the options are provided, he can also analyze automatically whether data results fall within normal range or not.

The most common coding system used to represent the laboratory test data is Logical Observation Identifiers Names and Codes (LOINC). Many hospitals use their local dictionaries as well to encode variables. A 2009–2010 Vanderbilt University Medical Center data standardization study found that for simple concepts such as "weight" and "height," there were more than five internal representations. In different places there are different field names for the same feature and the values

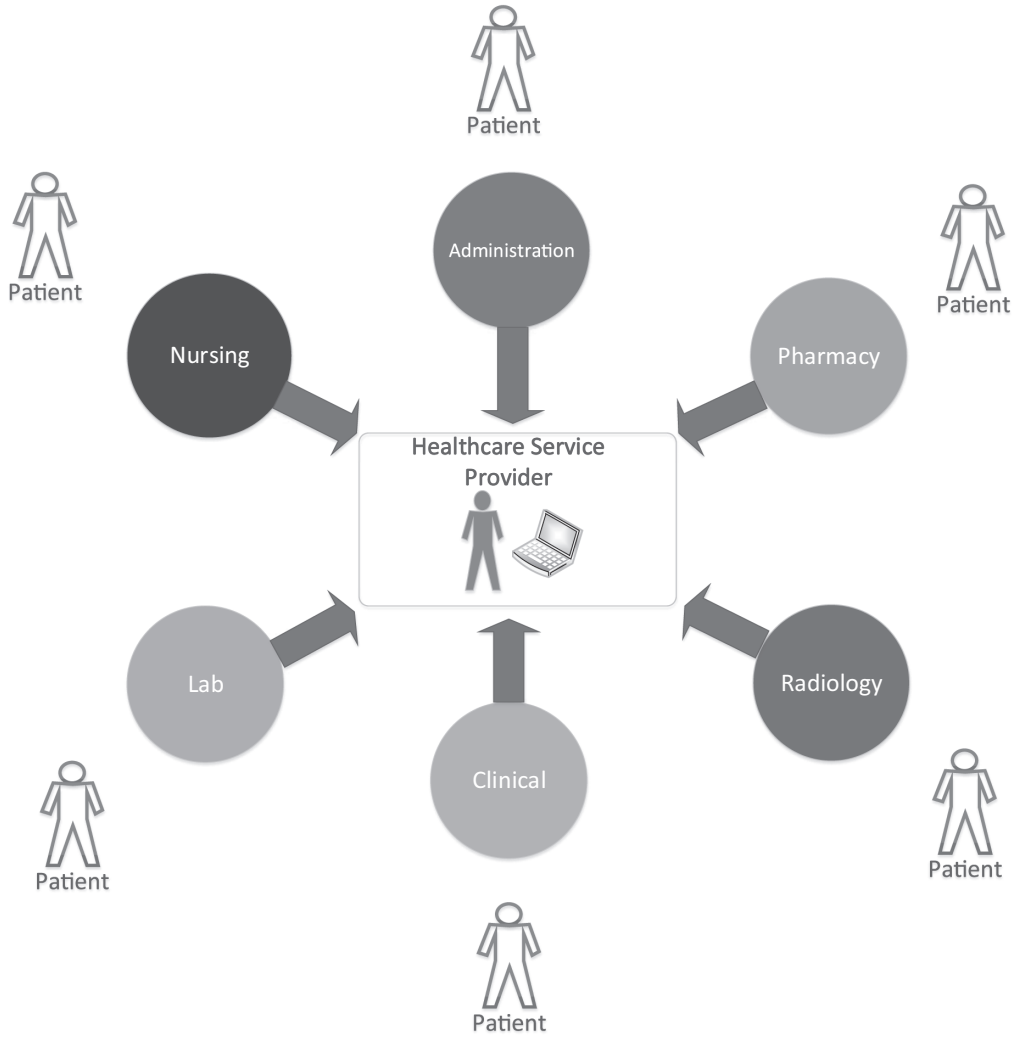

FIGURE 2.1: Various components of EHR.

are stored with different units (e.g., kilograms, grams, and pounds for weight; centimeters, meters, inches, and feet for height).

Vital signs are the indicators of a patient's general physical condition. It includes pulse, respiratory rate, blood pressure, body temperature, body mass index (BMI), etc. A typical EHR system must provide the option to accommodate these kinds of variables.

2.3.3 Radiology System Components

In hospital radiology departments, radiology information systems (RIS) are used for managing medical imagery and associated data. RIS is the core database to store, manipulate, and distribute patient radiological data. It uses Current Procedural Terminology (CPT) or International Classification of Diseases (ICD) coding systems to identify procedures and resources. Generally, an RIS consists of patient tracking, scheduling, result reporting, and image tracking capabilities. RIS is usually used along with a picture archiving communications system (PACS), which is a medical technology for

providing economical storage and convenient access to the digital images. An RIS can generate an entire patient's imagery history and statistical reports for patients or procedures. Although many hospitals are using RIS, it may or may not be integrated with the central EHR system.

2.3.4 Pharmacy System Components

In hospitals and clinics, the pharmacy department's responsibility is to maintain the inventory, prescription management, billing, and dispensing medications. The pharmacy component in EHR will hold the complete medication history of a patient such as drug name, dosage, route, quantity, frequency, start and stop date, prescribed by, allergic reaction to medications, source of medication, etc. Pharmacists serve an important public health role by administering immunizations and must have the capabilities to document these services and share this information with other healthcare providers and public health organizations. They assure safe and effective medication and supporting patient-centered care. Pharmacies are highly automated in large hospitals. Again, it may be independent of central EHRs. The Food and Drug Administration (FDA) requires all the drugs to be registered and reported using a National Drug Code (NDC). Coding systems used are NDC, SNOMED, and RxNorm.

2.3.5 Computerized Physician Order Entry (CPOE)

Computerized Physician Order Entry (CPOE) is a very important part of EHRs. It is a system that allows a medical practitioner to enter medical orders and instructions for the treatment of a patient. For example, a doctor can electronically order services to laboratory, pharmacy, and radiology services through CPOE. Then it gets propagated over a network to the person responsible for carrying out these orders. As a digital system, CPOE has the potential to reduce medication-related errors. It is possible to add intelligent rules for checking allergies, contradictions, and other alerts. The primary advantages of CPOE are the following: overcomes the issue of illegibility, fewer errors associated with ordering drugs with similar names, more easily integrated with decision support systems, easily linked to drug-drug interaction warning, more likely to identify the prescribing physician, able to link the adverse drug event (ADE) reporting systems, able to avoid medication errors like trailing zeros, create data that is available for analysis, point out treatment and drug of choice, reduce under- and overprescribing, and finally, the prescriptions can reach the pharmacy quicker. While ordering, a professional can view the medical history, current status report from a different module, and evidence-based clinical guidelines. Thus, CPOE can help in patient-centered clinical decision support.

If used properly, CPOE decreases delay in order completion, reduces errors related to handwriting or transcriptions, allows order entry at point-of-care or off-site, provides error checking for duplicate or incorrect doses or tests, and simplifies inventory and positing of charges. Studies have shown that CPOE can contribute to shortened length of stay and reduction of cost [8]. There are some risks involved in adopting CPOE as well. It may slow down interpersonal communication in an emergency situation. If each group of professionals (e.g., physicians and nurses) works alone in their workstations, it may create ambiguity about the instructions. These factors led an increase in mortality rate by 2.8%–6.5% in the Children's Hospital of Pittsburgh's Pediatric ICU when a CPOE system was introduced [8]. Frequent alerts and warnings may also interrupt workflow. The adaptation rate of CPOE is slow. It may be partly due to physicians' doubt about the value of CPOE and clinical decision support.

2.3.6 Clinical Documentation

A clinical document contains the information related to the care and services provided to the patient. It increases the value of EHR by allowing electronic capture of clinical reports, patient assessments, and progress reports. A clinical document may include [9]

- Physician, nurse, and other clinician notes
- Relevant dates and times associated with the document
- The performers of the care described
- Flow sheets (vital signs, input and output, and problems lists)
- Perioperative notes
- Discharge summaries
- Transcription document management
- Medical records abstracts
- Advance directives or living wills
- Durable powers or attorney for healthcare decisions
- Consents (procedural)
- Medical record/chart tracking
- Release of information (including authorizations)
- Staff credentialing/staff qualification and appointments documentations
- Chart deficiency tracking
- Utilization management
- The intended recipient of the information and the time the document was written
- The sources of information contained within the document

Clinical documents are important because documentation is critical for patient care, serves as a legal document, quality reviews, and validates the patient care provided. Well-documented medical records reduce the re-work of claims processing, compliance with CMS (Centers for Medicare and Medicaid Services), Tricare and other payer's regulations and guidelines, and finally impacts coding, billing, and reimbursement. A clinical document is intended for better communication with the providers. It helps physicians to demonstrate accountability and may ensure quality care provided to the patient. A clinical document needs to be patient centered, accurate, complete, concise, and timely to serve these purposes.

The clinical document architecture (CDA) [10] is an XML-based electronic standard developed by the Health Level 7 International (HL7) to define the structure. It can be both read by human eyes and processed by automatic software.

2.4 Coding Systems

Standards play an important role in enhancing the interoperability of health information systems and the purposeful use of EHR systems. Collecting and storing information following standard coding systems provide better and accurate analysis of the data, seamless exchange of information, improved workflow, and reduced ambiguity. A complete healthcare system is complex and requires various EHR products. Different vendors have implemented standards in their own way. This practice has resulted in a significant variation in the coding practices and implemented methods for which systems cannot interoperate. To create an interoperable EHR, standardization is critical in the following four major areas:

- Applications interaction with the users
- System communication with each other
- Information processing and management
- Consumer device integration with other systems and application

Interoperability between the different EHR systems is a crucial requirement in the "meaningful use of certified EHR technology" to receive incentives. That is why conforming to a standard coding system is very important. In a practical EHR, we need standards for

- Clinical vocabularies
- Healthcare message exchanges
- EHR ontologies

There are three organizations mainly responsible for developing the related standards: Health Level Seven (HL7), Comité Europeen de Normalisation-Technical Committee (CEN-TC), and the American Society of Testing and Materials (ASTM). HL7 develops healthcare-related standards that are widely used in North America. CEN-TC is a prominent standard developing organization working in 19 member states in Europe. Both HL7 and CEN-TC collaborate with ASTM. Along with the standards developed by these organizations, EHR systems must comply with the Health Insurance Portability and Accountability (HIPAA) Act [11] to conserve the security and privacy of patient information.

2.4.1 International Classification of Diseases (ICD)

ICD stands for International Classification of Diseases, which is the United Nations-sponsored World Health Organization's (WHO) official coding standard for diseases, diagnoses, health management, and clinical purposes [12]. It first appeared as the International List of Causes of Death in 1893, adopted by the International Statistical Institute. Since then it has been revised according to advancements in medical science and healthcare. Since the creation of WHO in 1948, WHO has maintained ICD. WHO published ICD-6 in 1949, and it was the first coding system in which morbidity was incorporated [13]. It also included mental disorders for the first time. The U.S. Public Health Services issued International Classification of Diseases, Adapted for Indexing of Hospitals Records and Operation Classification (ICDA) in 1959. It was revised regularly and used to classify diseases and mortality until WHO published the ninth revision of ICD.

The 1967 WHO Nomenclature Regulations specified that the member nations should use the most recent ICD version for mortality and morbidity statistics. Along with the storage and retrieval

of epidemiological and clinical information, it allows for the compilation of morbidity statistics for more than 100 WHO member nations. About 70% of the world's health expenditure in reimbursement and resource allocation is also done using ICD codes [14]. It is used to classify diseases and related problems, and provides a system of codes for a wide variety of diseases, signs, symptoms, abnormal findings, complaints, social circumstances, and external causes of injury or disease. It is the global foundation for providing common language in disease and health-related information and statistics exchange. ICD is comprehensive and organizes information into standard groups that allows for the following [15]:

- Easy storage, retrieval, and analysis of health information for evidence-based decision-making.
- Sharing and comparing health information between hospitals, regions, and countries.
- Data comparison in the same location across different time periods.

2.4.1.1 ICD-9

ICD ninth revision is the most popular coding system published by WHO in 1978. It was designed to promote comparability of classification, collection, processing, and presentation of mortality statistics. Its clinical modification, ICD-9-CM, was published by the U.S. Public Health Services in the following year to meet the statistical needs. The modified version had expanded the number of diagnostic codes and developed a procedure coding system. It has more than 13,000 codes and uses more digits representing the codes compared to ICD-9. It is the system that is used to encode all the diagnoses for healthcare services in the United States. It is maintained by the National Center for Health Statistics (NCHS) and the Center for Medicare and Medicaid Services (CMS). Both the departments are part of the federal department of Health and Human Services. The ICD-9-CM code set is organized in three volumes and consists of tabular lists and alphabetical indices.

- Volume 1: Disease and Injuries Tabular List
- Volume 2: Disease and Injuries Alphabetical Index
- Volume 3: Procedures Tabular List and Alphabetic Index

ICD-9-CM is updated every year to keep up-to-date with medical trends and diseases. NCHS has the responsibility to update Volumes 1 and 2, and CMS maintains Volume 3. Concerned parties from both the public and private sectors can propose changes to it. The major updates take effect on October 1 every year and minor updates occur on April 1. It is a statistical tool that converts the diagnoses and procedures into number codes. Its primary applications are

- Reporting and research
- Monitoring the quality of patient care
- Communication and transactions
- Reimbursement
- Administrative uses

2.4.1.2 ICD-10

The tenth version was endorsed by WHO in 1990 during the 43rd World Health Assembly. The first full version of ICD-10 was released in 1994. The first step of implementing ICD-10 was taken by NCHS awarding a contract to the Center for Health Policy Studies (CHPS) to evaluate ICD-10 for morbidity purposes within the United States. A prototype of clinically modified ICD-10 was developed after a thorough evaluation of ICD-10 by a technical advisory panel. After strong recommendations, NCHS proceeded with implementing a revised version of ICD-10-CM. During 1995–1996, further work on the enhancement of ICD-10-CM was done incorporating experiences from ICD-9-CM and through collaborating with many speciality groups like American Association of Dermatology, American Academy of Neurology, American Association of Oral and Maxillofacial Surgeons, American Academy of Orthopedic Surgeons, American Academy of Pediatrics, American College of Obstetricians and Gynecologists, American Urology Institution, and National Association of Children hospitals and other related institutions. In 1999, ICD-10 was implemented in the United States for mortality reporting. Death statistics and data regarding leading causes of death for the years 1999 and 2000 were published using ICD-10 [16]. In October 2002, ICD-10 was published in 42 languages. In June/July 2003, the American Health Information Management Association (AHIMA) and American Hospital Association (AHA) jointly conducted a pilot study to test ICD-10-CM. In their study, they have compared ICD-9-CM and ICD-10-CM and the initial results indicated ICD-10-CM is an improvement over ICD-9-CM; and ICD-10-CM is more applicable in non-hospital environments compared to ICD-9-CM. Canada, Australia, Germany, and others countries have their own revision of ICD-10 by adding country specific codes. The revisions are ICD-10-CA, ICD-10-AM, ICD-10-GM, and so on. The standard for procedure codes ICD-10-PCS was also developed during the same time frame to replace the Volume 3 of ICD-9-CM. The first revision of it was released in 1998.

ICD-9-CM is around thirty years old. Many of its categories are full, and there have been changes in technology. Some of them are also not descriptive enough. A newer coding system is needed, which would enhance reimbursement, better facilitate evaluation of medical processes and outcomes, and be flexible enough to incorporate emerging diagnoses and procedures. For example, in a scenario where a patient had a fractured left wrist and, after a month a fractured right wrist, ICD-9-CM cannot identify left versus right; additional information is required. However, ICD-10-CM can report distinguishing left from right. It can also characterize initial and subsequent encounters. Further, it can describe routine healing, delayed healing, nonunion, or malunion.

The major differences between ICD-10 and ICD-9-CM are [17]

- ICD-10 has 21 categories of diseases; while ICD-9-CM has only 19 categories.
- ICD-10 codes are alphanumeric; while ICD-9-CM codes are only numeric.
- ICD-9-CM diagnoses codes are 3–5 digits in length, while ICD-10-CM codes are 3–7 characters in length.
- Total diagnoses codes in ICD-9-CM is over 14,000; while ICD-10-CM has 68,000.
- ICD-10-PCS procedure codes are 7 characters in length; while ICD-9-CM procedure codes are 3–4 numbers in length.
- ICD-10-PCS total number of codes is approximately 87,000. The number of procedure codes in ICD-9-CM is approximately 4,400.

The Center for Medicare and Medicaid Services (CMS) guidelines mandated a conversion from ICD-9-CM to ICD-10-CM by October 1, 2014 in the United States. Adopting a new coding system will have the following benefits:

- Improve patient care. The increased detail in the coding system will improve the measurement of quality, safety, and efficacy of care, which will ultimately lead to improved patient care.
- Determine the severity of illness and prove medical necessity. ICD-10 codes are more granular and provide option to input the level of sickness along with complexity of disease of a patient in a code-based system.
- Improve research. The better and more accurate organization of code will be able to more precisely classify diseases and injuries, and correlate them with the cause, treatment, and outcome. The collected data will be less ambiguous and such a better-defined structure of the information will make data analysis easier. Information processing will be easier with newer coding system and it will open new opportunities for developing an intelligent prediction system. It will also allow the United States. to conduct comparative research with other countries that are already using ICD-10.
- Lend insight to the setting of health policy. With improved data analytics made possible through ICD-10, policy makers will be able to make informed policy decisions.
- Facilitate improved public health reporting and tracking. The comprehensive coding structure will allow concerned agencies to track public health risks and trends in greater detail.
- Improve clinical, financial, and administrative performance and resource allocation. The quality of data can reveal essential insights. It will allow the administrators to track time and workforce spent for procedures. This will help administrators to allocate resources more efficiently and achieve positive financial and managerial outcomes.
- Increase the accuracy of payment and reduce the risk that claims will be rejected for incorrect coding. Reduced number of claim denials is expected due to higher specificity of ICD-10. It will also create a better electronic record of evidence to receive proper payment from government payers, insurers, hospitals, health systems, and others.
- Make room for new procedures and techniques. The adaptation ability of ICD-9-CM is limited, where all the codes are already utilized and has no more room for new codes. The expanded coding of ICD-10 will be able to accommodate new procedures.
- It will have other facilities like reduced hassle of audits, help preventing and detecting healthcare fraud and abuse.

2.4.1.3 ICD-11

The World Health Organization is currently working on the eleventh revision of ICD. The final publication of ICD-11 is expected by 2017 [18]. The beta draft [19] was made public online for initial comments and feedback in May 2012. This development of ICD-11 revisions is taking place in a web-based platform called iCAT, where all the concerned parties collaborate. For interested groups or people, there are options to give structured input and field testing of revised editions. It will be available in multiple languages and free to download for personal use. In ICD-11, disease entries will have definitions and descriptions of the entry and category in human readable forms. The current version ICD-10 has only the title headings. There are 2,400 codes in ICD-11 that are different in the ICD-10 code set, where 1,100 codes are related to external causes and injury [20].

Although the beta version does not support any social network platforms, the support of websites such as Wikipedia, Facebook, Social Reader, LinkedIn, etc. is in the plan. The structure of definitions and other contents related to diseases and procedures will be defined more accurately. It will be more compatible with EHRs and other technologies.

2.4.2 Current Procedural Terminology (CPT)

Current Procedural Terminology (CPT) is a set of medical codes developed, maintained, and copyrighted by the American Medical Association (AMA). CPT codes are a list of descriptive terms, guidelines, and identifying codes of medical, surgical, and diagnostic services designed to provide uniform communication language among physicians, coders, patients, accreditation organizations, and payers for administrative, financial, and analytic purposes.

It was first created by the AMA in 1966. The first edition contained mainly surgical codes. A significant development took place for the second edition, which was published in 1970. The second edition contained 5 digits instead of 4 digits, and it included lab procedures. In 1983, the Health Claim Financial Administration (HCFA), which is now known as the Center for Medicine and Medicaid Services (CMS), merged its own Common Procedure Coding System (HCPCS) with CPT and mandated CPT would be used for all Medicare billing. Every year the new version is released in October. The Healthcare Common Procedures Coding System (HCPCS, often pronounced as "hick picks") is another set of codes developed by AMA based on CPT. Although the CPT coding system is similar to ICD-9 and ICD-10, it describes the treatment and diagnostic services provided while ICD codes describe the condition or the disease being treated. CPT is used only in inpatient settings.

2.4.3 Systematized Nomenclature of Medicine Clinical Terms (SNOMED-CT)

Systematized Nomenclature of Medicine Clinical Terms (SNOMED-CT) is a comprehensive, computer-processible, multilingual clinical and healthcare terminology, originally created by the College of American Pathologists (CAP). SNOMED was started as Systematic Nomenclature of Pathology (SNOP) in 1965 [21]. It was enhanced further and SNOMED was created in 1974. It had two major revisions in 1979 and 1993. In 1999, SNOMED-CT was created by the merger of SNOMED Reference Terminology (SNOMED-RT) developed by the CAP and Clinical Terms Version 3 (CTV3) developed by the National Health Services of the United Kingdom. This merged version was first released in 2002. SNOMED-RT had a vast coverage of medical specialities with over 12,000 concepts. It was designed for the retrieval and aggregation of healthcare information produced by multiple organizations or professionals. The strong suit of CTV3 was its coverage of terminologies for general practice. With more than 200,000 concepts, it was used to store primary care encounter information and patient-based records [22]. Currently SNOMED has more than 311,000 concepts with logic-based definitions organized into a hierarchy. In July 2003, the National Library of Medicine (NLM) on behalf of the U.S. Department of Health and Human Services signed a contract with CAP to make SNOMED-CT available for users. Since April 2007, it has been owned, maintained, and distributed by a newly formed Denmark-based nonprofit organization named International Health Terminology Standards Development Organization (IHTSDO) [9]. CAP collaborates with IHTSDO and continues to provide support for SNOMED-CT operations. More than 50 countries use SNOMED-CT.

SNOMED-CT is a valuable part of EHR. Its main purpose is to encode medical and healthcare-related concepts and support recording of data. It provides a consistent way to store, index, retrieve, and aggregate clinical data across different sites. It also helps to organize data in a more meaningful way and reduce the variability of the data collection and management process. Its extensive coverage includes clinical findings, symptoms, diagnoses, procedures, body structures, organisms and other etiologies, substances, pharmaceuticals, devices, and specimens [23].

SNOMED-CT has a logical and semantic relationship between concepts. It has a multiaxial hierarchy, which allows different level of details of information. Its extensible design permits the integration of national, local, and vendor specific requirements. It primarily consists of four components.

- Concept Codes: numerical codes to identify terms

- Descriptions: textual descriptions of the concept codes
- Relationships: represents relationships between the concept codes
- Reference Sets: used for grouping concept codes or descriptions. Supports cross mapping to other classification standards.

SNOMED-CT can be mapped to other well-known terminologies like ICD-9-CM, ICD-10, and LOINC. Renowned standards like ANSI, DICOM, HL7, and ISO are supported by it. In a joint project with WHO, it is providing insights for the upcoming ICD-11.

SNOMED-CT has some fundamental differences from ICD. It is mainly a terminology system while ICD is a classification system. SNOMED-CT is designed to encode and represent data for clinical purposes [24]. Information coded with ICD is used for statistical analysis, epidemiology, reimbursement, and resource allocation. SNOMED-CT facilitates the information input into the EHR and provides standardization for primary data purposes while ICD codes enable retrieval for secondary data purposes.

2.4.4 Logical Observation Identifiers Names and Codes (LOINC)

Logical Observation Identifiers Names and Codes (LOINC) is a universal code system for identifying laboratory observations and clinical test results. In response to the demand for electronic clinical data, it was created in 1994 by Regenstrief Institute Inc., an Indianapolis-based nonprofit research organization affiliated with Indiana University. It was originally called Laboratory Observations, Identifiers, Names, and Codes and the development was sponsored by NLM and other government and private agencies. Original sources of information include the following [25]:

- Silver book for International Union of Pure and Applied Chemistry
- International Federation of Clinical Chemistry
- Textbooks of Pathology
- EuCliD (European Clinical Database)
- Expertise and work of the LOINC members

LOINC coding system helps to improve the communication of information. In January 2009, Regenstrief Institute released a Windows operating system-based mapping software called Regenstrief LOINC Mapping Assistant (RELMA) where codes can be searched and local codes can be mapped to a LOINC database. The current version of LOINC is LOINC 2.46 released in December 2013. With more than 600 new users per month, it has 27,000 users from 158 different countries. LOINC vocabulary continues to grow till today.

Each LOINC record represents a single test result. A record consists of six fields [26].

- Component: what is measured and evaluated (e.g., glucose, hemoglobin)
- Kind of property: characteristics of the component that is measured (e.g., mass, length, concentration, volume, time stamp, etc.)
- Time: observation period of the measurement
- System: the specimen or the substance, in context of which the measurement was done (e.g., blood, urine)
- Scale: the measurement scale (e.g., quantitative, nominal, ordinal, or narrative)

- Method (optional): the procedure performed for measurement

Certain parameters and descriptors related to the test are explicitly excluded in LOINC from observation name. They are made as fields of test/observation report message [25]. These fields are

- The instrument used for testing
- Fine details of the sample or the site of collection
- The priority of the test
- Who verified the result
- Size of the sample
- Place of testing

LONIC's overall organization is divided into four categories: laboratory, clinical, attachments, and surveys. The laboratory component is further divided into subcategories such as chemistry, hematology, serology, microbiology (includes parasitology and virology), and toxicology. The clinical attributes are vital signs, hemodynamics, intake/output, EKG, obstetric ultrasound, cardiac echo, urologic imaging, gastroendoscopic procedures, pulmonary ventilator management, and other clinical observations [25]. It also contains information about nursing diagnoses and nursing interventions.

2.4.5 RxNorm

RxNorm is a drug vocabulary maintained and distributed by the National Library of Medicine [27]. It assigns standard names to the clinical drugs and drug delivery devices available in the United States. It is used as a basis for the capture and presentation of drug-related information in EHRs. In 2001, NLM started to develop RxNorm for modeling clinical drugs in the Unified Medical Language System (UMLS) in consultation with the HL7 vocabulary technical committee and the Veterans Administration [28]. It was developed to standardize the medication terminology that would reduce the missed synonymy in clinical drugs [29]. Additional goals were to facilitate electronic capture of related data, improve interoperability by supporting information exchange across platforms and systems, develop clinical decision support, and provide opportunity for research.

RxNorm follows a standard for naming drugs. The normalized name of a drug include the following components [28]:

- IN: Ingredient of the drug.
- DF: Dose form of the drug.
- SCDC: Semantic clinical drug component. It represents the ingredients and strength.
- SCDF: Semantic clinical drug form. It represents the ingredient and dose form.
- SCD: Semantic clinical drug. It represents the ingredient, strength, and dose form.
- BN: Brand name. This is the formal name for a group of drugs containing a specific active ingredient.
- SDBC: Semantic branded drug component. It represents the branded ingredient and strength.
- SBDF: Semantic branded drug form. It represents the branded ingredient and dose form.
- SDB: Semantic branded drug. It represents the branded ingredient, strength, and dose form.

RxNorm organizes drugs by concept. A concept is a set of names with similar meaning at a specific level of abstraction. It can distinguish similar drugs from different providers using concepts. The concepts and relationships between each other form a semantic network.

2.4.6 International Classification of Functioning, Disability, and Health (ICF)

The International Classification of Functioning, Disability, and Health, commonly known as ICF, is a classification of health-related components of function and disability. ICF concentrates on the functionality and body structure of people with a given health condition or disability rather than diagnosis or diseases. It does not account for the cause of disability. It is a unified and standard framework first developed by the World Health Organization (WHO) in 1980 [30]; initially it was known as International Classification of Impairments, Disabilities, and Handicaps (ICIDH). After years of coordinated revision, in May 2001, the 191 member states of WHO agreed to adopt ICF as the standard coding method of functioning and disability. In June 2008, the American Physical Therapy Association (APTA) joined WHO for endorsing ICF. ICF is the only method of its kind. It has been developed and tested for applicability in more than 40 countries.

Body functions and disability can be viewed as interactions between health condition and personal and environmental factors. ICF has mainly two parts: Functioning and disability, and Contextual factors. It can be categorized into further subparts. The components of ICF are listed below [31]:

- Functioning and disability
  - Body functions
    - Mental functions
    - Sensory functions and pain
    - Voice and speech functions
    - Functions of the cardiovascular, hematological, immunological, and respiratory systems
    - Genitourinary and reproductive functions
    - Neuromusculoskeletal and movement-related functions
    - Functions of the skin and related structures
  - Body structures
    - Structure of the nervous system
    - The eye, ear, and related structures
    - Structures involved in voice and speech
    - Structures related to cardiovascular, immunological, and respiratory systems
    - Structures related to digestive, metabolic, and endocrine systems
    - Structures related to genitourinary and reproductive systems
    - Structures related to movement
    - Skin and related structures
  - Activities and participation
    - Learning and applying knowledge
    - General tasks and demands
    - Communication
    - Self-care
    - Domestic life

    - Interpersonal interactions and relationships
    - Major life areas
    - Community, social, and civic life

- Contextual factors
  - Environmental factors
    - Products of technology
    - Natural environment and human-made changes to the environment
    - Support and relationships
    - Attitudes
    - Service, systems, and policies
  - Personal factors
    - Gender
    - Age
    - Coping styles
    - Social background
    - Education
    - Profession
    - Past and current experience
    - Overall behavior pattern
    - Character and other factors

ICF complements WHO's classification of disease scheme, ICD-10. ICD contains diagnosis and health condition-related information, but not functional status. Together they constitute the WHO Family of International Classifications (WHO-FIC) shown in Figure 2.2.

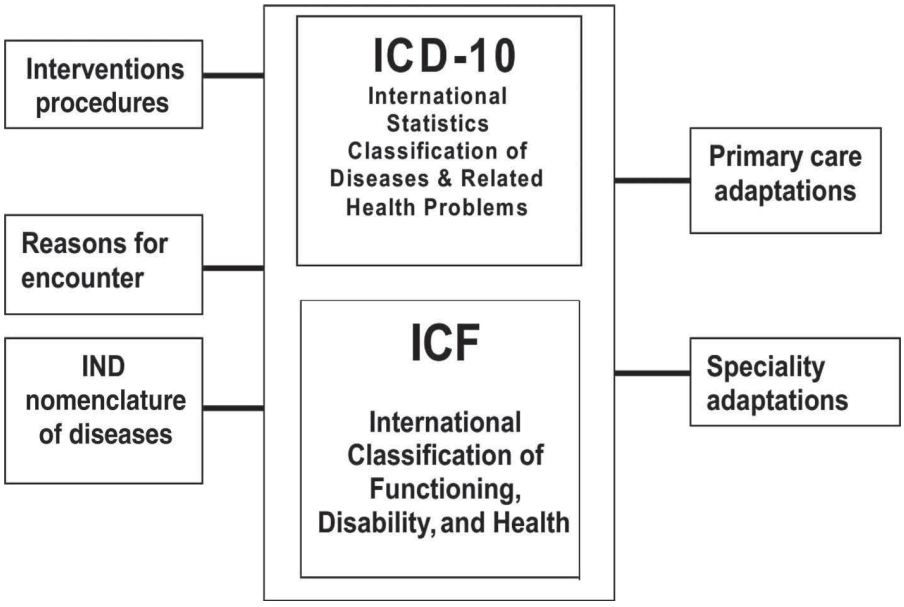

FIGURE 2.2: WHO Family of International Classifications taken from [32].

Diagnosis is used to define cause and prognosis of diseases, but by itself it does not predict service needs, length of hospitalization, or level of care of functional outcomes. Nor can it accurately provide support for disability. ICF allows incorporating all aspects of a person's life. The current ICF creates a more understandable and comprehensive profile of health forming of a person instead of focusing on a health condition [33]. It is used as a clinical, statistical, research, social policy, and educational tool. A common misconception about ICF is that it deals with only the disabled people. However, ICF has some limitations regarding the ability to classify the functional characteristics of developing children [34].

2.4.7 Diagnosis-Related Groups (DRG)

Diagnosis-Related Groups (DRG) are a patient classification scheme that group related patients and relate these groups with the costs incurred by the hospital. DRGs divide diagnosis and illness into 467 categories identified in ICD-9-CM [35]. The 467th group is "ungroupable." The classification is based on a patient's principal diagnosis, ICD diagnoses, gender, age, sex, treatment procedure, discharge status, and the presence of complications or comorbidities. The goals of developing DRGs were to reduce healthcare cost, and improve quality of care and efficiency of the hospitals. DRGs are by far the most important cost control and quality improvement tool developed [36].

It was first created at Yale University with the support from the Health Care Financing Administration, now known as the Center for Medicine and Medicaid Service (CMS). In 1980, it was first implemented in a small number of hospitals in New Jersey [37]. It is used to define the reimbursement amount of hospitals from Medicare. Medicare pays hospitals per patient and efficient hospitals receive better incentives. DRGs help to decide the efficiency of the hospital.

2.4.8 Unified Medical Language System (UMLS)

The Unified Medical Language System (UMLS) is a collection of comprehensive biomedical concepts and ontologies. It was developed by the U.S. National Library of Medicine (NLM) in 1986. It provides the development of computer-based systems that can behave as through they understand the biomedical and health concepts [38]. It is intended to be mainly used by medical informatics professionals. NLM maintains and distributes UMLS knowledge sources (database) and related software tools for developers to build enhanced electronic information system that can create process, retrieve, integrate, and/or aggregate health and biomedical-related information. The knowledge sources of UMLS are as follows [39]:

- Metathesaurus
  - Source Vocabularies
  - Concepts
- Relationships, Attributes
  - Semantic Network
  - Semantic Types (categories)
  - Semantic Relationships
- Lexical Resources
  - SPECIALIST Lexicon
  - Lexical Tools

Metathesaurus is a very large, multipurpose, and multilingual vocabulary database. It contains health and biomedical-related concepts of their various names and the relationships among them. It has 126 vocabularies in 17 languages [27]. It clusters similar terms into a concept. The semantic network provides consistent categorization of concepts defined in Metathesaurus. The network contains information regarding basic semantic types/categories that may be assigned to concepts and relationships between semantic types. In the semantic network, the semantic types are nodes and the relationships are links between them. In the current version of semantic network, there are 135 semantic types and 54 relationships [38]. The SPECIALIST Lexicon provides the lexical information needed for the SPECIALIST natural language processing tool.

2.4.9 Digital Imaging and Communications in Medicine (DICOM)

The Digital Imaging and Communications in Medicine (DICOM) is a medical imaging standard. It determines the data exchange protocol, digital image format, and file structure for biomedical images and related information [40]. DICOM was developed by the American College of Radiology (ACR) and National Electric Manufacturers Association (NEMA). The first version ACR/NEMA 300 was released in 1985. DICOM is generally used in the following application areas [40]

- Network image management
- Network image interpretation management
- Network print management
- Imaging procedure management
- Offline storage media management

DICOM allows the integration of scanners, servers, workstations, printers, and network hardware into a Picture Archiving and Communication Systems (PACS). It has been extensively used by the hospitals and other organizations. It provides a widely accepted foundation for medical imaging standards. It promotes interoperability between radiology systems.

2.5 Benefits of EHR

EHRs are transformational tools. The scope of paper-based systems is severely limited. We need EHRs to improve the quality of patient care and increase productivity and efficiency. In terms of the overall management and costs, EHRs are a better choice. They also help in complying with government regulations and other legal issues. The benefits of EHRs are described in this section.

2.5.1 Enhanced Revenue

An EHR system can capture the charges and bills for clinical services provided, laboratory tests, and medications more accurately. Utilization of electronic systems decrease billing errors [41]. They also provide a better documentation opportunity for these services that can be used to resolve financial disputes. Better management of information yield more accurate evaluation and increase reimbursements. According to experts, due to inaccurate coding systems, 3%–15% of a healthcare provider's total revenue is lost [42]. An EHR system can be programmed or configured to generate alerts for both patients and doctors when a healthcare service is due. This can aid better management of collecting revenue. It can be used to garner more revenues by incorporating services like

telemedicine, e-visits, virtual office visits, etc. *It is true that all kinds of services are not possible over the Internet or telephone network, but not all diseases will require extensive diagnosis and laboratory testing*. Diseases commonly treated through telemedicine include acne, allergies, cold and flu, constipation, diabetes, fever, gout, headache, joint aches and pains, nausea and vomiting, pink eye, rashes, sinus infection, sore throat, sunburn and urinary tract infections, anxiety and depression, etc.

2.5.2 Averted Costs

After adopting electronic systems, some costs associated with the previous way of operating a business are eliminated. The Center for Information Technology leadership suggested that the use of EHRs will save a total of $44 billion each year [43]. Adopting EHR has the following averted costs [44].

- **Reduced paper and supply cost:** To maintain paper-based health records an organization will require a lot of paper, printing materials, and other supplies. Adopting EHR will reduce these costs. After adopting EHRs, one organization estimated a reduction of 90% of paper usage within a few months [45].
- **Improved utilization of tests:** In electronic systems, test results are better organized. A healthcare staff no longer needs to carry the reports from one place to another. Identifying redundancy or unnecessary tests is easier. This can reduce the loss of information and ensure improved utilization of tests. A study by Wang et al. [41] reports better utilization of radiology tests after adopting EHRs.
- **Reduced transcription costs:** An EHR can reduce transcription costs for manual administrative processes [46, 47]. It utilizes structured flow sheets, clinical templates, and point-of-care documentation. In a typical outpatient setting, physicians generate about 40 lines of transcription per encounter. For a group of three practicing physicians, treating 12,000 patients annually at the cost of $0.11 for each transcription line results in over $50,000 per year [46]. A study of fourteen solo or small-group primary care practices in twelve U.S. states reports the median transcription cost saving to be $10,800, where a minimum saving was $8,500 and a maximum was $12,000 for the year 2004–2005 [47]. Other related research work also describes saving $1,000–$3,000 per physician, per month [48].
- **Improved productivity:** EHR helps to improve workflows by utilizing resources more efficiently and reducing redundancies. As a result, the overall productivity of individuals increases.
- **Better availability of information and elimination of chart:** In EHR, all the charts are in digital format. It eliminates the need to pull, route, and re-file paper charts [46]. A significant amount of effort is spent on creating, filing, searching, and transporting paper charts [49]. A study estimated that the elimination of paper charts can save $5 per chart pull [41]. It is also comparatively easier to manage digital charts.
- **Improved clinician satisfaction:** Electronic technology can save time by reducing the paperwork burden, which can create additional time for patient encounters and delivery of care [3]. A study reports the use of EHR has reduced the physician's office visit time by 13% and a nurse's pre-exam interview time by 1 minute [50]. This can improve satisfaction for professionals, which can indirectly enhance revenue.

2.5.3 Additional Benefits

EHR offers many additional benefits that are discussed in more detail below.

- **Improved accuracy of diagnosis and care:** EHR provides comprehensive and accurate patient information to physicians that can help to quickly and systematically identify the correct problem to treat. EHRs do not just contain the patient information; they have the capability to perform computation and make suggestions. They can also present comparative results of the standard measurements. A U.S. national survey of doctors demonstrates the following [51]:
  - 94% of the providers report EHR makes records readily available at the point of care.
  - 88% report that EHR produces clinical benefits for their practice.
  - 75% report that EHR allowed them to deliver better patient care.

  The gathered information can guide a physician in the emergency department to take prudent and safer actions. Such services are unimaginable with paper-based systems. Diagnostic errors are difficult to detect and can be fatal to a patient. A new study suggests that EHR can help to identify potential diagnostic errors in primary care by using certain types of queries (triggers) [52].
- **Improved quality and convenience of care:** EHRs have the potential to improve the quality of care by embedding options such as Clinical Decision Support (CDS), clinical alerts, reminders, etc. Research suggests that EHRs are linked to better infection control [53], improved prescribing practices [12], and improved disease management [42] in hospitals. In such applications, convenience is also an important measure. EHRs greatly reduce the need for patients to fill out similar (or even sometimes the same) forms at each visit. Patients can have their e-prescriptions ready even before they leave the facility and can be electronically sent to a pharmacy. Physicians and staff can process claims insurance immediately. Following are the results of a study on the effects of e-prescribing reports [54].
  - 92% patients were happy with their doctor using e-prescribing.
  - 90% reported rarely or only occasionally having prescriptions not ready after going to the pharmacy.
  - 76% reported e-prescribing made obtaining medications easier.
  - 63% reported fewer medication errors.
- **Improved patient safety:** Just like improving the quality of care, clinical decision support systems (CDSS) and computerized physician order entry (CPOE) have the potential to improve patient safety. Medication errors are common medical mistakes and in the United States it is responsible for the death of a person every day on average as well as injuring more than a million annually [55]. Research shows that utilization of CPOE can reduce medication errors [56, 57]. Medication errors can occur at any stage of the medication administration process from a physician ordering the drug, followed by the dispensing of the drug by the pharmacist, and finally the actual administration of the drug by the nurse. CPOE is a technology that allows physicians to act on a computerized system that introduces structure and control. Along with patient information, EHR holds the medication records for a patient. Whenever a new medication is prescribed, it can check for potential conflicts and allergies related to the particular medication and alert the physician. The system also can provide the chemical entities present in the drug and cross-reference allergies, interactions, and other possible problems related to the specific drug. Introducing technologies such as Barcode Medication Administration can make the system even more accurate. The Institute of Medicine (IOM) recommends CPOE and CDS as main information technology mechanisms for increasing patient safety in the future [58].

- **Improved patient education and participation:** In an EHR system, certain features can provide simplified patient education [42]. EHRs can be used by the provider as a tool to illustrate procedures and explain a patient's conditions. It can increase a patient's participation by offering follow-up information, self-care instructions, reminders for other follow-up care, and links to necessary resources. Information technology affects every part of our life. In this digital era, patients may feel more comfortable with an electronic system.

- **Improved coordination of care:** EHRs are considered essential elements of care coordination. The National Quality Forum defines care coordination as the following [59]: "Care coordination is a function that helps ensure that the patient's needs and preferences for health services and information sharing across people, functions, and sites are met over time. Coordination maximizes the value of services delivered to patients by facilitating beneficial, efficient, safe and high-quality patient experiences and improved healthcare outcomes." For a patient with multiple morbidities, a physician is responsible for providing primary care services and coordinating the actions of multiple subspecialists [60]. According to a Gallup poll [61], it is a common scenario for older patients to have multiple doctors: no physician 3%, one physician 16%, two physicians 26%, three physicians 23%, four physicians 15%, five physicians 6%, and six or more physicians 11%. EHRs allow all clinicians to document services provided and access up-to-date information about their patient. It streamlines the transition process and knowledge sharing between different care settings. This facilitates an improved level of communication and coordination [62]. Research suggests that the clinicians having 6+ months use of EHRs reported better accessing and completeness of information than clinicians without EHRs. Clinicians having EHRs have also reported to be in agreement on treatment goals with other involved clinicians [63].

- **Improved legal and regulatory compliance:** As organizations develop their systems, it is important to understand and comply with many federal, state, accreditation, and other regulatory requirements. A health record is the most important legal and business record for a healthcare organization. The use of an EHR system will provide more security and confidentiality of a patient's information and thus, comply with regulations like HIPAA, Consumer Credit Act, etc. Moreover, the Center for Medicare and Medicaid Services (CMS) has financial incentive programs for hospitals regarding the meaningful use of health information technology. To receive the financial reimbursement, professionals have to meet a certain criteria and can get up to $44,000 through Medicare EHR Incentive Program and up to $63,750 through the Medicaid EHR Incentive Program [64]. Adaptation of certified EHR can help providers get reimbursed.

- **Improved ability to conduct research and surveillance:** In conjunction with the direct use of EHR in primary patient care, there is an increasing recognition that secondary use of EHR data can provide significant insights [65]. Using quantitative analysis of functional values, it has the potential to identify abnormalities and predict phenotypes. Pakhomov et al. demonstrated the use of text processing and NLP to identify heart failure patients [66]. EHR data can be used to predict survival time of patients [67]. Data from different EHRs can be integrated into a larger database and geo-location specific surveillance is also possible.

- **Improved aggregation of data and interoperability:** Standards play a crucial role in data aggregation and interoperability between different systems. EHRs maintain standard procedure and follow defined coding system while collecting data. This accommodates easier aggregation of data and greater interoperability, which offer the following benefits [68].

  - Manage increasingly complex clinical care
  - Connect multiple locations of care delivery

  - Support team-based care
  - Deliver evidence-based care
  - Reduce errors, duplications, and delay
  - Support ubiquitous care
  - Empower and involve citizens
  - Enable the move to the Personal Health Paradigm
  - Underpin population health and research
  - Protect patient privacy

  We need high-quality aggregated data from multiple sources in order to make evidence-based decisions. The level of achievable interoperability using EHRs is unthinkable from paper-based systems. The American Medical Association recognizes that enhanced interoperability of EHRs will further help to attain the nation's goal of a high-performing healthcare system.

- **Improved business relationships:** A healthcare provider organization equipped a with superior EHR system can be in a better bargaining position with insurers and payers compared with less equipped ones. The next generation of business professionals will expect and demand a state-of-the-art information healthcare technology system.

- **Improved reliability:** Data is more reliable in a digital format. Due to the reduction of storage costs, having multiple copies of data is possible.

2.6 Barriers to Adopting EHR

Despite of having great potential of EHRs in medical practice, the adoption rate is quite slow and faces a range of various obstacles. Many other developed countries are doing far better than the United States. Four nations (United Kingdom, the Netherlands, Australia, and New Zealand) have almost universal use (each $\sim$90%) of EHRs among the general practitioners. In contrast, the United States and Canada have only around 10–30% of the ambulatory care physicians using EHRs [69]. Health informatics has been a high priority in other developed nations, while until recently, the degree of involvement and investment by the U.S. government in EHRs has not been significant. Major barriers to adopting EHRs are discussed below.

- **Financial barriers:** Although there are studies that demonstrate financial savings after adopting EHRs, the reality is that the EHR systems are expensive. Several surveys report that the monetary aspect is one of the major barriers of adopting EHRs [70, 71, 72, 73, 74, 75, 76]. There are mainly two types of financial costs, start-up and ongoing. A 2005 study suggests that the average initial cost of setting up an EHR is $44,000 (ranging from a minimum of $14,000 to a maximum of $63,000) and ongoing costs average about $8,500 per provider per year [47]. Major start-up costs include purchasing hardware and software. In addition, a significant amount of money is also required for system administration, control, maintenance, and support. Long-term costs include monitoring, modifying, and upgrading the system as well as storage and maintenance of health records. Besides, after the substantial amount of investment, physicians are worried that it could take up to several years for the return on the investment.

An EHR is not the only electronic system that exists in any healthcare provider like practice management. There might be other old systems that also need integration into the new system. It is important that an EHR system is integrated into other systems, and this integration can sometimes be very expensive. Surveys show that due to the high financial investment required, EHR adaptation was far higher in large physician practices and hospitals [77].

- **Physician's resistance:** To adopt EHRs, physicians have to be shown that new technology can return financial profits, saves time, and is good for their patients' well-being. Although research-based evidence is available, it is difficult to provide concrete proof of those benefits. As given in a report by Kemper et al. [76], 58% of physicians are without any doubt that EHR can improve patient care or clinical outcomes. Finally, adopting EHRs in a medical practice will significantly change the work processes that physicians have developed for years.

  Besides, physicians and staffs might have insufficient technical knowledge to deal with EHRs, which leads them to think EHR systems are overly complex. Many physicians complain about poor follow-up services regarding technical issues and a general lack of training and support from EHR system vendors [72]. A study reports that two-thirds of physicians expressed inadequate technical support as a barrier to adopting EHRs [75]. Some physicians are also concerned about the limitation of EHR capabilities. Under certain circumstances or as time passes, the system may no longer be useful [71, 74]. Besides, all physicians do not perform the same operations. EHR systems have to be customizable to best serve each purpose. Surveys suggest that one of the reasons for not adopting EHRs is that the physicians cannot find a system that meets their special requirements [71, 72, 73, 75, 78, 76]. However, an increased effort and support from vendors may play a role in motivating physicians towards adopting EHRs.

- **Loss of productivity:** Adoption of an EHR system is a time-consuming process. It requires a notable amount of time to select, purchase, and implement the system into clinical practice. During this period physicians have to work at a reduced capacity. Also, a significant amount of time has to be spent on learning the system. The improvement will depend on the quality of training, aptitude, etc. The fluent workflow will be disrupted during the transition period, and there will be a temporary loss of productivity [79].

- **Usability issues:** EHR software needs to be user-friendly. The contents of the software must be well-organized so that a user can perform a necessary operation with a minimal number of mouse clicks or keyboard actions. The interface of software workflow has to be intuitive enough. In terms of usability, a comprehensive EHR system may be more complex than expected. It has to support all the functionalities in a provider's setting. There might be a number of modules and submodules, so the user might get lost and not find what he is looking for. This has the potential to hamper clinical productivity as well as to increase user fatigue, error rate, and user dissatisfaction. Usability and intuitiveness in the system do not necessarily correlate to the amount of money spent. The Healthcare Information and Management Systems Society (HIMSS) has an EHR usability task force. A 2009 survey by the task force reported 1,237 usability problems, and the severity of 80% of them was rated "High" or "Medium" [80]. Apart from the workflow usability issue, other related issues are configuration, integration, presentation, data integrity, and performance. The task force defined the following principles to follow for effective usability [81]: simplicity, naturalness, consistency, minimizing cognitive load, efficient interactions, forgiveness and feedback, effective use of language, effective information presentation, and preservation of context.

- **Lack of standards:** Lack of uniform and consistent standards hinders the EHR adoption. Standards play an integral role in enabling interoperability. CMS reimbursement for meaningful use requires EHR systems to demonstrate the ability to exchange information. Many

of the currently used systems have utility only for certain specific circumstances. Different vendors have developed systems in different programming languages and database systems. They do not have any defined best practice or design patterns. This makes the data exchange difficult or impossible between the systems [73, 74, 78]. This lack of standardization limits the proliferation of EHRs [82]. While large hospital systems have moved to EHRs, many others are skeptical about the available systems. They fear that the EHR software they buy now might not work with standards adopted by the healthcare industry or mandated by the government later on.

- **Privacy and security concerns:** Health records contain personal, diagnostics, procedures, and other healthcare related sensitive information. Due to the immense importance of this information, an EHR system may be subjected to attack. Some of the medical diagnoses are considered socially stigmatized, like sexually transmitted disease. Some information relates to direct life threats, like allergies. Employers as well as insurance companies may be interested to know more about a patient to make unethical decisions whether to cover a patient and/or his specific diagnosis. It can also influence some of the hiring decisions. EHRs contain information like social security numbers, credit card numbers, telephone numbers, home addresses, etc., which makes EHRs attractive target for attackers and hackers. A patient might even be motivated to alter his or her medical records to get worker's compensation or to obtain access to narcotics. Therefore, it is important that the privacy and security of EHRs are well maintained. The most used certification for privacy and security is given by the Certification Commission for Healthcare Information Technology (CCHIT). The CCHIT website claims that by mid-2009, 75% of EHR products in the marketplace were certified [83]. In addition to that, the Health Information Technology for Economic and Clinical Health (HITECH) Act introduced a new certification process sponsored by the Office of the National Coordination for Health Information Technology (ONC) in 2009. In January 2010, the ONC released the interim final rule that provides an initial set of standards, implementation specifications, and certification criteria of EHR technology. Its requirement includes database encryption, encryption of transmitted data, authentication, data integrity, audit logs, automatic log off, emergency access, access control, and account of HIPPA release of information [84]. Physicians doubt the level of security of patients' information and records. According to Simon et al. [74], physicians are more concerned about this issue than patients. The inappropriate disclosure of information might lead to legal consequences. Testing the security of EHR products, a group of researchers showed that they were able to exploit a range of common code-level and design-level vulnerabilities of a proprietary and an open source EHR [85]. These common vulnerabilities could not be detected by 2011 security certification test scripts used by CCHIT. EHRs pose new challenges and threats to the privacy and security of patient data. This is a considerable barrier to EHRs proliferation. However, this risk can be mitigated by proper technology, and maintaining certified standards with the software and hardware components.

- **Legal aspects:** Electronic records of medical information should be treated as private and confidential. Various legal and ethical questions obstruct adoption and use of EHRs. The legal system that relies on the paper-era regulations does not offer proper guidance regarding the transition to EHRs. EHRs may increase the physicians' legal responsibility and accountability [86]. With computer-based sophisticated auditing, it is easy to track what individuals have done. The documentation is comprehensive and detailed in EHRs. It can both defend and expose physicians regarding malpractice. According to a *Health Affairs* article, malpractice costs around $55 billion in the United States, which is 2.4% of total healthcare spending [87]. A 2010 research reveals that it was unable to determine whether the use of EHR increases or decreases malpractice liability overall [86]. HIPAA's privacy standards also present reasonable barriers to EHR adaptation.

2.7 Challenges of Using EHR Data

The primary purpose of EHR data is to support healthcare-related functionalities. As a vast amount of data is being collected every day, the secondary use of EHR data is gaining increased attention in research community to discover new knowledge. The main areas of use are clinical and transitional research, public health, and quality measurement and improvement. Using the EHR data, we can conduct both patient-oriented and public health research. EHR data can be used for the early detection of epidemics and spread of diseases, environmental hazards, promotes healthy behaviors, and policy development. The integration of genetic data with EHRs can open even wider horizons. But the data does not automatically provide us the knowledge. The quality and accuracy of the data is an issue to be taken care of. Beyley et al. [88] presents an excellent survey of the challenges posed by the data quality.

- **Incompleteness:** Data incompleteness or missingness is a widespread problem while using EHR data for secondary purpose [88, 89, 90]. Missing data can limit the outcomes to be studied, the number of explanatory factors to be considered, and even the size of population included [88]. Incompleteness can occur due to a lack of collection or lack of documentation [91]. Hersh [92] reports the following reasons for inaccurate reporting by professionals.
  - Unaware of legal requirements
  - Lack of knowledge of which diseases are reportable
  - Do not understand how to report
  - Assumption that someone else will report
  - Intentional failure for privacy reasons

  A pancreatic malignancies study using ICD-9-CM code at the Columbia University Medical Center found that 48% of the patients had corresponding diagnoses or disease documentation missing in their pathology reports [93]. Authors also report a significant amount of key variables missing (see Table 2.1).

  Patients' irregularity of communicating with the health system can also produce incompleteness. Based on the application in hand, type of data and proportion of data that is missing, certain strategies can be followed to reduce the missingness of data [91].

TABLE 2.1: Percentage of Incompleteness of Variables in a Pancreatic Malignancies Study

Variables	**Endocrine**
Necrosis	20%
Number of Mitoses	21%
Lymph Node Metastasis	28%
Perineural/Lymphovascula Invasion	15%
Differentiation	38%
Size	6%
Chronic Pancreatitis	14%
Smoking—Alcohol	27%–29%
History of Other Cancer	35%
Family History of Cancer	39%
Tumor Markers	46%

Source: Taken from Botsis et al. [93].

- **Erroneous Data:** EHR data can be erroneous as well. Data is collected from different service areas, conditions, and geographic locations. Data is collected by busy practitioners and staff. Therefore, the data can be erroneous due to human errors. Faulty equipment can also produce erroneous data. Validation techniques should be used to both identify and correct erroneous data. Both internal and external validation measures can be applied. Internal validation is a way to check the believability of the data, e.g., unrealistic blood pressure, BMI values, etc. Dates can be used to check whether the result generated before a test has taken place. External validation includes comparing the data with other patients or historical values.

- **Uninterpretable Data:** The captured EHR data might be uninterpretable to a certain extent. It is closely related with data incompleteness. It may occur when some part of the data is captured but the rest is missing. For example, if a specific quantitative or qualitative measurement unit is not provided with the result value, it will be difficult to interpret.

- **Inconsistency:** Data inconsistency can heavily affect the analysis or result. Data collection technologies, coding rules, and standards may change over time and across institutions, which may contribute to inconsistency. For multi-institutional studies this issue might be common, especially because different healthcare centers use different vendors for providing apparatus, softwares, and other technologies [88]. A study in Massachusetts of 3.7 million patients found that 31% of patients have visited two or more hospitals in the course of five years [94].

- **Unstructured Text:** In spite of having many defined structures for collecting the data, a large portion of the EHR data contain unstructured text. These data are present in the form of documentation and explanation. It is easy to understand them for humans, but in terms of automatic computational methods, detecting the right information is difficult. Sophisticated data extraction techniques like Natural Language Processing (NLP) are being used to identify information from text notes [95].

- **Selection Bias:** In any hospital, the patient group will mostly be a random collection. It varies depending on the nature of practice, care unit, and the geographical location of the institution. It will not contain the diversity of demography. This is an important challenge to overcome. Therefore, EHR data mining findings will not be generalizable. This problem must be addressed while working with the secondary use of data.

- **Interoperability:** Lack of EHR interoperability is a major impediment towards improved healthcare, innovation, and lowering costs. There are various reasons behind it. EHR software from commercial vendors are proprietary and closed systems. Most software were not built to support communication with a third party and developing new interfaces for that purpose might be a costly undertaking. Absence of standard also contributes to the problem. Many patients are not lenient towards sharing their information. Besides EHR systems must comply with the HIPAA Act [11] to ensure the security and privacy of the data.

  In a recent *JAMIA* (*Journal of the American Medical Informatics Association*) article, the authors have specified 11 specific areas that present barriers to interoperability of C-CDA documents by inspecting 91 C-CDA documents from 21 technologies [96]. In June 2014, the office of the National Coordinator for Health Information Technology (ONC) unveiled a plan for robust healthcare information sharing and aggregation and interoperability increase by 2024 [97]. Its three-year agenda includes "Send, Receive, Find, and Use Health Information to Improve Health Care Quality." Its six-year agenda states "Use Information to Improve Health Care Quality and Lower Cost," and finally, its 10-year agenda proposes to achieve a "Learning Health System." The mentioned building blocks for attaining the goals are the following:

  - Core technical standards and functions
  - Certification to support adoption and optimization of health IT products and services

- Privacy and security protections for health information
- Supportive business, clinical, cultural, and regulatory environments
- Rules of engagement and governance

2.8 Phenotyping Algorithms

Phenotyping algorithms are combinations of multiple types of data and their logical relations to accurately identify cases (disease samples) and controls (non-disease samples) from EHR as illustrated in Figure 2.3 [98]. Based on the structure, EHR data can be broadly divided into two parts, structured and unstructured data. Structured data exists in a name–value pair while unstructured data contains narrative and semi-narrative texts regarding descriptions, explanation, comments, etc. Structured data include billing data, lab values, vital signs, and medication information. Billing and diagnosis-related data are collected using various coding systems like ICD, CPT, and SNOMED-CT. These codes are important parts of the phenotyping process. ICD codes generally have high specificity but low sensitivity [99]. Table 2.2 lists different characteristics of EHR data.

The primary purpose of EHR data is to support healthcare and administrative services. Information is produced as a byproduct of routine clinical services. They are not a suitable format for performing research tasks. They often require further processing to be used for phenotyping algorithms. Within existing EHR systems, querying for a particular diagnosis or lab test across all patients can be a not-trivial task. An EHR can quickly pull the information related to a patient's current medications, and easily find any test results. But combining different data with a temporal relationship might require manual processing of data. From clinical operational settings, data are often extracted and reformatted to make them more convenient and suitable for doing research, typically storing them in relational databases. Researchers have created a number of Enterprise Data Warehouses (EDWs) for EHR data. Examples include Informatics for Integrating Biology and the Bedside (i2b2) [100], the Utah Population Database [101], Vanderbilt's Synthetic Derivative [102], etc. Commercial EHR vendors are also developing research repositories. For example, EPIC users can add the "Clarity" module to their system, which will convert the EHR data into SQL-based database for research purposes.

To build a phenotype algorithm, first we need to select the phenotype of interest, followed by the identification of key clinical elements that define the phenotype. It may contain billing codes, laboratory and test results, radiology reports, medication history, and NLP-extracted information. The gathered information may be combined with a machine learning method. For example, in [103], the authors have applied Support Vector Machine (SVM) to a both naive and well-defined collection of EHR features to identify rheumatoid arthritis cases. A medication record can be used to increase the accuracy of case and control identification of phenotyping algorithms. Patients who are believed to be controls must be having a different medication profile. They may not even have any medications prescribed to them at all. Sufficient dosage of a particular medication serves the confirmation that a person is having the disease of interest. For example, a patient treated with either oral or injectable hypoglycemic agents will be having diabetes. These medications are highly sensitive and specific for treating diabetes.

Studies have shown that CPT codes can accurately predict an occurrence of a given procedure [104]. The standard terminology codes for lab tests are LOINC. On the other hand, clinical notes are in free-text format. To be used for phenotyping algorithms, it has to undergo subsequent text processing. Certain procedures and test results may also exist in a combination of structured and unstructured form. For example, an electrocardiogram report typically contains structured interval

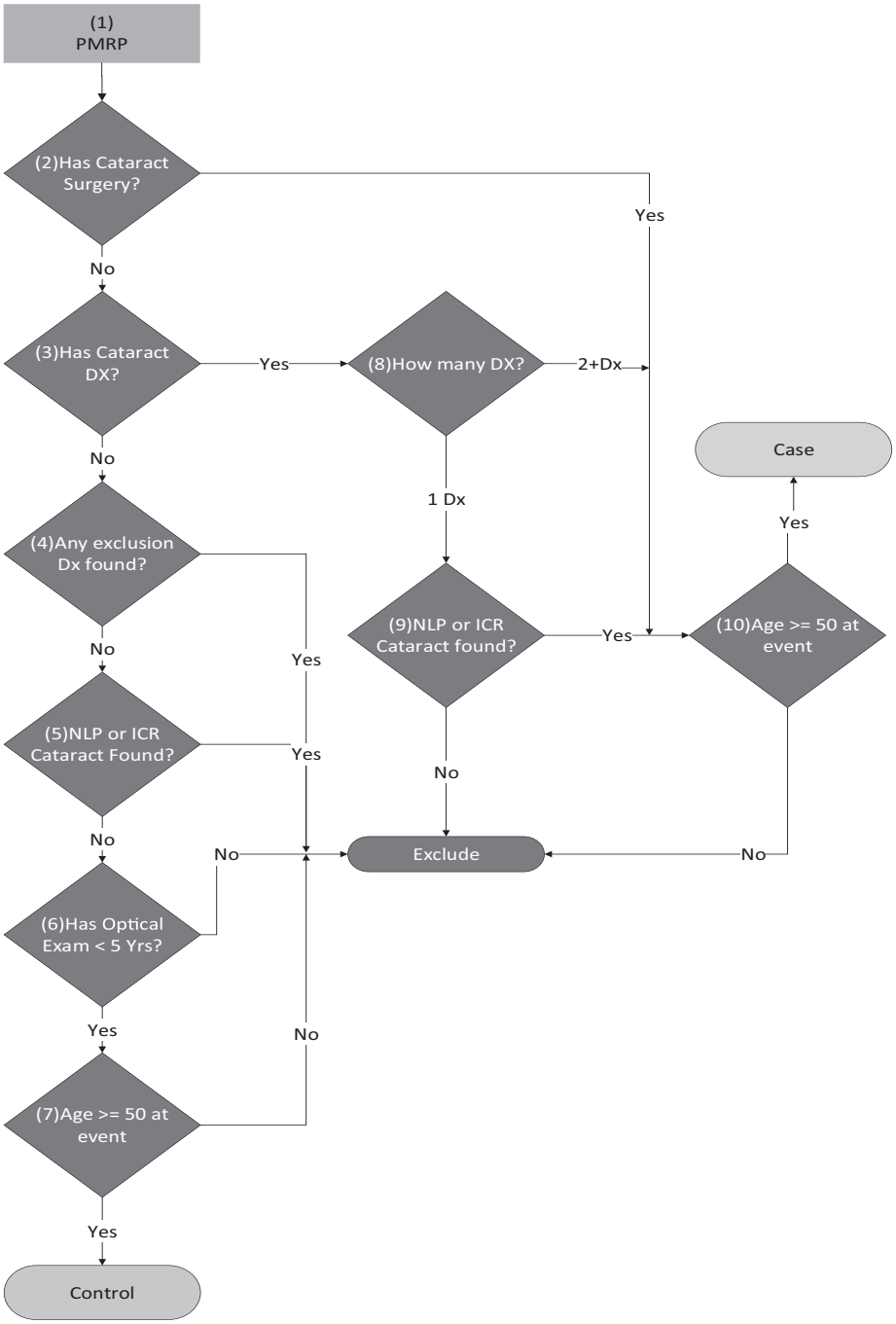

FIGURE 2.3: Flowchart for cataracts phenotyping algorithm taken from [98].

durations, heart rates, and overall categorization, along with a narrative text of cardiologist's interpretation of the result [105].

Recently, researchers have been linking EHR data with biological databanks (biobanks). The most popular biobanks are the collection of DNA samples. Hospitals and clinics can collect DNA

TABLE 2.2: Characteristics of Different EHR Data

	ICD	**CPT**	**Lab**	**Medication**	**Clinical notes**
Availability	High	High	High	Medium	Medium
Recall	Medium	Poor	Medium	Inpatient: High Outpatient: Variable	Medium
Precision	Medium	High	High	Inpatient: High Outpatient: Variable	Medium/High
Format	Structured	Structured	Mostly	Structured	Structured
Pros	Easy to work with, good approximation of disease status	Easy to work with, high precision	High data validity	High data validity	More details about the doctors' thoughts
Cons	Disease code often used for screening, therefore disease might not be there	Missing data	Data normalization and ranges	Prescribed not necessarily taken	Difficult to process

Source: Taken from Denny [106].

samples from a patient's blood sample that is used in routine tests. The Personalized Medicine Research Population (PMRP) project in Marshfield Clinic has a biobank of 20,000 individuals [107]. Similar DNA biobanks exist at eMERGE Network sites, Northwestern University, Geisinger Health System, Mount Sinai School of Medicine, and at other places. The eMERGE network is funded and organized by the National Human Genome Research Institute (NHGRI) and until today it has created and validated twenty-one EHR-derived phenotyping algorithms (see Table 2.3). Its mission is to develop, disseminate, and apply methods to combine DNA biorepositories and EHR systems for large scale and high throughput genetic research [108]. But the phenotype information extracted from EHRs may be challenging. Validation of phenotypes is important before integration of EHRs into genetic studies. By validating EHR-derived phenotypes from eMERGE network, Newton et al. report the following points [109]:

- Multisite validation improves phenotype algorithm accuracy
- Targets for validation should be carefully considered and defined
- Specifying time frames for review of variables eases validation time and improves accuracy
- Using repeated measures requires defining the relevant time period and specifying the most meaningful value to be studied
- Patient movement in and out of the health plan (transience) can result in incomplete or fragmented data
- The review scope should be defined carefully
- Particular care is required in combining EMR and research data
- Medication data can be assessed using claims, medications dispensed, or medications prescribed
- Algorithm development and validation will work best as an iterative process
- Validation by content experts or structured chart review can provide accurate results

TABLE 2.3: Phenotyping Algorithms Developed by eMERGE Network

Phenotype	**EHR data used to characterize phenotype**	**Institution**
Atrial Fibrillation — Demonstration Project	CPT Codes, ICD 9 Codes, Natural Language Processing	Vanderbilt University
Cardiac Conduction(QRS)	CPT Codes, ICD 9 Codes, Laboratories, Medications, Natural Language Processing	Vanderbilt University
Cataracts	CPT Codes, ICD 9 Codes, Medications, Natural Language Processing	Marshfield Clinic Research Foundation
Clopidogrel Poor Metabolizers	CPT Codes, ICD 9 Codes, Laboratories, Medications, Natural Language Processing	Denny's Group at Vanderbilt, VESPA — Vanderbilt Electronic Systems for Pharmacogenomic Assessment
Crohn's Disease — Demonstration Project	ICD 9 Codes, Medications, Natural Language Processing	Vanderbilt University
Dementia	ICD 9 Codes, Medications	Group Health Cooperative
Diabetic Retionapathy	CPT Codes, ICD 9 Codes, Laboratories, Medications, Natural Language Processing	Marshfield Clinic Research Foundation
Drug Induced Liver Injury	ICD 9 Codes, Laboratories, Medications, Natural Language Processing	Columbia University
Height	ICD 9 Codes, Laboratories, Medications	Northwestern University
High-Density Lipoproteins (HDL)	ICD 9 Codes, Laboratories, Medications, Natural Language Processing	Marshfield Clinic Research Foundation
Hypothyroidism	CPT Codes, ICD 9 Codes, Laboratories, Medications, Natural Language Processing	Vanderbilt University, Group Health Cooperative, Northwestern University
Lipids	ICD 9 Codes, Laboratories, Medications	Northwestern University
Multiple Sclerosis — Demonstration Project	ICD 9 Codes, Medications, Natural Language Processing	Vanderbilt University
Peripheral Arterial Disease	CPT Codes, ICD 9 Codes, Laboratories, Medications, Natural Language Processing	Mayo Clinic
Red Blood Cell Indices	CPT Codes, ICD 9 Codes, Laboratories, Medications, Natural Language Processing	Mayo Clinic
Rheumatoid Arthritis — Demonstration Project	ICD 9 Codes, Medications, Natural Language Processing	Vanderbilt University
Severe Early Childhood Obesity	ICD 9 Codes, Medications, Natural Language Processing, Vital Signs	Cincinnati Children's Hospital Medical Center
Type 2 Diabetes — Demonstration Project	ICD 9 Codes, Laboratories, Medications, Natural Language Processing	Vanderbilt University
Type 2 Diabetes Mellitus	ICD 9 Codes, Laboratories, Medications	Northwestern University
Warfarin dose/response	Laboratories, Natural Language Processing	Vanderbilt University
White Blood Cell Indices	CPT Codes, ICD 9 Codes, Laboratories, Medications	Group Health Cooperative

Source: Taken from [110].

Before the use of a phenotyping algorithm, data has to be normalized to standard representation. Natural Language Processing (NLP) based tools have gained much popularity to extract structured information from free text. Several studies have shown that coded data are not sufficient or accurate to identify disease cohorts [111, 112]. Information from narrative text complements the structured data. There are studies that report NLP-processed notes provide more valuable data sources. For example, Penz et al. reports ICD-9 and CPT codes identified less than 11% cases in detecting adverse events related to central venous catheters, while NLP methods achieved a specificity of 0.80 and sensitivity of 0.72 [113]. Widely used general-purpose NLP tools include MedLEE (Medical Language Extraction and Encoding System) [114], cTAKES (clinical Text Analysis and Knowledge Extraction System) [115], MetaMap [116], and KnowledgeMap [117]. All of them have been successfully applied to phenotyping using EHR data. Task-specific NLP methods are available that aim to extract specific concepts from clinical text.

The DNA sequence of a person can be huge in size (ranging from hundreds of gigabytes to terabytes) in raw format that exceeds the capability for using the current EHR systems. Storing, managing, and transferring a repository of such a large volume of data is difficult. Efficient data compression techniques can be applied to solve this problem. Genome Wide Association Study (GWAS) became the mainstay of genetic analysis over the last decade. In general, GWAS investigates around 500,000 genetic variants (Single Nucleotide Polymorphisms) or more to see the association of variations with observable traits. It compares the SNPs of cases versus controls to find meaningful knowledge. Besides traits, we can also identify SNPs that determine a particular drug response. One individual might react adversely to a particular drug while others might not. The genetic profile of an individual can be used for personalized medicine. One big advantage of genetic data is that the SNPs are the same for that individual and do not change based on a given/suspected disease. The same set of data can be used for different phenotype investigations as well. Researchers are working to integrate genetic information for enhanced clinical decision support. For example, researchers in Vanderbilt University are working on implementing Pharmacogenomic Resource for Enhanced Decisions in Care and Treatment (PREDICT) [118]. St. Jude Children's Research Hospital also has a multiplexed genotyping platform for providing decision support [119].

2.9 Conclusions

Electronic health records are the obvious and inevitable future of patient care in hospitals and medical practices. This chapter discusses several aspects of the EHRs. EHR systems are gaining nationwide popularity in the United States recently due to "Meaningful use legislation and reimbursement [120]. It is being widely installed in hospitals, academic medical centers," and outpatient clinics throughout the nation. Besides healthcare benefits like improved patient care, safety and reduced costs, it creates great opportunity for clinical and translational research. Widespread adoption of EHRs can foster the improvement of quality in healthcare services, safety and efficiency, and most importantly, public health. Having great potential for benefits, successful deployment of EHRs has several challenges to overcome. There are notable limitations of the use of EHR data in research purposes. In the era of technology, the necessary laws lag far behind. While other developed countries have showed widespread adoption, in the United States, the overall adoption is considerably low. Bigger Government initiatives and enhanced standardization today can lead to a brighter healthcare tomorrow.

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