Public Health Informatics

25

Saira N. Haque, Brian E. Dixon, Shaun J. Grannis, and Jamie Pina

Learning Objectives
At the end of this chapter, the reader should be able to accomplish these objectives:

- Define public health informatics.
- Explain the impact of informatics on population health.
- Identify different types of information systems used to support public health.
- Describe how public health informatics relates to the field of clinical informatics.
- Discuss how clinical and public health informaticians work together to monitor and improve population health.

Practice Domains: Tasks, Knowledge, and Skills
The following core competencies are covered in this chapter:

- K021. Determinants of individual and population health
- K047. Social determinants of health

S. N. Haque (✉)
Medical Outcomes and Analytics Group, Medical Affairs, Pfizer, New York, USA
e-mail: saira.haque@pfizer.com

B. E. Dixon
Department of Epidemiology, Indiana University Richard M. Fairbanks School of Public Health, Indianapolis, IN, USA

Center for Biomedical Informatics, Regenstrief Institute, Indianapolis, IN, USA

S. J. Grannis
Department of Family Medicine, Indiana University School of Medicine, Indianapolis, IN, USA

Center for Biomedical Informatics, Regenstrief Institute, Indianapolis, IN, USA

J. Pina
Association of State and Territorial Health Officials, Waltham, USA

Key Terms
Disease registries, immunization registries, population health, public health, surveillance systems

Case Vignette
Local payers and hospital systems started Safe Community Health Information Exchange (SCH) to promote information sharing throughout the community. As SCH grew, additional stakeholders became involved in exchanging clinical data to support care coordination and quality improvement activities within the hospitals and physician practices. These stakeholders included laboratories, long-term and post-acute care facilities, federally qualified health centers, and local and state public health agencies.

Providers in the community used the SCH infrastructure to submit electronic laboratory results for communicable diseases to public health authorities, and public health agencies used the electronic health records (EHRs) to investigate disease outbreaks. For example, a local measles outbreak originated from a group of people who had not received the vaccine. This was discovered by tracing a cluster of children who arrived at different emergency departments.

SCH's functionality was tested during the novel coronavirus (COVID-19) pandemic. During the pandemic, SCH looked up patient information to support contact tracing, identify those with exposure, and give them directions about quarantining. Once vaccines became available, the connection among the state's immunization information systems (IIS, also known as immunization registries) became of increased importance. However, some challenges occurred because SCH and the IIS possessed fragmented information about vaccines administered, where they were administered, and by whom. The IIS tracked those who had been vaccinated at a site with an IIS connection, whereas SCH had access to data on those vaccinated at clinical sites with commercial EHRs. SCH was able to share clinical data with the local Department of Veterans Affairs (VA) clinic, but federal law prohibited the VA from submitting vaccine administration records to the IIS.

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As states moved towards broader vaccination coverage of the population, providers wanted to ensure that specific patient populations (e.g., those with cancer or hypertension) were vaccinated. Providers became frustrated when they could not access information on those who visited public health-operated mass vaccination and mobile vaccination sites as well as VA clinics because data from those sites were not connected to SCH. Moreover, it was difficult to query the regional health information organization (RHIO) for unvaccinated people because the IIS was not integrated into the RHIO's infrastructure.

Lack of integration was determined to be mainly due to lack of funding at the state health department, which receives most of its revenue from federal grant dollars. Because the state agency's budget had mostly flatlined and had been periodically reduced, it had only enough funding to support minimal services provided by SCH. Although SCH leadership was passionate about public health, business owners had to be good stewards of their limited funding. They could not afford to offer many free-of-charge services to the state health department. A local philanthropic foundation stepped up to provide the funding necessary to support integration between SCH and the IIS.

As SCH and IIS integration was completed, state health authorities could query records to identify teachers and school-aged children who had not yet been vaccinated for COVID-19. Analysis of the results identified three geographic areas with a high concentration of unvaccinated people. The health department then set up vaccine clinics at public schools in those areas, providing information to community residents about the benefits of vaccination and offering free vaccines. With support from health care, school, religious, and community leaders, vaccination rates increased, and the outbreak subsided, so schools could reopen. From that point, epidemiologists could more efficiently monitor community vaccination rates for COVID-19 and other vaccine-preventable diseases, and clinicians in SCH could efficiently query the IIS to receive up-to-date vaccine forecasts for their patients. For the VA clinic, the state health department had to implement a workaround with SCH to enable epidemiologists to view VA immunization records.

Introduction

Informatics is the *science of information*, studying the representation, processing, and communication of information by computers, humans, and organizations [1]. Informatics draws on a broad spectrum of theories from the computer, information, and social sciences. It seeks to fill the gap between (1) the correctness problem (how to assure the correct working of a program) and (2) the pleasantness problem (how to build adequate programs and systems to support the people using them) [2]. In practice, informatics often requires

three components: (1) knowledge of the domain in which it is being applied (e.g., business, health care), (2) knowledge of how information systems are to be designed and developed to appropriately manage data and information, and (3) knowledge of how organizations and people interact with or use information systems to achieve their goals (e.g., treat patients, transact business).

The term *public health informatics (PHI)*, the subject of this chapter, is often used synonymously (or confused) with a host of similar-sounding but distinct "adjectives" as noted by Hersh [3], including *clinical informatics*, *health informatics*, and the broader field of *biomedical informatics (BMI)*. BMI is an interdisciplinary field that studies and pursues effective uses of biomedical data, information, and knowledge for scientific inquiry, problem-solving, and decision making, driven by efforts to improve human health [4]. BMI is often conceived of in the United States as encompassing health informatics in addition to clinical and public health informatics, as depicted in Fig. 25.1 [5]. Although clinical informatics applies health information technologies in the provision of individual clinical care [6], PHI seeks to apply health information and technologies to improve population health, including the surveillance and prevention of disease and general health promotion [7].

The Scope of Public Health Informatics

Although public health professionals have utilized information and communication technologies (including the fax machine) to capture, store, manage, exchange, and analyze information about populations, the rise of PHI as a discipline within public health and informatics began at the start of the twenty-first century. During the first decade, PHI efforts around the world were characterized by a focus on the core public health function of monitoring populations: early detection of bioterrorism [8], such as the anthrax attacks in the United States [9] and the Tokyo subway attacks [10], and global health threats such as severe acute respiratory syndrome [11], the H1N1 pandemic [12], and the COVID-19 pandemic [13]. The threat of a large-scale epidemic has not diminished in recent years, as evidenced in 2014 by Middle East respiratory syndrome [14, 15] and Ebola [16], but changes in national policies and funding priorities have steered PHI in new directions [17]. Today, PHI not only supports core public health functions [18] but also contributes to the following activities in support of population health and strengthening the public health infrastructure [19]:

1. *Implementations of informatics systems such as electronic health record (EHR) systems and health information exchange (HIE)*. PHI often contributes to an eHealth strategy established by a nation's health ministry by supporting capturing, managing, and exchanging data to
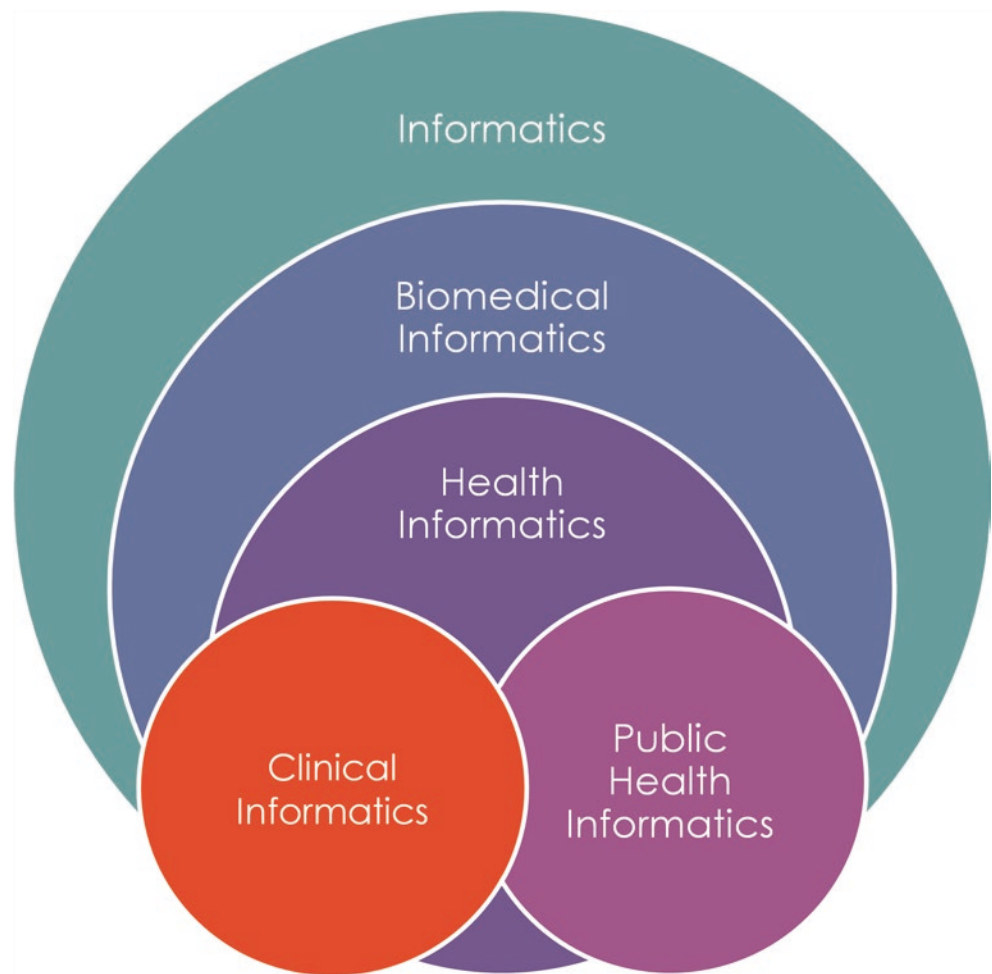
monitor population health across local, regional, and national levels. Recent efforts by the U.S. Centers for Disease Control and Prevention (CDC) have focused on the adoption of technologies related to meaningful use [20], including electronic laboratory reporting (ELR), syndromic surveillance, immunization information systems (IIS), and cancer registries.

2. *Measurement of population health indicators within and across jurisdictions*. Just as EHR systems contribute to better measurement of clinical outcomes using e-measures (refer to Chap. 5), PHI focuses on developing population-level health indicators. Public data sets, including CDC's Behavioral Risk Factor Surveillance System and the US Census Bureau's American Community Survey, are integrated and leveraged to create the County Health Rankings [21], composite scores representing the health of the population living in a geographical county within the United States [22].

3. *Implementation of patient-centered care models that support broader public health system strategies to achieve better, coordinated care while reducing costs (e.g., the Triple Aim)*. Patient-centered care models seek to consider patient preferences, self-management, and self-

reported outcomes in clinical decision-making (refer to Chap. 24). Contributions from PHI include leveraging social media and short message service (SMS) text messages (1) to identify disease outbreaks [23], (2) to improve maternal and child health outcomes [24, 25], and (3) to inform at-risk populations about methods for lowering their risk of infection [26].

Informatics Capacity in Public Health Agencies

Informatics is challenging in public health, given limited resources and a limited workforce. Budget reductions in public health following the 2009 American economic recession as well as H1N1 pandemic limit the ability of public health agencies to develop, purchase, and deploy new informatics systems [27, 28]. For example, although the Health Information Technology for Economic and Clinical Health (HITECH) Act provided billions of dollars for health care providers to adopt EHR systems, it provided only $30 million for public health agencies to enhance their infrastructure to receive and analyze data from EHRs [29]. The lack of

support for public health agencies is particularly problematic because with increased provider EHR implementation comes more data in different formats for public health agencies to process. A shrinking public health workforce compounds limited financial resources. In a 2017 survey of the public health workforce, nearly half of workers in state and local agencies reported they planned to leave within 5 years [30]. Fewer experienced workers places stress on agencies to compute and analyze increasing volumes of data with fewer human resources.

The most up-to-date information on the PHI workforce comes from the same 2017 survey of local and state public health agency workers. Approximately 1% of the public health workforce is employed to deploy or operate PHI systems [31], and this proportion is lower in local health departments versus state health agencies. Moreover, less than one-third of public health informaticists report working in an informatics division. Most are employed in epidemiology, vital records, and communicable disease divisions [31].

The CDC currently sponsors an official, registered apprenticeship program in PHI [32] that supports approximately ten fellows each year placed in state and local health departments. Anecdotal information suggests that the volume of fellows has picked up in recent years, especially in the wake of the COVID-19 pandemic. However, it is unlikely that the fellowship at the CDC can fulfill the training needs of the nation's public health system. Therefore, more investment in PHI education and training is required [28, 31]. It is hoped that a recent training program in PHI announced by the U.S. Department of Health and Human Services' (HHS) Office of the National Coordinator for Health Information Technology (ONC) [33] will train approximately 4000 PHI specialists who can transform the nation's public health infrastructure.

Public Health Informatics Education and Training

Although the current PHI workforce is limited, recent shifts in opinion are favorable to the future. Since 2012, several stakeholder groups have convened independently to discuss the challenges facing modern public health. First, CDC reorganized its division responsible for national public health surveillance coordination. The division hosted strategic planning sessions culminating in several reports detailing national surveillance activities' challenges [34]. Second, the Council of State and Territorial Epidemiologists updated its "Blueprint" for public health surveillance, outlining the challenges facing state-level surveillance activities [35]. With support from the Robert Wood Johnson Foundation, the Public Health Informatics Institute (PHII) convened a series of meetings with local health department epidemiologists to discuss and outline future requirements for surveillance systems at that level of public health. Finally, the Association of

Schools and Programs of Public Health (ASPPH) convened a panel to review and update the Master of Public Health (MPH) core to reflect twenty-first century challenges [36].

Although convened independently, these groups reached very similar conclusions regarding the role of informatics in public health. CDC created a division within its surveillance core to focus on PHI. The revised Blueprint for surveillance and PHII workshops identified PHI as critical to the future of surveillance practice. Finally, ASPPH identified PHI as a core competency for future public health leaders. These efforts in recent years should stimulate change within schools of public health and other public health training programs that will lead to a public health workforce knowledgeable about PHI and a larger segment of the workforce that concentrates on PHI.

There is a range of approaches to meet the goals of PHI education [37]. Approaches include integrating literature search training, hands-on/real-world experiences, didactic modules, and case studies. Topical areas cover the disciplines of health and health care, social and behavioral science, and information science and technology.

Major Players in Public Health Informatics

Numerous entities are interested in the public health system is complex, with various organizations at local, state, and federal levels. At the federal level, CDC remains the leading public health institute in the United States. Although many groups within CDC are engaged in PHI work, the largest and most active center is the Center for Surveillance, Epidemiology, and Laboratory Services [38]. This center is driving data modernization and informatics innovation for public health and has increased efforts in the wake of the COVID-19 pandemic, highlighting the need for public health to improve data coordination across all stakeholders [39]. In 2008, several public health associations came together to form the Joint Public Health Informatics Taskforce (JPHIT). Since then, others from the public health and informatics communities have joined JPHIT to create an open forum that enables coordinated and collaborative development and implementation of PHI priorities, a unified voice on national PHI policy issues, and a focus on improving the performance of the public health system through informatics [40]. The list of members and affiliates of JPHIT provides a "who's who" of PHI and includes (as of 2021) the following associations:

- American Immunization Registry Association (AIRA), which promotes the development, implementation, and interoperability of IIS.
- American Medical Informatics Association (AMIA), the professional home of leading informaticians: clinicians, scientists, researchers, educators, students, and other informatics professionals who rely on data to connect

people, information, and technology. Specifically, its PHI working group focuses on the intersection between technology and public health.

- American Public Health Association (APHA) is focused on improving public health. The Health Informatics Information Technology member section is specifically focused on PHI.
- Association of Public Health Laboratories (APHL), which advocates for public health laboratories and provides guidance on the development and implementation of laboratory information management systems.
- Association of State and Territorial Health Officials (ASTHO), which represents public health agencies and includes an e-Health portfolio that provides resources to state health agencies.
- Council of State and Territorial Epidemiologists (CSTE) works to advance public health policy and epidemiologic capacity.
- National Association of County and City Health Officials (NACCHO) serves local health departments in the United States and fosters informatics in local health agencies.
- National Association of Health Data Organizations (NAHDO) seeks to improve health care data collection and use.
- National Association for Public Health Statistics and Information Systems (NAPHSIS) represents the state vital records and public health statistics offices in the United States.
- North American Association of Central Cancer Registries (NAACCR) develops and promotes uniform data standards for cancer registration, certifies population-based registries, aggregates and publishes data from central cancer registries, and promotes the use of cancer surveillance data and systems.

Several groups are working on various aspects of PHI. No matter the effort, PHI's success is predicated on a large volume of available individual patient data. As more providers implement EHRs, the availability of information that can be used in the aggregate to support public health will also increase. Examples of specific systems that are used to support public health are outlined in the next section.

Examples of Public Health Information Systems

Public health practice uses a wide variety of data types, data sources, and data management techniques. Although many data necessary for public health processes are generated during routine clinical care, public health agencies require a broader set of data captured directly or indirectly from non-clinical sources. Clinical data are often insufficient to address environmental, genetic, social, and behavioral factors

required to address major population health challenges [41, 42]. For example, consider the challenge of addressing increasing rates of diabetes in a community. Clinical data sources, including the EHR, will have robust data on patients with known diabetes diagnoses and/or patients taking prescription medications to treat diabetes. However, EHR systems may not be the best source for identifying individuals with undiagnosed diabetes who are not currently receiving care.

Moreover, individuals in the community who are prediabetic may not be in care or receive regular screenings for diabetes. To identify these individuals, public health agencies may need to hold community screening events. They may further need to work with clinics and hospitals to encourage all residents to schedule a wellness exam with a primary care provider to identify individuals with undiagnosed diabetes.

Non-clinical information can include a patient's geospatial location, socioeconomic status, school affiliation, and proximity to risk factors such as elevated soil lead levels within a community [43–47]. Civil registration records, such as birth and marriage certificates and tax records, are examples of data sources that could provide useful non-clinical data for assessing population health. Thus, clinical data must be augmented with additional, non-clinical data sources to fully inform public health processes and improve population health outcomes. This is often a critical role public health agencies play in their community.

Additionally, clinical systems often lack sophisticated information extraction techniques and case detection algorithms to identify clinical data needed for public health processes [48]. For example, although EHR systems can route the results of a laboratory culture for methicillin-resistant *Staphylococcus aureus* (MRSA), clinical systems cannot consistently identify whether the result was positive or negative. Case detection techniques and strategies may include natural language processing (NLP), rules engines, and machine learning algorithms; these techniques can substantially improve case identification [49, 50]. Finally, because clinical and non-clinical data are often stored in separate databases as separate islands of information, public health agencies often lack efficient access to integrated population-level health data, hindering the ability to identify and manage a community's specific public health needs. Thus, effective integration with EHR systems, HIE networks, and other health data systems is needed to optimize digital support of public health processes [51].

Electronic Laboratory Reporting

ELR refers to the process of electronically transmitting laboratory reports that identify reportable conditions from laboratories to public health stakeholders and has been

shown to improve the timeliness and completeness of disease reporting [52]. Most states can receive electronic reports from laboratories [53], and the volume of electronic reporting to state agencies is expected to increase given that the meaningful use and Promoting Interoperability Programs [20] require eligible hospitals and encourage eligible providers to submit notifiable disease laboratory results to public health agencies using ELR. However, limitations of ELR have been reported [54]. Laboratories often lack detailed patient demographic information required by public health departments. Certain diseases cannot determine when a test result reflects a new case or chronic disease.

As clinical data are increasingly captured electronically, there is greater potential for more complete and timely reports through increased automated electronic public health reporting. An automated ELR system that leverages data from an integrated HIE can overcome some of the aforementioned limitations by enhancing population-based reporting with additional data such as recent laboratory results, improved patient and provider demographics, and medication history [8, 55]. For example, Overhage and colleagues [52] compared ELR messages identified by an HIE with manually reported cases from physicians and hospital infection control professionals (Fig. 25.2). The analysis revealed that an automated ELR detection system implemented with fairly basic rules could significantly improve the identification of cases that need to be reported to public health authorities.

Electronic Case Reporting

Although ELR messages move laboratory results directly to public health agencies, ELR data alone is often insufficient to support disease surveillance efforts. Public health agencies also desire to receive electronic case reporting (eCR) messages sent from physician practices or hospitals. These messages include details beyond what can be sent in an ELR message, such as the patient's disposition at the time of clinical diagnosis and medication prescribed for disease treatment. An eCR message might also contain details about the patient's vaccination history, social determinants, and symptoms. Disease investigation specialists at the public health department can use these details to identify suspected or probable cases before laboratory reporting. In the 2019 Promoting Interoperability Program, the U.S. Centers for Medicare & Medicaid Services (CMS) promoted eCR as a valid public measure for hospitals. The requirement nudges hospitals to send "production data" to public health authorities in their jurisdiction.

Today, most eCR messages are electronic faxes sent from physician offices. Although known to most public health informaticians, the whole world now knows that clinician reporting is largely fax-based, thanks to the COVID-19 pandemic. Reporters from *The New York Times* and other major news outlets ran stories showing how piles of faxed reports were accumulating in local public health agencies during the crisis [56]. Because faxed reports had to be manually entered into information systems during the pandemic, it could take

Fig. 25.2 Overhage and colleagues' comparison of ELR messages identified by an HIE to manually report cases from physicians and hospital infection control professionals [52]
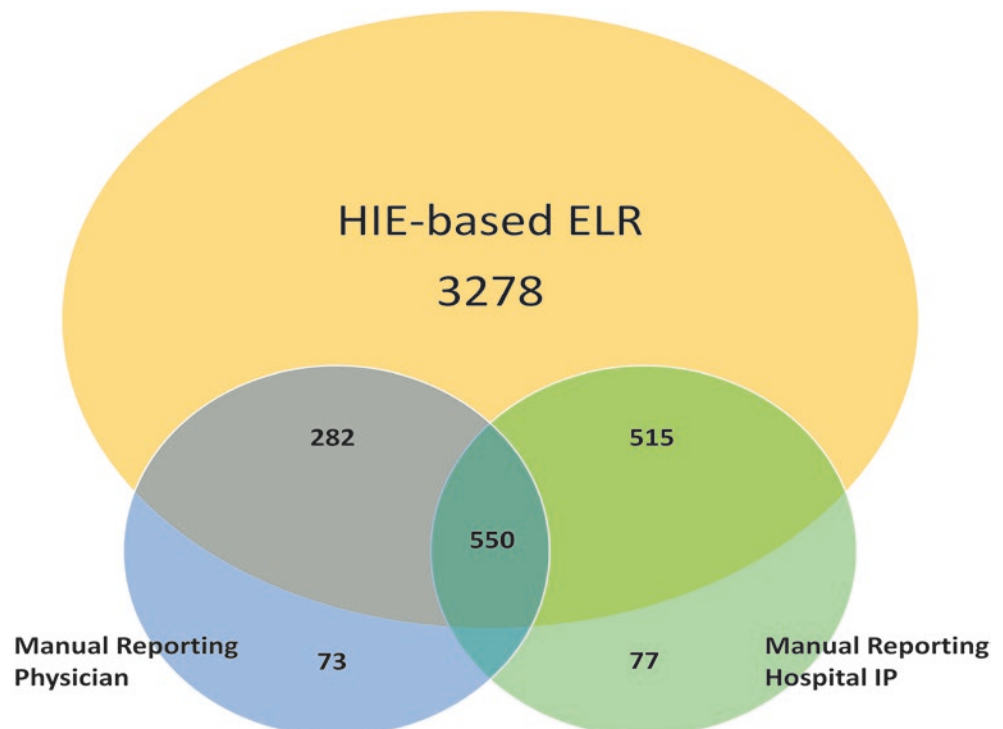
at least two weeks for a case to be entered and sent to CDC for surveillance. Reporters and the public were shocked to find out that in 2020, the world relied on 1980s technology to track disease spread in communities.

To advance the transition to eCR, CDC and multiple health agencies are working to improve US public health infrastructure [35]. For example, the Digital Bridge initiative facilitates a series of pilot programs across the United States [36, 37]. Public health agencies receive structured eCR messages from hospitals exported from EHR systems. Major EHR vendors partnered with the Digital Bridge consortia to implement a standards-based data exchange on notifiable disease cases. A more experimental demonstration project involving CDC, Georgia Tech Research Institute, and the Regenstrief Institute leveraged the emerging standard FHIR (Fast Health Interoperable Resources, detailed in the chapter *Health Information Exchange and Interoperability*) to query eCR data elements from an EHR after an ELR message is received from a physician practice [41]. In 2021 and beyond, these initiatives are hoped to bring production-grade solutions to HIE networks and EHR systems.

Syndromic Surveillance

Syndromic surveillance refers to a spectrum of processes that focus on real-time use of early disease indicators derived from prediagnostic data to detect and characterize events requiring public health investigation before definitive diagnoses are made [55]. Many states leverage syndromic surveillance systems for their entire populations [8, 57]. Furthermore, CDC created the National Syndromic Surveillance Program (NSSP) to support national surveillance efforts [38]. Local and state health agencies, as well as CDC, use the NSSP to monitor health trends.

Several studies demonstrate that electronic data from emergency department encounters, hospital admissions, and retail and pharmaceutical sales can signal the onset and evolution of disease outbreaks earlier than traditional surveillance methods [58]. Today, most syndromic surveillance systems utilize emergency department information in combination with hospital admissions data (e.g., ICD-10-CM codes). However, syndromic data can come from any one of the following sources [59]:

- Emergency department visits
- Laboratories
- Over-the-counter medication sales
- School absenteeism records
- Social media
- Emergency medical and management services
- Poison control center records
- Nurse call (triage) lines

The aforementioned data sources provide public health agencies with a wide range of structured and unstructured (free-text) data. Syndromic surveillance systems increasingly use NLP techniques to examine unstructured data to find disease indications or combinations of symptoms that constitute a syndrome (e.g., influenza-like illness). The performance of syndromic surveillance systems can be improved with better techniques for parsing and interpreting unstructured data. However, modern approaches are useful for tracking influenza and other seasonal illnesses, including heatstroke. Some health departments further use syndromic surveillance systems to identify bicycle accidents and food poisoning events.

Population Health Disease Registries

Population-based registries contain records for individuals residing in a defined geographical area who meet the criteria for a specific disease. Public health has traditionally maintained disease-specific population registries to support various public health functions, including traditional epidemiological analyses and emerging use cases that closely coordinate population health management with clinical stakeholders [60–62]. These registries increasingly rely on integration with electronic clinical systems.

Chronic Disease Registries

To allow public health officials to capture and analyze chronic disease data, the Council for State and Territorial Epidemiologists identified six categories of information captured by chronic disease registries: cancer, cardiovascular disease, tobacco and alcohol use, physical activity and nutrition, other diseases, and risk factors, and overarching conditions [63]. Because chronic disease registries span a wide spectrum of conditions, their implementation and supporting systems vary.

Immunization Registries

Immunization registries, often called IIS, have demonstrated the ability to increase population coverage rates for vaccines and mitigate the administration of duplicate immunizations [64, 65]. The Promoting Interoperability Programs encourage health care providers to transmit immunization records to IIS. The introduction of the COVID-19 vaccine in late 2020 also pushed many public health agencies to require electronic submission of vaccination data from hospitals, clinics, pharmacies, and local health agency sites where the vaccine was offered. Consequently, clinical care systems have deployed automated unidirectional electronic transmission of immunization data to public health. However, although routine bidirectional information exchange between clinical systems and IIS is not widely deployed, strategies for doing so are emerging [66, 67].

Cancer Registries

Cancer registries capture details on each cancer case in the United States to effectively monitor and address cancer burden, including patient history, diagnosis, treatment, and status. Data are first collected by local cancer registries and contribute to population-based registries. The data support various analyses, including determining cancer incidence, calculating survival rates, evaluating clinical outcomes, treatment modalities' efficacy, quality of life; assessing referral patterns; and informing geographic distribution of resource allocations [68, 69]. Although cancer case reporting is comprehensive, early case reporting can be delayed and incomplete [70, 71]. Electronic sources may help address these shortcomings [72].

Community Health Assessment

Integrating EHR data with non-clinical data holds great promise for addressing the social determinants of health (SDOH) [73] and health inequities such as lack of access for racial and ethnic minorities [74]. Although EHRs are rich in location-specific clinical data that allow us to uncover geographically dependent inequities in health outcomes, several other information systems outside of health care delivery complement those data to support analysis of community-level characteristics relating to health. For example, the US Census Bureau's American Community Survey captures data on education, housing, and transportation in a community at levels more granular than the ZIP Code. These SDH account for a significant proportion of a person's overall health and well-being. When meaningfully integrated, clinical and social determinant data enable clinicians, researchers, and public health professionals to actively address the social etiologies of health disparities [52, 75, 76] (see Fig. 25.3).

Although efforts are underway to increase support for capturing SDH data in EHR systems, some experts contend that the EHR may not be the best system for capturing and managing SDH data [77]. Instead, efforts are underway to enable EHR- and HIE-based tools that allow providers to identify patients at risk for social and behavioral needs [78] and connect them to services, including community-based organizations, that can address those needs in support of health and well-being. For example, Aunt Bertha (company.auntbertha.com) is a popular tool that allows medical practices to find social and behavioral services in the community to refer their patients. Tackling upstream problems, such as housing instability, through a population health program designed to address economic needs can reduce morbidity and increase life expectancy in a community when paired with robust screening and treatment plans for medical needs.

Contact Tracing Applications

The COVID-19 pandemic put a spotlight on contact tracing, a long-standing epidemiological process in which individuals with a newly diagnosed case of a notifiable disease are linked to their social network to identify individuals who may have transmitted the disease or those who may have received the disease. Contact tracing is an important tool for identifying sexual partners in cases of HIV, syphilis, chlamydia, and gonorrhea [79]. In previous outbreaks of international concern, including an Ebola outbreak in 2014 [80] and a measles outbreak on an international flight [81], contact tracing was considered to play a key role in identifying secondary cases.

The COVID-19 pandemic highlighted the need for better and more integrated digital contact tracing solutions that scale across local, state, and federal levels. Several countries, including Taiwan, South Korea, and China, touted the benefits of digital contact tracing apps in helping to flatten the curve in those nations [82, 83]. In the United States, Apple and Google provided tools to help states integrate contact tracing capabilities in mobile phones with case reporting systems. Yet, only a few states implemented the standards-based platform. Mistrust in big technology companies, fueled by concerns over privacy of the data captured in contact tracing apps, limited adoption and use of the technology in the United States [84]. So, although promising, digital contact tracing has a long way to go before it can be scaled and effective in the next global pandemic or national disease outbreak.

Toward Public Health Decision Support

As discussed in Chap. 7, clinical decision support (CDS) provides clinicians, staff, patients, or other individuals with relevant knowledge and person-specific information, intelligently filtered or delivered at appropriate times, to enhance health and health care decision making [85]. Among other quality and safety outcomes, CDS has been shown to effectively improve clinician adherence to preventive care guidelines and alert clinicians to potentially adverse medication outcomes [86–88]. Various forms of CDS have been introduced into current care processes through the implementation of EHR systems [89, 90].

Illustration

In recent years, the scope of CDS has been expanding to incorporate public health contexts and use cases. Traditional examples of patient-centered CDS alert clinicians when abnormal, unexpected, or harmful clinical results are noted,
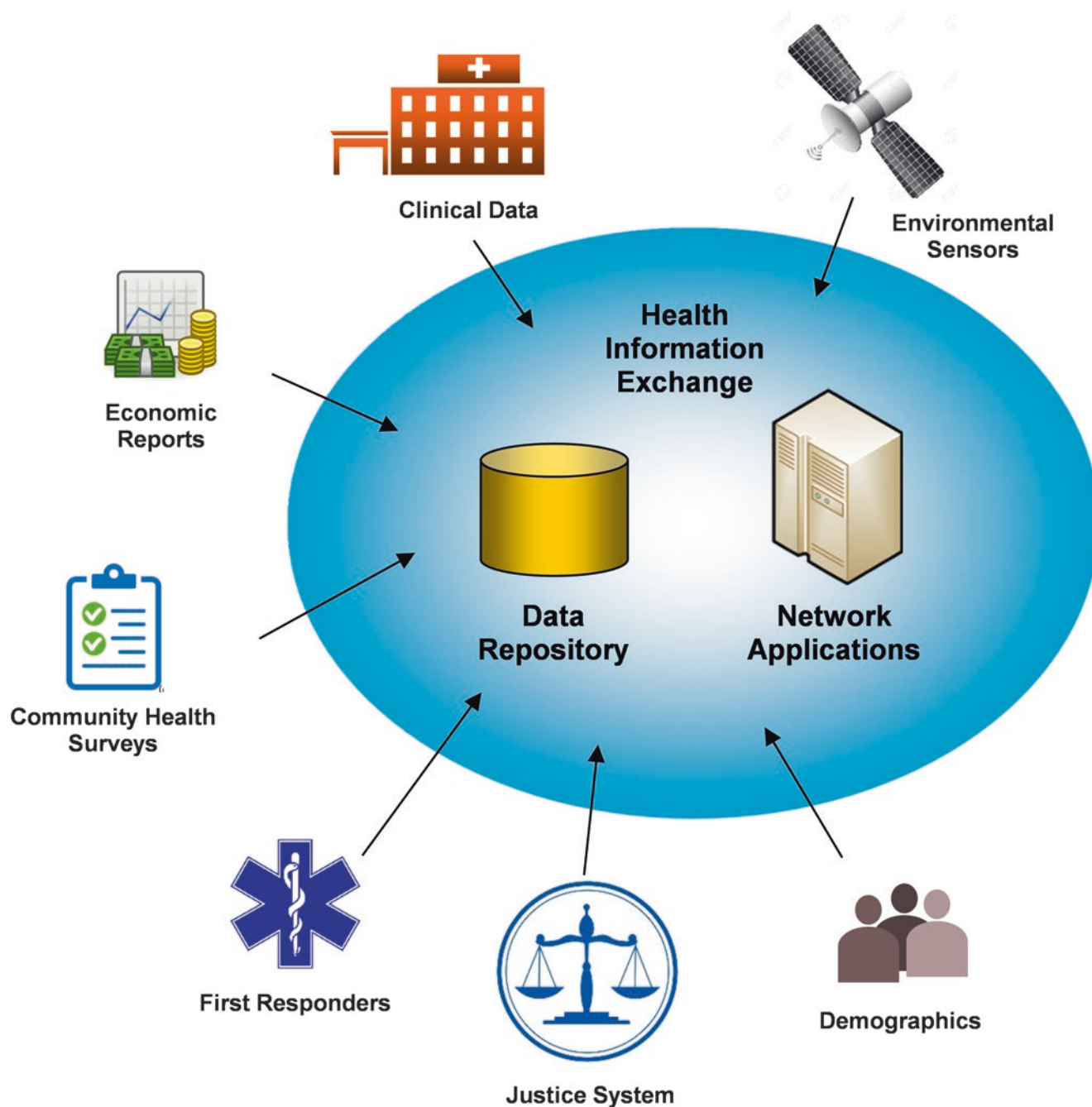
Fig. 25.3 Example of integration of different types of information in Indiana

such as when a laboratory value is out of the normal range or when a patient may be allergic to a newly prescribed medication. Extending that model, public health decision support (PHDS) can be exemplified in a scenario where clinicians receive an alert from the local health department that describes a newly discovered contaminant in the water supply that impacts neighborhoods near the clinic, placing its patient population at risk for waterborne illness. The alert may further recommend ordering stool samples for patients who present with gastrointestinal symptoms. This scenario illustrates computer-based PHDS, providing relevant knowledge to inform decisions involving the health and well-being of populations using electronic information [91].

Public Health EHR Alerting

The New York City Department of Health and Mental Hygiene developed and deployed 40 PHDS alerts, such as screening measures for influenza and pneumococcal vaccines, to more than 2000 physicians via commercial EHR systems [92]. This work enabled public health stakeholders

to distribute public health alerts during important events, such as infectious disease outbreaks.

Case Reporting Reminders

Conventional reporting processes require health care providers to complete paper-based notifiable condition reports, which are transmitted by fax and mail to public health agencies. These processes result in incomplete reports, inconsistencies in reporting frequencies among different diseases, reporting delays [93], and time-consuming follow-up by public health agencies to get needed information [94]. To address these issues, medical informatics scientists at the Regenstrief Institute electronically prepopulate report forms with available clinical, laboratory, and patient data to streamline reporting workflows, increase data completeness, and ultimately provide more timely and accurate access surveillance data for public health organizations. This work has continued to demonstrate promise as a resource to increase the frequency and reliability of reporting [95].

Infrastructure to Support Bidirectional Exchange

Although these examples highlight the promise of PHDS, to fully realize its potential, advanced clinical information systems must transmit data to public and population health systems and consume information from public health agencies. Immunization data exchange represents one such use case [96]. Today, many clinical systems transmit vaccination data to an IIS, which increased dramatically in 2021 due to COVID-19 vaccination efforts. Electronically exchanging information to and from public health, so-called "bidirectional communication" [97], requires a robust HIE infrastructure, which remains nascent in many communities.

Current public health infrastructures tend to focus on unidirectional approaches, maximizing the ability to receive and analyze health care data typically originating from clinical systems. Suboptimal and often manually intensive methods are used to communicate information back to providers. For example, health departments commonly send letters via US Mail when informing clinicians about events such as influenza disease burden and localized enteric outbreaks. These messages are likely to arrive outside of clinical workflow, making the information unusable by frontline clinicians. Furthermore, current methods may render the information obsolete if clinicians read it many days or weeks after the public health threat.

A more promising approach would leverage available population or contextual information to inform clinical decision-making in real-time. For example, a recent clinical trial could automate the query for adolescents' human papillomavirus (HPV) vaccination status [98]. The trial used the information to identify whether the adolescent in the pediatric clinic had received zero, one, or two doses of the HPV vaccine series. This information triggered a CDS prompt for the clinician to ask whether the adolescent and/or guardian would like to initiate or finish the vaccination series while in the office. The CDS prompt was effective [99], and the information further supported the delivery of educational resources to the adolescent and family while the patient awaited the provider in the exam room [100]. Targeting education and just-in-time prompts supported significant increases in vaccination rates, especially among boys who are often under-vaccinated for HPV.

Emerging Trends

As the context in which health care is delivered changes, the application of informatics to public and population health will evolve. Especially in the wake of the COVID-19 pandemic, broad changes to health care delivery and system reorganization are likely to impact public and population health efforts. For example, the pandemic highlighted the need for better system-level integration between hospitals or clinics and public health agencies [28]. Efforts within health systems to evolve EHR systems, expand telehealth services, and align operations with public health efforts to address SDOH will affect population health's information systems and informatics needs. In this section, we describe trends and emerging needs in public and population health informatics.

Post-Pandemic Recovery and Health System Evolution

The COVID-19 pandemic significantly affected health systems across the globe. Routine care, especially primary care, was disrupted, and urgent care facilities and hospitals were overrun with large populations in acute respiratory distress. By the time of this publication, the acute phase of the COVID-19 pandemic may have passed, and the next phase [101] of any pandemic is recovery.

Recovery from COVID-19 will take many forms, but fundamentally, it will require the evolution of the health systems. Scholars and health leaders in the United States have begun to advocate for a new health system that aligns with the Public Health 3.0 framework created before the pandemic by the US Department of Health and Human Services [102, 103]. The Public Health 3.0 framework urges a transformation in which there is a greater focus on building a culture of health, including cross-sector collaboration and an emphasis on health and health equity in all policies [28].

Implementing a new, evolved health system will require significant investment in information technologies and

infrastructure to support collaboration across health care delivery and public health. Not only will data need to flow seamlessly from clinical to public health operations, but knowledge from public health will also need to flow down to hospitals and clinics to keep providers aware of community health trends and incidents. Health care and public health systems will need to work together to address community health needs, including chronic disease burden. Immediately after the COVID-19 pandemic, we anticipate the nation's need to address mental health needs and pent-up demand for primary care services. There were national shortages of providers in both these areas before the pandemic, which will require health care delivery organizations to work closely with public health systems and community organizations (e.g., churches, Red Cross, older adult alliances) to organize efforts to screen, refer, and treat mental health disorders such as post-traumatic stress disorder, major depression, and anxiety induced by months of lockdown and/or social isolation. Primary care providers will be needed not only to support mental health needs but also to focus on preventive health needs for individuals who put off care during the pandemic and potentially exposed themselves to poor health behaviors, such as overeating, overconsumption of alcohol, and substance abuse, to mitigate impacts of the pandemic.

Information systems will play a critical role in standardizing and analyzing data and information captured across the health system and shared among the various private and public health partners. Interoperability will be critical to Public Health 3.0 efforts, requiring the development and use of standards and governance of information shared broadly across primary care, mental health, and public health providers (and community organizations). Referrals to public health and providers outside an integrated delivery network will be necessary to address patients' SDOH and community health needs fully. Documentation of those services provided outside clinical environments will need to be captured and shared with primary care and other providers. Patients will also likely share data and information on community and public health platforms that will require integration with clinical systems. All of these innovations are largely nascent with some current pilot work. Continued research and development will be necessary to realize the Public Health 3.0 concept.

Policy Landscape

The HITECH Act and related policy activities (refer to Chap. 3) enhanced the adoption and use of EHR systems in clinical settings. The meaningful use (MU) program enhanced health care delivery and public health activities within local and state health departments. For example, several MU criteria for public health, including syndromic surveillance and ELR, increased data transmission to public health authori-

ties. At the same time, other MU measures, such as the requirement to document smoking status in the EHR, support public health authorities' capacity to aggregate data at a community level to monitor health behaviors and risk factors. Policies like MU are important to stimulate clinical–public health partnerships and interoperability.

The MU program sunset just before the COVID-19 pandemic. Currently, CMS encourages providers to send syndromic and eCR information to public health agencies through the Promoting Interoperability Program [20]. This program expanded the menu of public health options, which will continue to encourage interoperability between EHR systems and public health information systems. Public health agencies will receive billions in investment from CDC due to the American Rescue Plan Act of 2021. This legislation appropriated significant funding for data modernization efforts in local and state health departments. These efforts will likely focus on the information systems described in this chapter, strengthening efforts to streamline receiving ELR and eCR data from clinical providers. This will shift efforts away from faxing information to stronger integration with commercial EHR systems—finally!

The functions called out specifically in programs like MU and Promoting Interoperability are only the tip of the iceberg concerning PHI's possibility. For example, monitoring community levels of MRSA or antibiotic resistance is possible only when public health agencies can integrate data from multiple sources. Some health departments are using syndromic surveillance systems to capture not only data streams from emergency departments, hospitals, and primary care settings but also from poison control centers [104], over-the-counter pharmacy sales [105], and social media [106, 107]. Other ideas include merging geotagging or enhancing syndromic surveillance data with geospatial characteristics, with environmental information such as clean air ratings to support asthma management or extreme weather alerts to address heat- and cold-related injury and mortality. Newer uses of surveillance systems are in their infancy, necessitating more work to develop the most appropriate algorithms and methods for computing and inferring knowledge from the growing number of electronic data sources available to public health authorities.

Improvements in Technology

HIEs are playing an increasing role in coordinating care and in addressing outbreaks of disease. HIEs are gaining favor as the centralizing authority in a complex group of stakeholders that impact public health, including physicians, laboratories, and state and federal health agencies. As public health informaticians work to integrate these sources, COVID-19 has served as a catalyst to reconsider (and reconfigure) the policy and technology that drive interoperability [108].

Health care reform is similarly changing the relationship between clinical and public health informatics. The shift toward accountable care organizations has also brought the need for community health assessments at the hospital and health system levels—work that public health authorities Public health informatics: have traditionally performed. Change has ushered in new partnerships between health systems and public health, including much-needed resources to support health assessment in a community. The informatics front has also brought new ideas around how best to leverage EHR data for measuring health in a community. EHR systems and HIE networks might be sources of more objective data around health status or at least sources to complement the traditional population-based surveys conducted by public health authorities [109]. Such approaches are promising, but they need to be studied and refined over time. This is another area for collaboration between clinical and public health informaticians.

Technological changes will also impact PHI and the capture of electronic data for use in population health. The vast array of patient-centered devices and technologies (refer to Chap. 24) entering the market could open public health authorities to new sources of data on population behaviors and health status. For example, health agencies are increasingly interested in the potential of social media information and internet user search queries [109, 110]. In 2020, Zhang and colleagues identified 25 major themes to describe the use of data from social media platforms to supplement or develop public health research, including a variety of diseases and public health concerns [111]. In the context of health and disease outbreaks, social mobility refers to the movement of individuals and their proximity to others. Recent research has explored the use of mobile devices and mobile applications to assess the physical proximity of individuals during times where social distancing is recommended to prevent disease transmission using Twitter data and Google mobility data [112, 113]. Yet although there was initial promise and excitement with the release of data sources such as Google Flu Trends [114], later analyses concluded that "[Google Flu Trends] data may not provide reliable surveillance for seasonal or pandemic influenza and should be interpreted with caution until the algorithm can be improved and evaluated" [23]. There is an even greater promise with consumer devices such as the new Apple Watch and many Fitbit devices. These devices and new data sources will need to be evaluated and refined in the coming years to produce accurate, current assessments and predictive models of population health.

Consumer-facing mobile applications could impact public health by collecting information about vaccine hesitancy, mask-wearing, and social distancing during the COVID-19 pandemic. Various mobile applications have been developed, with research now emerging to explore the utility of this approach [115].

Improving Health Equity and Creating a Culture of Health

Health IT, and PHI by extension, can play a role in the reduction of health disparities. This can occur by identifying and addressing SDOH through technology-enabled assessments and interventions [116]. In addition, data standards that codify SDOH in EHRs are now supporting public health practice [117].

Summary

Information systems and technologies are revolutionizing the delivery of health care and the practice of public health. Just as we have observed a growing demand for informatics capacity in health care organizations, we have seen a similar process unfolding in the public health sector. Public health authorities today are using a growing array of information systems to capture, manage, use, and exchange data. Many of the data, like in medicine, are fragmented; and a growing number of new clinical and non-clinical data sources is on the horizon. There is an opportunity for clinical and public health informaticians to work together to incorporate novel uses of technology while enhancing the science and practice of public health, leading to better population health outcomes for communities.

Questions for Discussion

1. How does public health informatics complement clinical informatics? In what ways are they distinct?
2. What roles do various stakeholders and information systems play in public health informatics?
3. Why is increased electronic health record adoption important for public health informatics?
4. What is the importance of syndromic surveillance?
5. Which methods, tools, or systems from public health informatics might be useful for clinical informaticians within health systems?
6. How has COVID-19 changed public health information systems?

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