CHAPTER 2

Health Informatics Overview

Jiban Khuntia, Matilda Mustapha, and Joseph Tan

LEARNING OBJECTIVES

- Explore the evolution of the HI discipline
- Identify the more established HI domains
- Review key issues and challenges in HI
- Recognize the need for workflow alignment for HI future success

KEY TERMS

Informatics	Biomedical informatics	Home health informatics (HHI)
Health informatics (HI)	Pathology informatics (PI)	Data qualitymanagement
Medical informatics (MI)	Imaging informatics (ImI)	Workflow alignment
Nursing informatics (NI)	Public health informatics (PHI)	

1. Introduction

With advances in medical technologies and innovations, **informatics** has emerged to become an integral part of health care, providing numerous benefits and opportunities to address challenges long faced by the healthcare industry. Briefly, **healthcare informatics (HI)** integrates technology and various health sciences to analyze and manage health information to improve patient records, clinical decision-making, prediction outcomes, and health policymaking. In this dynamic field, HI professionals must develop core knowledge and skills to enhance their understanding and effective use of data and information systems (IS) to address pressing healthcare needs and, more specifically, to reduce clinical errors, augment workflow, and enhance decision-making to improve patient care safety and/or outcome. This growing field also deals with processing key health resources to acquire, store, and retrieve medical practice information.

Electronic health record (EHR) systems are the most cited systems to manage patient records more efficiently (Seckman & Carter-Templeton, 2019). Other aspects of HI have also emerged: medical (or biomedical) informatics, pathology informatics, clinical research informatics, imaging informatics, public health informatics, community health informatics, home health informatics, nursing informatics, and consumer health informatics. Each of these aspects aims to identify critical requirements and establish a systematic approach to providing high-quality care. With increased innovations, regulatory requirements, and a rapid transition into value-based care, clinicians, patients, and other key stakeholders rely on health information technology (HIT) and informatics to guide routine and critical clinical decisions and practices.

Moreover, HI tools such as big data and predictive analytics have provided the healthcare learning systems with the ability to track epidemics, disease trends, and identify critical issues or predict future occurrences, including risks for poor clinical outcomes. Depending on how HI is applied, the value-based care systems will drive new policies, improve care quality, decrease inflationary costs for health care, and better educate health consumers to provide a safer care environment. Hence, adopting an HI framework to understand health issues and challenges will benefit the patients and health provider organizations as well as employers and payers. It will further decrease the cost to both patients and facilities, aid in hospital operational efficiencies, prioritize health outcomes and efficacy to all patients seeking care, and ensure care provider engagements and coordinations.

2. HI Evolution

The HI field has evolved from the time computer technology emerged as a tool to manage enormous data in health-related domains. Dentistry informatics, for instance, has benefitted from imaging and the recording of data electronically. Yet, it was not until the 1960s that HI began to gain traction. According to the Healthcare Information and Management Systems Society, electronic data recording, a tribute to early EHR systems, was first established by the American Society for Testing and Materials. These recordings included laboratory message exchange, earlier forms of EHR systems, and health information systems. Subsequently, bioinformatics was introduced in the late 1970s to study biological data and genetic sampling (University of Illinois Chicago, 2020).

Going forward, medical practitioners and government entities continued extensive research into patient care format from registration to insurance claims to discharge. Other facets of health care such as radiology and pharmacy also developed specialty forms of informatics for record-keeping. In 2009, delivered under the American Recovery and Reinvestment Act, the HITECH (Health Information Technology for Economic and Clinical Health) Act was passed as part of President Obama's economic stimulus package. Before introducing the HITECH Act, very few hospitals had EHR capabilities. This created little to no improvement in record-keeping in compliance with the Health Insurance Portability and Accountability Act (HIPAA) privacy and security rules. After the law's passage, patients could view their records online and manage and restrict health information disclosure. The law aims to improve care coordination efficiently and augment hospital collaboration for more straightforward diagnosis and patient referrals.

Since the HITECH Act, the United States has paid more than $35 billion in incentives to eligible hospitals and physicians for EHR adoption and "meaningful use" compliance. By 2017, 86% of office-based physicians had adopted an EHR, and 96% of nonfederal acute care hospitals have implemented certified health informatics (HIPAA, 2018). Today, imaging informatics and pharmacy informatics are two uniquely specialized areas of study that continue to grow tremendously. HI has since become a catalyst for a value-driven care model (Middleton, 2014).

3. Key HI Domains and Subfields

HI includes many domains and subfields in biomedical, clinical, pharmacy, dental, public and community health, and nursing informatics.

Specific examples of those more established domains include medical (or biomedical) informatics, pathology informatics, clinical research informatics, **imaging informatics (ImI)**, public health and community health informatics, **home health informatics (HHI)**, nursing informatics, and consumer health informatics (CHI). Next, we give an overview of each of these subfields to reflect on their significant contributions to HI.

3.1 Medical (or Biomedical) Informatics and Precision Medicine

In the United States and around the world, **biomedical informatics** has played an influential role in popularizing informatics concepts, particularly the evolution of **medical informatics (MI)**. Briefly, the biomedical field applies multidisciplinary thinking to understand computational biology better while applying bioengineering methods to enhance informatics practice. In this way, the workforce of professionally qualified informaticians from all walks of life has been instituted through organizations such as the American Medical Informatics Association (AMIA), which have been committed to the professional certification of clinicians and other professionals working at the interface of clinical practice, research, and technology to employ HI methods.

Broadly, medical informatics technology as applied to improve data, clinical practice, population health, and other information relevant to patient care and community health is the fruit of biomedical informatics evolution. In the 19th century, a form of MI was introduced with Herman Hollerith's punched-card data-processing system used in the U.S. census and later employed to support public health science and epidemiology (Shortliffe et al., 2001). MI consists of various fields of epidemiology, cognitive, and information sciences. Further, MI deals with the resources, devices, and optimization of data accession, storage, retrieval, and data use in biological sciences. Technology has proven to help streamline care navigation in medical practice. Model-informed precision dosing (MIPD) is a precision medicine (PM) technology that predicts drug concentrations and drug responses based on individual patient characteristics. This novel technology is labeled PM to address clinical concerns, track patient records, and improve cost-effective patient care.

PM targets patients' needs based on genetic, biomarker, phenotypic, or psychosocial characteristics. This is significant because each patient is uniquely observed and treated distinctively from other patients with similar clinical presentations. A further consideration in PM is molecular diagnostics for pharmaco- and immunotherapy in oncology and hematology. Although many still find PM a bit too elite, a study shows that a similar MIPD, sometimes called clinical pharmacometrics, has produced tremendous MI results (Polasek et al., 2019). Clinical pharmacometrics predicts drug concentrations or exposure in the body based on a patient's biodata. In cases where drug action mechanisms are relatively simple, like neurology and psychiatry, this process achieves maximum success. However, dose predictions before starting drug treatment and dose adjustment via Bayesian feedback after initial drug exposure and/or a biomarker of response is known in a particular patient (Polasek et al., 2019).

In more recent times, artificial intelligence (AI) has been used in 3D imaging to diagnose care and predict treatment outcomes via machine learning (ML), which is discussed in more detail in a later chapter of this text. This high-performance, data-driven medicine has changed the way physicians and clinicians practice medicine. The process uses an algorithmic process where data-fed information such as heart rate, blood pressure, magnetic resonance imaging scans, and images of biopsy tissue samples is entered for analysis. This is then turned into labeling or classification of the observed anomalies. Another example of AI technology developed to help with recording and documentation is the Nuance Dragon Ambient experience, otherwise known as Nuance Dax, developed by Nuance Communications, a South Jersey company specializing in intelligence communications. The Nuance Dax is a leading-edge technology that allows doctors and clinicians to process data promptly.

With automated processing, information is or can be typically entered orally and then churned or transcribed into documented transcripts for further analysis and recording. This model is built on the Microsoft Azure platform. It is programmed with speech recognition and identification. Its main goal is to automatically translate voice into data and minimize the need for information reentry and after-work documentation.

With the increased use of innovative MI technologies such as AI and ML, many patients now complain about the loss of human touch in patient care as physicians try to enter information and discuss patient diagnosis and plan of care simultaneously. Although AI is a great innovation, it must be understood that care is not solely a scientific inquiry but also one entailing the application of intense human relationships in which treatment responds throughout the course of interactions also between patients and providers (Kulikowski, 2019).

3.2 Nursing Informatics

The American Nursing Association defines **nursing informatics (NI)** as a field that integrates nursing science with analytical sciences to identify and communicate data, information, and knowledge in nursing practice. NI is essentially the end-user clinician who is the driving force behind the development, implementation, and optimization of electronic medical records (EMRs), point-of-care clinical decision support, and computerized provider order entry (CPOE).

Before 2004, NI was always conceived as an outflow of MI and clinical decision-making; however, between 2005 and 2014, the NI materialized in patient diagnosis and patient records. By early 2016, NI began to support public health, telehealth, primary care, home care, and care of disabled persons and stroke patients. NI also began to address managing nutrition, diabetes, and medications (Vosner et al., 2020). Today, NI comprises health research, data integration, user-centered medication, and social media.

The most widely used technologies in NI are information and communication technologies (ICT), the EHR/EMR, telecare, and online training and education resources in nursing practices. One form of ICT is hospital information systems (HIS) or monitoring devices. Lately, studies have shown that ICT, robots, and sensors technologies are among the most frequently explored technologies in NI. These technological tools are used for patient records/clinical records, telephone triage, telehealth and telecare systems, online consultations, and electronic reservation and appointment systems (Dewsbury, 2019). Although NI, in and of itself, is complex, it supports an essential nursing function with formulating a patient care plan and executing this plan electronically.

Some researchers have indicated that the home care nursing environment may lend itself to incomplete and inaccurate documentation. This is especially true when nurses cannot document in the patient's home and must rely on their memory when they document later. Hence, this makes EHR an equally important part of home nursing care. Conversely, others have argued that NI needs more support regarding EHR because studies have shown a correlation between EHR use and professional burnout. As nurses are the largest end-users of EHR, organizations must explore EHR patterns of use by acute care nurses and the relationship of EHR use to nurse satisfaction and burnout (Krick et al., 2019). Therefore, for NI to achieve the efficiency and effectiveness of its tools, several forms of technology must be employed as no treatment should be isolated or independently administered. Yet, owing to the broad number of potentially relevant technologies emerging in the coming years, producing a concise taxonomy of competencies and a systematization of functionality for NI training and technological tools may help synergize the future vision for directing nursing care and prevent burnout of nurses.

3.3 Pathology Informatics

Pathology informatics (PI) is a systematic approach to providing high-quality pathology in a healthcare learning system responsible for services across large geographic areas. PI enables patients in varying locations to access reporting of the specimen by the right pathologist at the right time. It also uses a discrete data reporting module with documented quality assurance activities for workload measurement. Since the inception of this multifunctioning practice, pathology platforms support efficient surgical pathology and hematopathology. The resulting complexities of reporting have been the driving force of electronic data in pathology.

PI transformative technology has had a significant impact on laboratory medicine. This shift in technology offers room for automated lab testing and increasingly complex molecular diagnostics, which are key moves that will span an entirely new medical practice. The scope of modern pathology encompasses many disciplines and technologies, including lab hematology, medical microbiology, anatomic pathology, molecular genetics, and clinical biochemistry. Whole slide imaging in histology is also in the scope of PI. An example of PI is the use of immune-histochemistry to identify non-small-cell-lung-cancer (NSCLC) patients who may respond to anti-programmed death-ligand 1 (PD-1)/PD-L1 immunotherapies (Brieu et al., 2018).

This immunotherapy was developed by researchers at Johns Hopkins Kimmel Cancer Center for people with advanced melanomas. The therapies aim not to kill cancer cells directly but to block a pathway that shields tumor cells from immune system components able and poised to fight cancer (Johns Hopkins, 2020). In the immune-histochemistry study, automated scoring of PD-L1+ tumor cells (TC) in whole slide images of resected NSCLC was strategized.

As shown in **Figure 2.1**, a convolutional neural network can classify tissue regions into three classes: (a) regions of membrane-positive epithelial tumor cells TC(+), (b) regions of membrane-negative epithelial tumor cells TC(−), and (c) other regions that may affect scoring. Such a classification would include macrophages, positive and negative lymphocytes, stroma, and/or necrosis. The ratio of the classified areas is then measured. This is an excellent view of the significance of PI. It entails the intriguing corporation of deep learning and expertise (Brieu et al., 2018).

Pathology has not gone without challenges. One of its greatest challenges is the number of pathologists available to sustain the field (Volynskaya et al., 2018).

3.4 Clinical Research Informatics

In the past, clinical research was often conducted operationally, and this comes with compressional complexities. Some of the earlier parts of EHR's challenge was the human interface with its minimal computational ability. This made it very difficult to perform practical clinical trials and comparative effectiveness research.

With advances in technology, efficiency in data collection, organization, clinical care practice progress, and analysis has improved significantly. The National Institutes of Health have begun an extensive review of operational, clinical research by formulating ways to improve the management and oversight of clinical trials. The goal is to encourage pragmatic clinical trials that include integrated health systems and their EHRs as the common data source. In turn, this would promote the efficiency and quality of scientific research (Smith et al., 2020). The uniqueness of clinical research informatics (CRI) is its emphasis on study protocols, which represent the scientific and computational design in research.

CRI would include classifying and creating specialized chapters to capture clinical informatics as its underlining scientific process. This constitutes a scientific process for generating, interpreting, and applying knowledge rather than the usual operational process of conducting clinical studies (Sim et al., 2018). Such integrated systems provide a common approach to clinical research practices. An example of the CRI adoption is evident in the use of geospatial methods to connect clinical data from Duke Medicine, the Durham County Health Department, and Lincoln Community Health Center (Durham's Federally Qualified Health Center) with data on housing, neighborhoods, social stressors, environmental exposures, and culture. A predictive model was developed via the identification of the early onset of disease by a computable phenotype. The outcome minimized some of the complexities of clinical research and reduced cardiovascular deaths and diabetes (Spratt et al., 2015).

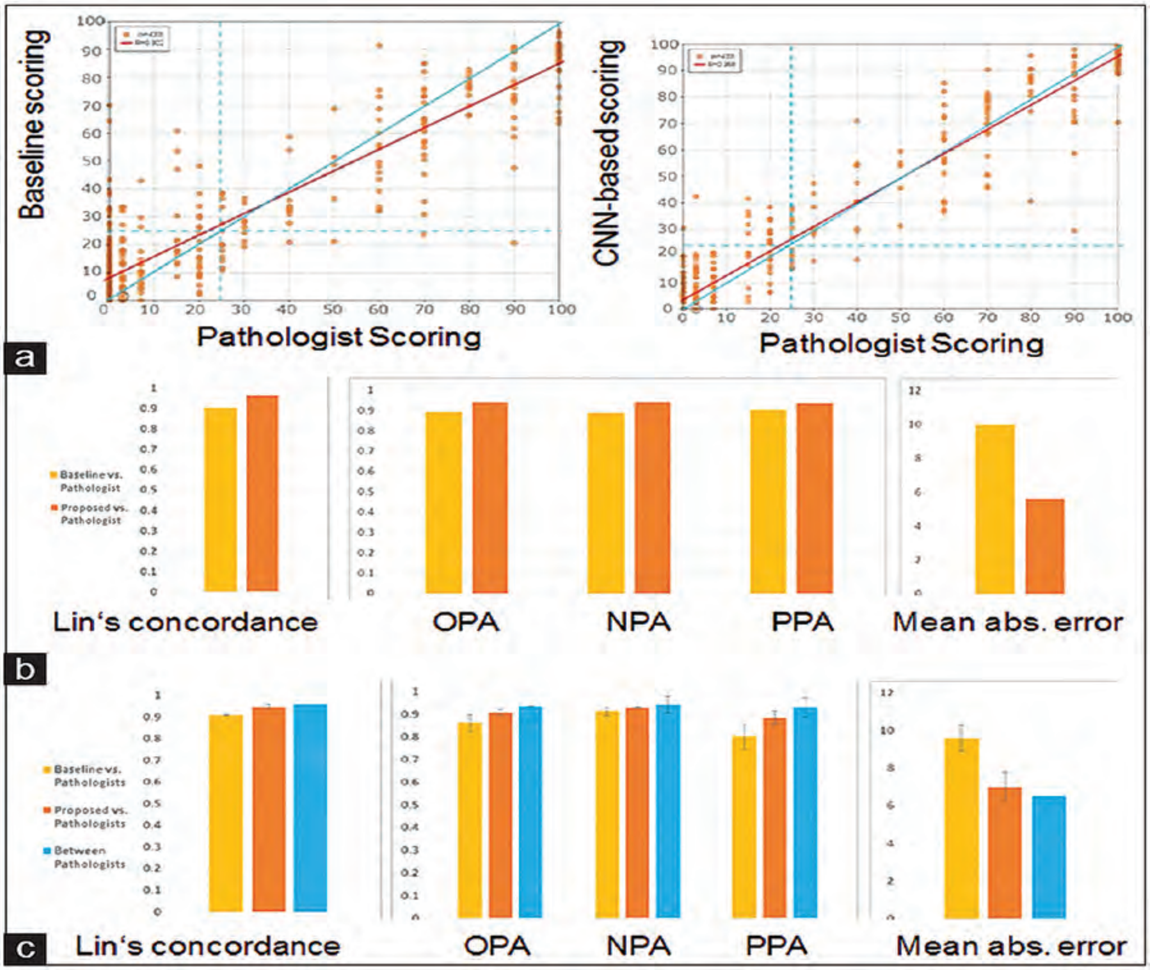

Figure 2.1 (a) Evaluation of the deep learning-based PD-L1 tumor cell proportion scoring against pathologists on the unseen restates NSCLC slides; (b) Pairwise scatter plots between the first reference visual scores by pathologists and the automatic scores, generated either using the baseline heuristic approach (left) or the proposed deep learning approach (right); (c) Quantitative concordance measures between the first visual scores by pathologists and the two automatic scoring approaches; On the subset of samples with two visual scores by pathologists available, mean and standard deviation of the aforementioned measures for the two approaches over these two visual scores, and concordance between these two visual scores

Reproduced from Brieu, N., Armin, M., Ansh, K., Aleksandra, Z., Craig, B., Marietta, L.S., Tobias, W., Moritz, W., Keith, S., Marlon, C.R., & Schmidt, G. (2018). *Deep learning-based PD-L1 tumor cell scoring of resected no small-cell-lung-cancer.* Pathology Informatics Summit. https://www.jpathinformatics.org/viewimage.asp?img=JPatholInform_2018_9_1_50_249129_f11.jpg

3.5 Imaging Informatics

The American Board of Imaging Informatics defines image informatics (ImI) as how medical images are used and exchanged throughout the complex healthcare systems. ImI encompasses ML, natural language processing, semantic representation, and computer reasoning. A virtuous triangle supports ImI: (a) it is multidisciplinary as it is associated with other natural sciences; (b) it entails clinical partnerships that help address clinical problems; and (c) it supports the transformation of research prototype into clinically approved products.

The current framework of the ImI computational model includes a simulation of the human physiology and anatomy structure from a molecular to an organic level (Ayache, 2016). Such computational models require an algorithmic process that considers all aspects of the human body; the algorithmic process is used to provide measurements on the patient's condition for accurate diagnosis. It is also used to observe pathological changes to assess prognosis better. Finally, it is used in planning and simulating effective therapy.

Progress in the ImI technology has helped reactive medicine toward personalized, precise, preventive, and predictive medicine. Several image acquisition techniques are boosted by widely available large databases of medical images and large-scale ML methods (Ayache, 2016) with the most significant benefit being the systematized exchange of medical images within an increasingly sophisticated care system.

3.6 Public Health Informatics

Public health informatics (PHI) is the synergistic bridging of various disciplines, including information science, data analytics, and technology to benefit population health instead of focusing just on individuals. Over the past 10 years, the U.S. healthcare EMR strategy was designed to meet the needs of medical providers' health insurance billing, internal organizational management, and regulatory reporting (Gamache et al., 2018). Except for a few highly integrated medical delivery systems, public health officials were mainly focused on the documentation of outbreaks and epidemiological effects. The neglect of prioritization of services over the years was due mainly to the lack of foresight, low availability of electronically linked data, the lack of data analytics skilled among professionals, and early informaticians who are unfamiliar with innovative software as a result of inadequate technology.

With the shifting emphasis to EHR largely because of policy changes and more functional data sharing protocols in recent years, the need for a transformative public health system is becoming more evident in medical homes, extended services such as telehealth programs in communities, and multispecialty group systems. The significance of such an encompassing venture is the ability to promote and elevate preventative care. The cost of health care has skyrocketed to the point of economic impairment with the worldwide digital universe estimated to double to 40 zeta bytes by 2020, equivalent to more than 5,200 gigabytes for every person on earth. This estimated digital explosion is almost a 50-fold growth from the beginning of 2010 to 2020 (Sepúlveda, 2014). With the massive shift to urbanization, government agencies are finding challenges to improve healthcare operations' speed, efficiency, and unit cost. State and federal policies have also shifted their focus to providing incentives for care provider organizations, thereby allowing clinicians to apply their digital resources to analyze the social determinants of health and reallocate needed resources more appropriately.

Adopting big data analytics and cognitive computing has also helped capture sensors at both the municipal and population levels. This quantification level gives room for redefining public health systems from surveillance to research strategies and mobilization to assessment and forecasting. It also creates the potential for public health intervention at a population level via modeling and simulation (Ash et al., 2017). In the recent case of COVID-19, it becomes evident in the way state-to-state and province-to-province monitoring, contact tracing, and simulation of the pandemic spread. This has also fostered the synthesis of health learning systems and public health systems to better manage population and community care gaps. Awareness and attention from multiple stakeholders have increased their focus and willingness to spend on several scientific tools to optimize the synthesis and evaluation of large volumes of complex data on issues such as outbreaks, pandemics, exposure, and syndromes.

As part of the PHI, the healthcare workforce can now better deal with regulatory practices, access, policy changes, and confidentiality. Many of the digital transformation in health care are also evident in the recent COVID-19 pandemic. As observed, public health officials and governments have resorted to and relied heavily on the contributions of PHI during the COVID-19 pandemic, which include, among other things, the design and development of rapid testing strategy with high accuracy, the design of reliable and usable personal protection equipment, intelligent contact tracing and roll-out of vaccinations with patient confidentiality, and privacy to be safeguarded via mobile applications for self-monitoring and similar activities. Additionally, priority has to be given to the health and well-being of first responders and healthcare frontrunners, making new distancing measures such as telehealthcare servicing the core of PHI strategies. The development of trend data by using computational modeling and simulations was also key to managing the current COVID pandemic.

Importantly, the current healthcare workforce has to be reskilled in data collection and literacy to pursue innovative care strategies. Health policy informatics has also improved in incorporating AI-related strategies. The crucial function is integrating a large volume of structured and unstructured clinical data in a data warehouse. The data are collected by evaluating digital surveillance systems that use various ML techniques for computational analysis. Social media has become a significant source of information for the surveillance of various public health outcomes on a real-time basis. For example, foodborne illnesses are quickly identified and recalled owing to better evaluation of the validity of the applied surveillance tools. Heat alert warnings and influenza safety guidelines are quickly dispersed via developed metrics and measurement tools for public information. Even COVID-19 self-assessment and alerts have helped experts and researchers in monitoring its effects and spread. Other forms of surveillance are antibiotic consumption, and the effects of drugs on community and population at large (Thiébaut et al., 2019).

3.7 Home Health Informatics

Home health informatics (HHI) uses data-driven approaches to support information needs and provide decision support for in-home care and community practice. This system is efficiently interoperable across systems so that better healthcare outcomes may be achieved. One of the most common categories of HHI is telehealth, which includes but is not limited to remote patient monitoring, smart home for health care, data-driven medicine, and predictive, preventive, personalized, psychocognitive, and participatory medicine (Sapci & Sapci, 2017).

In the early 1990s, the Sahlgrenska University Hospital in Sweden developed an adaptable home system where telemedicine was used to monitor premature infants with respiratory distress syndrome. The system proved that telehealth applications can be adapted for use in infant care at home. In the United Kingdom, families of hospitalized deficient birth weight infants were videoconferenced from their homes to the neonatal intensive care unit (NICU). This was crucial as it gave the families an element of control and increased care satisfaction. In recent years, the Fit-baby prototype was developed to monitor and track observations of health-related data of premature children (Gund et al., 2013). A similar project called the NICU-2-HOME was developed in the United States to transition infants from the hospital to home via a mobile application. The data structures interact with health data and capture and store index data from medical devices and sensors. These data are then stored for clinical access (Young et al., 2011).

Equally important is the aging structure of the world's population. The United Nations reports that baby boomers (60 years old and over) will surpass 3 billion in 2100. This age group is living longer than ever before, and their health and self-management strategies must be developed to improve health outcomes and quality of life. Technology such as home-based patient-monitoring devices and smart homes will allow clinicians to develop new disease management strategies and prevention. Wireless, wearable devices, and digital health (DH) technologies have benefitted and improved patient outcomes. Other smart home devices such as motion detectors, pressure sensors, and smart appliances can allow clinicians and family members to monitor the physiological, mental, early diagnosis, and social well-being of the elderly (Sapci & Sapci, 2017).

A blueprint of the home-health laboratory consists of multiple examples of HHI such as AMD-3300 12-lead electrocardiogram gloves for at-home monitoring, a diagnostic device data, 40" HDTV, Amazon Echo, remote thermometers and monitoring systems, infrared monitor sensors, cordless monitor-bed alarms, caregiver pagers with motion sensor, sleep tracking devices, waterproof medical alert systems, motion sensors, iHealth Sense wireless wrist blood pressure monitors, Feel wireless blood pressure monitors, Smart wireless glucose-monitoring systems, wireless pulse oximeters, Smart Caregiver fall guard cordless monitor, Smart Caregiver GCT-WI cordless chair sensor pad with the transmitter, Secure Wireless caregiver pager and PIR motion sensor for patient wandering and fall prevention, telephone gadgets, and more (National Institutes of Health, 2017). **Figure 2.2** summarizes the conceptual design of a smart home training laboratory.

4. Key HI Issues and Challenges

Many challenging issues surround HI implementation, use, and successful adoption by end-users

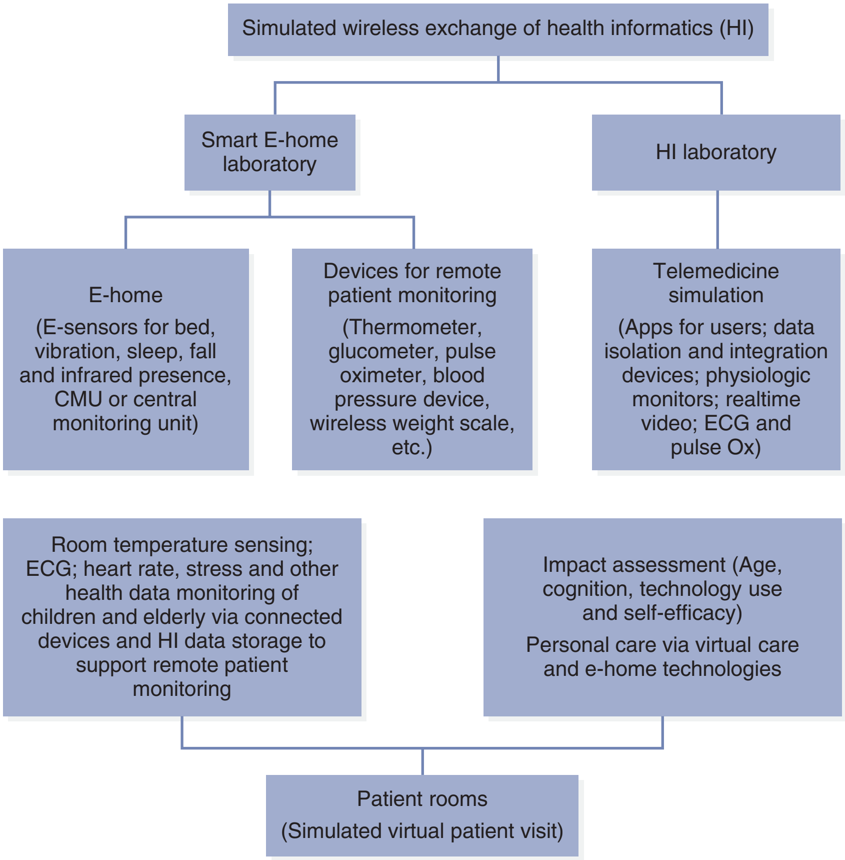

Figure 2.2 Wireless Health Data Exchange Simulations

Reproduced from Sapci, A. H., & Sapci, H. A. (2017). The effectiveness of hands-on health informatics skills exercises in the multidisciplinary smart home healthcare and health informatics training laboratories. *Applied Clinical Informatics, 8*(4), 1184–1196. https://doi.org/10.4338 /ACI-2017-08-RA-0136 because of the complexity of integrating technologies into human routines and interactive decision-making processes. We discuss the primary issues and challenges next.

4.1 Data Management

Health data management entails the organization's ability to acquire, store, process, and retrieve health information in digital forms with the primary goal to promote and improve patient care while ensuring the security and privacy of patient information. According to Aromatario et al. (2019), the worldwide forecast for mobile phone users has amounted to 4.68 billion with half of these users relying on mobile health applications.

Smart technology, including smartphones and tablets, have provided interactive ways for health promotion, communication, health monitoring, and reminders to take medication or motion detectors (Aromatario et al., 2019). Organizations estimate that over $2 million per year is wasted owing to deficient data management, which can slow and inhibit the effective delivery of services. A key challenge has to do with how organizations manage their data processing; many organizations do not see data as an asset, even when they should.

Data management can be categorized into three systems: measuring, managing, and monetizing. An organization should effectively implement a system to measure the value contributed by its data resources properly. As important as the collection and use of data, so is the management of such data. Ignoring the key role data play within the care system is detrimental, and efficiency is at the core of its data management. Healthcare organizations must see data as a powerful asset and invest in leveraging data efficiently. Managing data includes having data under control for easy access vis-à-vis a centralized operating system within an organization. With such a system, data can help the organization to track data lineage and monitor access and acquisition.

With the recent need for public and population health and management, data have shifted from health organizations to the field and community. This type of data management would embody end-to-end value chain analysis and minimize the high cost of care. A clear data plan must be employed with manageable and reasonable goals with an iterative focus from population health to patient care. The recent shift to focus on comorbidities during the COVID-19 pandemic is a great example of the importance of giving strict attention to high-risk patient data.

Data relating to hypertension, heart disease, cancer, kidney disease, cancer, and more can help care practitioners focus and manage infection rates in high-risk populations. Proper data management is key as it provides information on what data you have, where they are located, and stored for retrieval. Indeed, American Health Information Management Association needs to create programs for health information management (HIM) professionals to be informed, giving them the latest educational tools for understanding, managing, analyzing, and protecting data.

4.2 Data Quality Management

A well-implemented data infrastructure can bring substantial benefits to HIM, including but not limited to higher quality personalized care of individuals, timely aid with data synergy within different hospitals for individual patients, the potential to use predictive modeling for analysis, tracking healthcare trends within communities, maintaining proper business intelligence, aligning physicians with organizational objectives, and creating an excellent feedback loop within the organization. The ultimate success of all such activities will also be dependent on the quality of data being well managed.

Most notably, high-quality data are influenced by the integrity of the data collection systems. Here, the need for competency assessment (CA) of staff such as informatics implementors and care professionals who would be the data collectors as well as end-users come into question. CA programs can be simple, such as a direct observation of technicians and practice test to complete certain data-related activities, or more sophisticated submission of data verification and integrity tests, data trends and analysis of treatment and/or the understanding of the overall quality of laboratory processes (Scherz et al., 2017).

Above all, quality management entails upholding the quality of data input and processes throughout the handling of data and having various quality control mechanisms and performance metrics in place.

4.3 Data Security and Privacy

With just a click away from the patient record, the threat to data security is immense. Data sensitivity has created challenges for health provider organizations, hence, the need for quality assurance professionals that would oversee and follow proper protocols in data security and management.

The prevention of inappropriate access, creation, or modification of patient health information is a major focus on information security. Simply, the most significant security risk to many healthcare organizations is the CPOE that can be executed without an alert system and safety checks. Also, the compounding integration system makes the process of protection even more challenging. The information-sharing system was designed to serve hospitals, home health agencies, long-term care facilities, physicians, and patients, which may have unintended consequences. Hence, The Nationwide Health Information Network, an initiative developed by the Office of the National Coordinator for promoting HIT use and data exchanges has inadvertently posed additional privacy challenges and security of health records.

Essentially, the three primary ways to protect data are following the Family Educational Rights and Privacy Act, HIPAA, Gramm–Leach–Bliley Act, and other industry standards. First, the HITECH Act has expanded the HIPAA security rule requirements to include business associates and their agents and subcontractors. Second, there are criminal and civil penalties prescribed for the breach of HIPAA regulations, for instance, in April 2017, the U.S. Department of Health and Human Services announced that wireless health services provider Cardio Net agreed to a $2.5 million settlement regarding potential noncompliance with HIPAA Privacy and Security Rules. This suit was initiated in 2012 when an employee's laptop was stolen from the person's car. The device contained the electronically protected health information of 1,391 individuals. This was a case of poor data management and risk management (HHS.gov, 2017). Finally, a breach in healthcare records compromised over 12 million medical records, and a cybersecurity organization Trap-X has identified MEDJACK as a tool for hackers to infiltrate hospital records.

Altogether, proper staffing and resource planning would aid in investigating and providing firewalls to protect the hospital and patient information (Cisco Systems Incorporated, 2017). Organizations have been further mandated to conduct or review a security risk analysis and implement security updates and to correct any identified security deficiencies as part of their risk management process. Proper risk analysis and assessment will help control and reduce security threats while preserving the confidentiality, integrity, and availability of computer-based information.

4.4 Other Challenges

With the shift from manual to electronic data recordkeeping, there are significant implications for this changing landscape. The shift from manual recording to EHR creates many other challenges aside from the aforementioned issues; for example, an international study found that nurses from 45 countries, including the United States, are generally dissatisfied with exisiting EHRs because of poor usability, system integration, lack of interoperability, poor accessibility, and poor training (Seckman & Carter-Templeton, 2019).

For years, clinical research has often been conducted operationally, and these come with compressional complexities; as such, there is a gross imbalance in the expenditures for care delivery compared to a job, housing and food, and education. Information extraction, data analytics, and specific device usage skills have become crucial for health informatics professionals and clinicians. Investing in data informatics is not yet a core strategy for solving health concerns in the community. The process of data exploitation and repositories has been slow to develop.

Further, in the systematic evaluation of data informatics, there is no real reference point to begin the steps, and when realized, it is rarely perfect, and multisource information is often used. A repeated evaluation is needed as the evaluation system is real-time, often making the transfer from research to practice challenging. For example, Höller et al. (2014) cited a study in which the system evaluation in an emergency department (ED) showed no significant impact on clinical outcome. The impact of these surveillance techniques should be evaluated in the degree to which it changes healthcare professionals' practice or how informative and vital is the alert. The use of informatics requires specialized training along with specific infrastructure and equipment. In training and development, health practitioners may be knowledgeable about HI theoretical foundations but are unwilling to participate in practical training to build hands-on skills needed for realtime patient monitoring.

The Commission on Accreditation for Health Informatics and Information Management Education and International Medical Informatics Association continue to develop curriculum to teach hands-on skills, yet they are still underdeveloped and vague. Sapsi and Sapsi (2017) note that a program evaluation conducted in 2013 determined students to continue to request hands-on experience. Some HI programs have recently started adopting educational EHR training tools such as information retrieval, knowledge representation, ontology, networking, statistics, data structures, and modeling into the curriculum.

The impact of increasing IT sophistication on clinical outcomes can be overcome with enhanced communication, improving clinical processes, or better oversight. Ganapathy et al. (2014) indicated no universally accepted nursing home IT maturity model to trend IT adoption and determine the impact of increasing IT maturity on quality. Such hands-on skills are especially needed for managing IT integration projects within homecare clinical informatics, medical informatics, and administrative activities.

5. Rethinking Health IT in the Digital Age

The use of health IT in care provider organizations has evolved rapidly over the last decade. Health IT is transcending from the digitization and archiving role via health records such as EHR, EMR, and personal health records to evolve as an enabler of transformation with value propositions (Agarwal et al., 2010). In the emerging role, the potential of health IT is beyond just supporting the automation or information handling function to a more strategic role in healthcare delivery and management.

Specifically, newer models of telehealth platforms are enabling community-wide care delivery models, using different levels of specialists and experts who are available at the time of need via digital access (Scott et al., 2012). As well, health exchanges are enabling models that can achieve seamless integration of care across geographical and institutional boundaries, and health infomediaries are evolving as extended-care models beyond those well-established hospitals or clinic-based models, empowering patients for self-management of health by sharing and exchanging knowledge in health platforms (Khuntia et al., 2017).

Irrespective of these developments, critics have argued that the anticipated value of health IT investments in healthcare organizations has not been achieved. Subtly, underlying this concern is the mismatch between health IT strategies and actual need. Here, we must reconcile the remarkable role of health IT in care organizations and attempt to improve on the mismatch or misalignment of health IT to operations. The missing puzzle piece is to look at the operations and workflow in health care. Business models do not work unless the operations are well aligned vis-à-vis value creation using IT; for example, earning revenue from health information exchange (HIE) involves a level of operational maturity. In this context, we suggest bridging research and practice to give an inward look to explore **workflow alignment** issues around health IT.

5.1 The Concept of Workflow Alignment

Workflows are routines involving work structure, processes, decisions, and the formulation of work relevant to practices and implementation. Workflows lead to choices that pertain to the structure and capabilities at the process level of a firm to execute its customer service choices. Workflows evolve, remain as a practice, and mostly do not change unless driven to alter their underlying structure and processes by some issues or challenges. Healthcare operations and workflows are based on best practices that have evolved over time. Inefficiencies are built into the process, and the workflows remain inefficient, yet functional.

The concept of workflow alignment is based on two fundamental assumptions:

1. The service performance is directly related to the ability to create an alignment between the service and design of appropriate workflow structure to support its execution. This assumption is consistent with the accepted argument that workflow design needs to follow a consistent pattern and routine; yet, there are variations based on unit and subunit levels of organizational structure.
2. We assert that the workflow alignment is inherently dynamic. The choices made by one unit, or subunit or even a firm, will over time evoke and follow normative and imitative actions by other units or subunits—which necessitates subsequent evolution of the workflow, integration, and response of service rendering activities (Russ et al. 2010).

5.2 Leveraging Health IT to Change Workflows

The thought of improving workflows by bringing in technology may be overwhelming, given the need to align workflow demands in real time depending on changing situations. The overall premise is based on the concept that workflow alignment is not a single-time event but a process that involves continuous change, adaptation, and integration to service activities. In this process, health IT can suggest new servicing models, improving on existing ones. Traditional processes may be reprogrammed.

Examples of IT-leveraged reengineering models are abundant in sectors other than health care, and one common example will clarify this proposition. McDonald's, and similar fast-food restaurant chains, used to follow the traditional food-serving models. Traditionally, waiter order taking was a lengthy process of menu offerings and choices; cooking involved flipping burgers, making sandwiches, and adding French fries and drinks; and then serving the customers. Although the model may be effective, it was certainly not cost efficient to serve one drive-in customer in a minute, with a $1 burger meal plan. Incorporating IT to take orders in drive-in was part of the solution. Yet, more important was the creation of combo meals, shared understanding from the customer to kitchen, and the subsequent information and workflow coordination to create tremendous efficiencies with effective value creation via the reengineering approach. We call for such an undertaking in health care, that is, how care organizations can change their workflows and processes leveraging on health IT, rather than implementing IT to fit existing workflows.

5.3 Where Do We Start and How?

Our suggestion is not complex: look inwards, understand the processes, but rethink the need and accompanying workflow, that is, reengineer.

Take a traditional practice in health care on the call bell in hospital patient rooms. Invented by

Florence Nightingale in 1800s, the first instance of a call bell was installed in the hospital, where a patient could ring from the bed and the bell would sound in the corridor. A mechanical valve was attached to the bell, which opened when the bell rang. The valve remained open so that a nurse could see who had rung. That guided the nurse to a specific ailing patient, rather than running up and down to see how patients are doing, often climbing too many stairs. In those times, hospitals had wards, in which patient beds were shared. As soon as a care provider walked across this room, a view of almost all patients can be obtained, or at the very least, a glance that showed how patients are doing.

Hospitals evolved from the ward-based rooms to private rooms; hence, the visual-oriented visit advantages were lost. More recently, hospital patients have private secluded rooms. Owing to this seclusion of patients, the need for a call bell became higher as an artifact for nurse–patient constant connection and communications (Lasiter 2014). Additionally, the call bell provided a sense of security. Communication systems, in general, have advanced; even so, a century later, the call bell is still an inconvenient yet indispensable necessity in hospital rooms and often been viewed as a nuisance when patients ring it repeatedly without any reason, or it creates alarm fatigue for nurses, cause frequent interruption of tasks, more so for high-risk, high-involvement tasks (Khuntia et al., 2015). For example, while calculating medications, mixing chemo drugs, or making phone calls, a call bell is very much interruptive. These activities need constant attention and substantial focus, so that no error occurs. Often nurses attending a "focal" patient are distracted by another patient. Confusion can exist regarding coverage of answering the calls: who is responsible: is this nursing assistants, licensed practical nurses, registered nurses, and/or the unit clerks. These are risks, and negative perceptions, associated with call bells.

On the positive side, call bells remain a key driver of patient satisfaction, and the emerging reimbursement models demand the inclusion of satisfaction and responsiveness as measures for payments (Roszell et al., 2009). Call bells help providers to address questions, resolve issues remotely, attend to accidental calls, assist with intravenous pump, toileting, pain medication, repositioning or more. Call bell response strategies have also emerged in respect of minimum time limit benchmarks to be adhered in responding to patients. As well, patient expectations regarding managing call bell systems and responses have increased. Hospitals are struggling to provide a team-based approach, sharing tasks and collaborative managements to call bell responses.

Impatience and frustrations around call bell mismanagements have been studied (Deitrick et al., 2010; Roszell et al. 2009; Torres 2007). Lack of call bell responses has led to disastrous circumstances. Some hospitals have taken a team-based approach from a practical viewpoint, with a quality of care and quality-of-work-environment principle approach. It has been suggested to follow a softer approach to call bell responses such as smiling, doing humor, creating reassurance, bringing in compassion, kindness, gentle touch, and the like. Addressing patients by name has become a norm. A few strategies have emerged to eliminate the call bell from the patient room, perhaps by implementing concepts such as "intentional multipurpose rounding." In addition, some call bell answering strategies have been automated, where the calls are escalated to higher levels, if not responded well. Amid these developments, the call bell concept (pressing a button to call the nurse when in need from a patient room) has not changed, whereas managing it has evolved quite extensively.

5.4 What to Do Going Forward?

The call bell case has led us to explore if existing communications and strategy of response via call bells are still relevant in current hospital workflow. Are there better avenues? Given the healthcare patient-visit practice has evolved, what would be the new workflow? Plausibly, innovations in health IT can address the issues, inefficiencies, and workflow challenges that still persist in call bell operations and offer a better solution to nurse–patient communication.

Technologically as with most airplanes, call bells have been replaced with call lights for the customers, retaining the original workflow structure. The call station is often located at the nurse's desk, which might be far away from where the particular nurse is when the call lights go off. Rooms have lights above them but it is difficult to see the particular room from far away. Many tasks can be accomplished by nursing assistants and keep the workflow efficient for the nurses. During busy times, responses to call lights might often take longer than expected.

With newer technology, changes may be implemented such as providing a menu-based call bell system, differentiating bath calls from calls for water and food or something else. Further, each one can ring at separate locations, based on work allocations. Some of these changes have created more confusion, while complicating the solution. For instance, several call lights can go off at the same time without a way to triage the importance of these competing calls, that is, requests for light or bed adjustments, pain administration, bathroom assistance, or something more serious such as a change in health status. The aggregated call bell response model is now disaggregated. A few hospitals have implemented a call-escalating system, which calls cell phones or similar mobile devices rather than disturbing alarms (Khuntia et al., 2016). That has turned the noisy call bell to a silent one; however, sometimes glitches in the system lead the calls to be sent to the phone of a single nurse, as s/he tries to differentiate the purpose of the call, creating more waste of time and confusion. Sparse ideas have emerged to use tracking software to monitor the frequency of call lights, reasons for activation, and response times. Reviewing these data could help identify patterns of call bell use, such as meal times, bed times, or shift changes. Using these data new approaches to staffing and staff utilization could be implemented to match peak call bell times. Or the data could drive process improvement whether it be response time or development of strategies to prevent the need for calls in general. An example would be frequent rounding on patients to ask them about needs before they have the opportunity to use their call bells. Notwithstanding, implementing and leveraging such systems are sparse.

Is it possible to eliminate call bells altogether from hospital workflows? The answer is a definitive "yes," if we go back to our earlier note, that is, if the visualization process is implemented throughout the hospital, like it used to be in the wards. Technologies like video camera integrated mobile screens that can show how patients are doing have a role here. The patient and nurse can then see each other rather than just talk. Video-Call button perhaps may work better, and the nurse then need not run. Arguably, such solutions, although realistically achievable, require a robust routine nursing rounding program to address many of the issues that the patients need, which would preclude them from having to use call bells. A reengineering approach via such technologies is certainly needed in the patient rooms, although such an upgrade comes with a cost. The resistance to change is dependent more on financial considerations rather than everyone's acknowledgment that the problem needs to be addressed. With increased transparency and online evaluations there is a much larger motivation for change and perhaps higher demands to meet the patient's expectations.

6. Conclusion

Thanks to expanding digitization of information, practitioners and patients can easily retrieve information right from their computer screens. In the clinic, practitioners can choose to speak instead of type, while taking a patient's history, therefore saving time.

The AMIA board of directors has sponsored creating an EHR-2020 task force for next-generation health information to chart the informatics competencies needed among clinical informatics practitioners in health care. AMIA is also committed to professional certification of clinicians and other health professionals , as well as others working at the interface of clinical practice, research, technology, certification for physicians, and advanced interprofessional clinical informatics certification for health professionals (Middleton, 2014). Further, the National Insititutes of Health have developed a review of operational, clinical research with better oversight of quality and efficient clinical trials (Smith et al., 2020). Data integration must be employed with sufficient metadata that can be interpreted and used appropriately across time in the healthcare ecosystem. This implies that data used across time must be secure, properly managed, and controlled even when sharing within the healthcare system. It also encourages competing healthcare delivery organizations to share patient information within a sound design patient-centered process appropriately. In the era of Big Data, where data are quantified and genomic, geospatial, social, and environmental data emerge on the Internet of things, care must be taken to ensure data security. Importantly, the right funding for the expansion of informatics will materialize excellent patient outcomes.

Finally, why is a call for workflow-alignment issues critical in the age of digital health? Apparently, both the practice and academic bodies of literature suggest that in the discourse of health and IT, digital transformation can be achieved only via an integrative perspective. Yet, discussions (and debates) surrounding the role of health IT often lean toward IT perspectives; simply, IT should aid health care in providing solutions to problems. This lopsided concept has missed the point that it is not just the IT that brings value, but value creation depends on the changed workflows, processes, and businesses due to IT.

In this light, for the IT-workflow alignment to create value, a number of factors are necessary. First, IT should be seen as an engine of innovation for continuous business and revenue stream to lead these transformations. Although this may not be true for all healthcare-related organizations, or may not be realized for all, the emerging health IT landscape is moving toward such a transformational impact of IT in health care. Second, we anticipate that the overarching goal of the organization is clear to IT and health professionals. Hence, both IT and health professionals in the organization understand how the organization makes (or loses) money. Third, IT need to be aligned to service provisions (for internal and external customers). This alignment is a well-understood objective in the organization. Third, IT responsibility is not restricted to only IT professionals. IT and health professionals have combined responsibilities for IT. Finally, the work practice and culture, even though differentiated at the work/unit practice level, are vibrant in the organization, both for IT and health professionals.

Healthcare operations and workflow are based on quite a set path that has evolved with time. However, some inefficiencies are built into the process while workflows remained inefficient yet functional. The thought of improving the workflows by bringing in IT is challenging but this is necessary for practicing digital health. Although there has been quite a demand to align DH technologies to workflows in health care, the concept of reengineering the workflows aligned to IT remains elusive; thus, we need to improvise ways of working around to achieve a distant objective in health care. In the DH era, such a call is a positive step in that direction.

Discussion Questions

Q1. What is healthcare informatics (HI) and health information management (HIM)? Discuss current developments and status of HI.
Q2. What is the main objective of HI? What are some of the more established versus newer HI domains?
Q3. Discuss innovation applications of some of the more established domains of HI, for example, clinical informatics (CI) and nursing informatics (NI).
Q4. What is the significance of data privacy and security?
Q5. What are the HIPAA regulations for HIM?
Q6. What are some of the issues and challenges of HI and HIM?
Q7. Why is there a need to call for workflow-alignment issues and challenges to be addressed in the digital age?
Q8. Provide an example of how health IT may be leveraged within a traditional workflow to improve process efficiencies and save costs.

References

Agarwal, R., Gao, G., DesRoches, C., & Jha, A. K. (2010). Research commentary—The digital transformation of healthcare: Current status and the road ahead. *Information Systems Research*, *21*(4), 796–809.

Aromatario, O., VanHoye, A., Vuillemin, A., Foucaut, A.M., Crozet, C., Pommier, J., & Cambon, L. (2019). How do mobile health applications support behavior changes? A scoping review of mobile health applications relating to physical activity and eating behaviors. *Public Health*, *175*, 8–18. https://doi.org/10.1016/j.puhe.2019.06.011

Ash, A. S., Mick, E. O., Ellis, R. P., Kiefe, C. I., Allison, J. J., & Clark, M. (2017). Social determinants of ealth in managed care payment formulas. *JAMA Internal Medicine*, *177*(10), 1424–1430. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5710209/

Ayache. N. (2016). Medical imaging informatics: Towards a personalized computational patient. *Yearbook of Medical Informatics*, (*Suppl. 1*), S8–S9. https://pubmed.ncbi.nlm.nih.gov/27199191/; https://doi.org/10.15265/iys-2016-s0022

Blažun Vošner, H., Carter-Templeton, H., Završnik, J., Kokol, P. (2020). Nursing informatics: A historical bibliometric analysis. *Computers, Informatics, Nursing*, *38*(7), 331–337. https://doi.org/10.1097/CIN.0000000000000624. PMID: 32404730. https://pubmed.ncbi.nlm.nih.gov/32404730/

Brieu, N., Armin, M., Ansh, K., Aleksandra, Z., Craig, B., Marietta, L. S., Tobias, W., Moritz, W., Keith, S., Marlon, C. R., & Schmidt, G. (2018). Deep learning-based PD-L1 tumor cell scoring of resected no small-cell-lung-cancer. Pathology Informatics Summit short abstracts. *Journal of Pathology Informatics*, *9*, S13–S14. https://www.jpathinformatics.org/text.asp?2018/9/1/50/249129

Cisco Systems Incorporated. (2017). *Midyear cybersecurity report*. https://www.cisco.com/c/dam/global/es_mx/solutions/security/pdf/cisco-2017-midyear-cybersecurity-report.pdf

Deitrick, L. M., Bokovoy, J., & Panik, A. (2010). The "dance" continues... evaluating differences in call bell use between patients in private rooms and patients in double rooms using ethnography. *Journal of Nursing Care Quality*, *25*(4), 279–287.

Dewsbury, G. (2019). Use of information and communication technology in nursing services. *British Journal of Community Nursing*, *24*(12), 604–607. https://doi.org/10.12968/bjcn.2019.24.12.604. PMID: 31800320. https://pubmed.ncbi.nlm.nih.gov/31800320/

Gamache, R., Kharrazi, H., & Weiner, J. P. (2018). Public and population health informatics: The bridging of Big Data to benefit communities. *Yearbook of Medical Informatics*, *27*(1), 199–206. https://doi.org/10.1055/s-0038-1667081

Ganapathy, L., Tran, T., Brownstein, J., & Niescierenko, M. (2014). Leveraging health informatics for global health needs assessment at home. *Annals of Global Health*, *80*(3), 161–162. https://doi.org/10.1016/j.aogh.2014.08.020

Gund, A., Sjöqvist, B. A., Wigert, H., Hentz, E., Lindecrantz, K., & Bry, K. (2013). A randomized controlled study about the use of eHealth in the home health care of premature infants. *BMC Med Inform Decision Making*, *13*(22). https://doi.org/10.1186/1472-6947-13-22

Höller, J., Tsiatsis, V., Mulligan, C., Karnouskos, S., Avesand, S., & Boyle, D. (2014). *From Machine-to-Machine to the Internet of Things: Introduction to a New Age of Intelligence*. ScienceDirect. https://doi.org/10.1016/B978-0-12-407684-6.00001-2

HHS.gov. (2018). *$2.5 million settlement shows that not understanding HIPAA requirements creates risk*. https://www.hhs.gov/about/news/2017/04/24/2-5-million-settlement-shows-not-understanding-hipaa-requirements-creates-risk.html

John Hopkins. (2020). Anti-PD-1: *A novel immunotherapy*. Johns Hopkins Kimmel Cancer Center. https://www.hopkinsmedicine.org/kimmel_cancer_center/cancers_we_treat/melanoma/research/anti_pd_1.html

Khuntia, J., Tanniru, M., Fregoli, F., & Nawrocki, M. (2016). Information systems impact on nurse call response—Role of velocity and uncertainty. *Pacific Asia Journal of the Association for Information Systems*, *8*(1). https://aisel.aisnet.org/pajais/vol8/iss1/3/

Khuntia, J., Tanniru, M., & Weiner, J. (2015). Juggling digitization and technostress: The case of alert fatigues in the patient care system implementation. *Health Policy and Technology*, *4*(4), 364–377.

Khuntia, J., Yim, D., Tanniru, M., & Lim, S. (2017). Patient empowerment and engagement with a health infomediary. *Health Policy and Technology*, *6*(1), 40–50.

Krick, T., Huter, K., Seibert, K., Domhoff, D., & Wolf-Ostermann, K. (2019). Measuring the effectiveness of digital nursing technologies: development of a comprehensive digital nursing technology outcome framework based on a scoping review. *BMC Health Services Research*, *20*(243). https://doi.org/10.1186/s12913-020-05106-8

Kulikowski, C. A. (2019). Beginnings of artificial intelligence in medicine (AIM): Computational artifice assisting scientific inquiry and clinical art—with reflections on present AIM challenges. *Yearbook of Medical Informatics*, *28*(1), 249–256. https://doi.org/10.1055/s-0039-1677895

Lasiter, S. (2014). "The button" initiating the patient–nurse interaction. *Clinical Nursing Research*, *23*(2), 188–200.

Middleton, B. (2014). Chairman's column: health informatics and healthcare transformation—entering the post-EMR era. *Journal of the American Medical Informatics Association*, *21*(6), 1141–1142. https://doi.org/10.1136/amiajnl-2014-003337

National Institutes of Health. (2017). Smart home and health informatics laboratories: Conceptual design. *Applied Clinical Informatics*, *8*(4), 1184–1196. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5802301/figure/FI170136ra-1/

Polasek, T. M., Shakib, S., & Rostami-Hodjegan, A. (2019). Precision medicine technology reality, not hype—The example of model-informed precision dosing. *F1000Research*, *8*, 1709. https://doi.org/10.12688/f1000research.20489.2

Roszell, S., Jones, C. B., & Lynn, M. R. (2009). Call bell requests, call bell response time, and patient satisfaction. *Journal of Nursing Care Quality*, *24*(1), 69–75.

Russ, A. L., Saleem, J. J., Justice, C. F., Woodward-Hagg, H., Woodbridge, P. A., & Doebbeling, B. N. (2010). Electronic health information in use: Characteristics that support employee workflow and patient care. *Health Informatics Journal*, *16*(4), 287–305.

Sapci, A. H., & Sapci, H. A. (2017). The effectiveness of hands-on health informatics skills exercises in the multidisciplinary smart home healthcare and health informatics training laboratories. *Applied Clinical Informatics*, *8*(4), 1184–1196. https://doi.org/10.4338/ACI-2017-08-RA-0136

Scherz, V., Durussel, C., & Greub, G. (2017). Internal quality assurance in diagnostic microbiology: A simple approach for insightful data. *PLoS ONE*, *12*(11), e0187263. https://doi.org/10.1371/journal.pone.0187263

Scott, J. D., Unruh, K. T., Catlin, M. C., Merrill, J. O., Tauben, D. J., Rosenblatt, R., Buchwald, D., Doorenbos, A., Towle, C., & Ramers, C. B. (2012). Project ECHO: A model for complex, chronic care in the Pacific Northwest region of the United States. *Journal of Telemedicine and Telecare*, *18*(8), 481–484.

Seckman, C., & Carter-Templeton, H. (2019). Summer Institute in Nursing Informatics 2019 healthcare informatics. *CIN: Computers, Informatics, Nursing*, *37*(11), 558–563. https://doi.org/10.1097/CIN.0000000000000599

Sepúlveda, O. (2014). Public health informatics and the public health workforce in an era of change. *American Journal of Preventive Medicine*, *47*(5), 386–387. http://www.sciencedirect.com/science/article/pii/S074937971400381X; https://doi.org/10.1016/j.amepre.2014.07.014

Shortliffe, E. H., Perreault, L. E., Wiederhold, G., & Fagan, L. M. (2001). *Medical Informatics: Computer Applications in Health Care and Biomedicine*. Springer Verlag. https://doi.org/10.1007/978-0-387-21721-5

Sim, I., Tu, S. W., Carini, S., Lehmann, H. P., Pollock, B. H., Peleg, M., & Wittkowski, K. M. (2014). The Ontology of Clinical Research (OCRe): An informatics foundation for clinical research science. https://www.science.gov/topicpages/c/clinical+research+informatics.html

Smith, L. S., Siegel, G., & Kennedy, A. (2020). Assessing the operational complexity of a clinical trial: The experience of the National Institute of Mental Health. *Clinical Researcher*, *34*(3). https://acrpnet.org/2020/03/10/assessing-the-operational-complexity-of-a-clinical-trial-the-experience-of-the-national-institute-of-mental-health/

Spratt, S. S., Batch, B. C., Davis, L., Dunham, A., Easterling, M., Feinglos, M., Granger, B., Harris, G., Lynn, M., Maxson, P., Shah, B., Strauss, B., Thomas, T., Califf, R., & Lynn, M. (2015). Methods and initial findings from the Durham Diabetes Coalition: Integrating geospatial health technology and community interventions to reduce death and disability. *Journal of Clinical & Translational Endocrinology*, *2*, 26–33. https://core.ac.uk/download/pdf/82795331.pdf

Thiébaut, R., Cossin, S., & Section Editors for the IMIA Yearbook Section on Public Health and Epidemiology Informatics. (2019). Artificial intelligence for surveillance in public health. *Yearbook of Medical Informatics*, *28*(1), 232–234. https://doi.org/10.1055/s-0039-1677939

Torres, S. M. (2007). Rapid-cycle process reduces patient call bell use, improves patient satisfaction, and anticipates patient's needs. *Journal of Nursing Administration*, *37*(11), 480–482.

University of Illinois Chicago. (2020, July 8). *A brief history of health informatics*. https://healthinformatics.uic.edu/blog/a-brief-history-of-health-informatics/

Volynskaya, Z., Chow, H., Evans, A., Wolff, A., Lagmay-Traya, C., & Asa, S. (2018). Integrated pathology informatics enables high-quality personalized and precision medicine: Digital pathology and beyond. *Archives of Pathology & Laboratory Medicine*, *142*(3), 369–382. http://dx.doi.org/10.5858/arpa.2017-0139-OA

Young, L. S., Chaysinh, S., Garfield, C., Hassan, S., & Noel, M. (2011). NICU-2-HOME: Supporting the transition to home from the Neonatal Intensive Care Unit using a mobile application. In *CHI EA 2011—29th Annual CHI Conference on Human Factors in Computing Systems, Conference Proceedings and Extended Abstracts* (pp. 2257–2262). https://doi.org/10.1145/1979742.1979947