State of the Art in Clinical Informatics: Evidence and Examples

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Summary

Objective: The field of clinical informatics has expanded substantially in the six decades since its inception. Early research focused on simple demonstrations that health information technology (HIT) such as electronic health records (EHRs), computerized provider order entry (CPOE), and clinical decision support (CDS) systems were feasible and potentially beneficial in clinical practice.

Methods: In this review, we present recent evidence on clinical informatics in the United States covering three themes: 1) clinical informatics systems and interventions for providers, including EHRs, CPOE, CDS, and health information exchange; 2) consumer health informatics systems, including personal health records and web-based and mobile HIT; and 3) methods and governance for clinical informatics, including EHR usability; data mining, text mining, natural language processing, privacy, and security.

Results: Substantial progress has been made in demonstrating that various clinical informatics methodologies and applications improve the structure, process, and outcomes of various facets of the healthcare system.

Conclusion: Over the coming years, much more will be expected from the field. As we move past the "early adopters" in Rogers' diffusion of innovations' curve through the "early majority" and into the "late majority," there will be a crucial need for new research methodologies and clinical applications that have been rigorously demonstrated to work (i.e., to improve health outcomes) in multiple settings with different types of patients and clinicians.

Keywords

Informatics; evidence-based practice; medical order entry systems; decision support systems, clinical; data mining

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Introduction

The field of clinical informatics has expanded substantially in the six decades since its inception. When clinical informatics was first introduced, simple demonstrations that various information technology-enabled processes such as clinical documentation, order entry, medical diagnosis, or therapy planning were possible were sufficient to gain attention, funding, and even limited clinical use. As these techniques and technologies have become more widely available, the need for high-quality evaluations to provide scientific evidence has increased. With the recent emphasis on comparative effectiveness research [1], the need to develop new methods for and conduct rigorous evaluations of all aspects of health information technology (HIT) [2] will continue to grow.

In this paper, we present a survey of the evidence for various clinical informatics approaches. We divided the evidence into three primary themes: 1) clinical informatics systems and interventions for providers, 2) consumer health informatics systems, and 3) methods and governance for clinical informatics. The first theme, clinical informatics systems and interventions, includes two main topics: a) electronic health records (EHRs), computerized provider order entry (CPOE), and clinical decision support (CDS); and b) health information exchange (HIE). The second theme, consumer health informatics systems includes two main topics: a) personal health records (PHRs); and b) web-based and mobile HIT. The third theme, methods and governance for clinical informatics, includes three main topics: a) EHR usability; b) data mining, text mining, and natural language processing (NLP); and c) privacy and security. For each topic, we present an overview of clinical informatics approaches, a review of recent literature, and an assessment of the evidence in the United States to date.

Evidence for Clinical Informatics Systems and Interventions for Providers

Electronic Health Records, Computerized Provider Order Entry, and Clinical Decision Support

Over the past decade, clinicians and healthcare organizations have focused on implementation of HIT such as EHRs and CPOE with embedded CDS to improve quality of care and reduce costs [3]. This new focus has resulted from landmark studies [4], Institute of Medicine reports [5, 6], the American Recovery and Reinvestment Act (ARRA) stimulus with its Health Information Technology for Economic and Clinical Health (HITECH) Act [7], and the Meaningful Use Regulation, led by the Centers for Medicare and Medicaid Services and the Department of Health and Human Services [8, 9].

During this time, numerous publications have described the effect of EHRs, CPOE, and CDS on patients, processes, and cost outcomes

[10, 11]. Despite initially anticipated success of HIT at improving patient outcomes, investigators have had difficulty in demonstrating significant, positive findings [11]. Further, much of the literature reporting positive findings has evaluated locally developed HIT systems in large, academic medical centers [10, 12]. However, evidence about improved process outcomes has been consistently positive; one systematic review by Bright et al. reported increased random-effects combined odds ratios for adherence to recommendations for preventive services (OR=1.42), ordering clinical studies (OR=1.72), and prescribing appropriate treatments (OR=1.575) [11]. On the other hand, reports of cost-effectiveness of HIT have been mixed [11]. Recent manuscripts report overall improved efficiency, although initial investment costs of HIT implementations are high [13, 14]. Also affecting costs is the Meaningful Use regulation, which includes incentive payments for those attesting to "Meaningful Use" of an EHR prior to 2015 and penalties beginning afterward for those who have not attested [8].

One unintended consequence of the increased adoption of HIT is the substantial amount of clinical data, including medications, laboratory test results, problems, allergies, notes, visits, and health maintenance items that exist within these systems and that must be reviewed by clinicians at each visit. Researchers have found that presenting such large amounts of data to clinicians trying to retrieve information about patients' care can be overwhelming, leading to frustration, inefficiency, and often errors. However, automated clinical summarization and medication reconciliation may soon be capable of addressing such problems that result during practice and care transition [15-17].

Overall, evidence for EHRs, CPOE, and CDS is positive, and little has changed in the literature over the past several years [10, 11, 13, 18]. Additional evidence from more rigorous studies in diverse settings covering additional workflow processes are necessary to fully describe the benefits or drawbacks from implementation of such HIT and to ensure that these systems improve patient care [19, 20].

Health Information Exchange (HIE)

HIE is the process of sharing patient information between two or more organizations, and it has been an important topic in the last few years, with considerable attention in the technical, policy and research domains [21]. In the United States, the Office of the National Coordinator for Health Information Technology (ONC) began providing substantial financial incentives to HIEs [22, 23]. ONC certification requirements mandate that all certified EHRs be able to send and receive HL7-standard continuity of care documents (CCDs) [8], and the ONC has also sponsored work on the Nationwide Health Information Network (NHIN) Direct suite of standards for sharing health information [24].

Recently, several studies looked at the effects of HIE on quality and cost outcomes. Hebel et al. found a 49% reduction in laboratory test ordering after Partners HealthCare introduced an internal HIE connecting its member hospitals [25]. Likewise, Bailey et al. studied the effect of HIE on neuroimaging in headache patients treated in emergency departments and found a significant reduction in unnecessary neuroimaging (OR = 0.38) and increased adherence to evidence-based guidelines (OR = 1.33) but no significant reduction in overall costs [26]. The same team, studying HIE more broadly, found a significant cost savings associated with HIE adoption, driven largely by a reduction in hospital admissions in emergency departments after HIE was introduced [27]. On the other hand, a study by Jones et al. found no association between HIE use and hospital readmission rates [28]. Surveys have found that physicians generally express positive attitudes toward the idea of HIE [29, 30], but in practice they often find that data they need are not available [29].

Despite these positive attitudes and results, HIE adoption in the United States has been fraught with challenges in financial sustainability [31, 32], and, as grant funds are expended, several HIEs have shut down due to lack of funds. Alternative business models have been proposed, including a "health record bank" approach where providers submit clinical data to a patient-controlled repository [33], though the long-term business model for this type of HIE is also still uncertain. Internationally, Jha et al. studied HIE strategy and adoption in Australia, Canada, Germany, the Netherlands, New Zealand, the United Kingdom and the US and found that most countries had a national HIE strategy and some pilot programs in place, but that widespread adoption of HIE, even in the highest performing countries, was still quite low [34].

Given the apparent value of and satisfaction with HIE, coupled with more widespread adoption of interoperable health information technology, we believe HIE adoption will increase over the next several years. That said, considerable work needs to be done to identify and develop sustainable business models for HIE, and more work needs to be done to ensure that technical standards are in place to permit the exchange of coded, interoperable health data.

Evidence for Consumer Health Informatics Systems

Personal Health Records (PHRs)

PHRs are applications that are available for patients or caregivers to view and maintain a record of health status and clinical data items, such as medications and allergies, and to communicate with providers [35]. A key dimension of PHRs involves control of the clinical data and can range from stand-alone applications, under sole control of a patient, to tethered applications, under the control of the healthcare organization that provide patients with a limited view of their providers' EHR. Several of the early providers of stand-alone PHRs have recently withdrawn their offerings from the market, most notably Google Health [36]. Therefore, for this review, we will focus on tethered PHRs that provide patients with several key features, notably the ability to send and receive secure messages with their healthcare providers and the ability to review recent laboratory test results [37].

Secure messaging has been shown to improve several health outcomes, including glucose control in diabetics [38], adherence to anti-depressive medications [39], and pharmacists' management of hypertension [40]. It has also been shown to improve patient satisfaction [41], but its effect on patient resource utilization has been mixed. Specifically, Palen et al. found significant increases in both in-person and telephone-based clinical services among younger (< 50 years old) and older (> 50 years old) patients, as well as those with chronic conditions [42].

The evidence for the impact of giving patients direct access to their laboratory test results is still open for debate [43]. While several studies have demonstrated that pa-

tients will use these systems, there are no studies available that investigate changes in patient health outcomes.

In summary, even though PHRs and patient portals have garnered much attention over the past 10 years, there is little high-quality evidence of their effect on improving cost, quality, or access to health care [44].

Web-Based and Mobile Health Information Technology

The Internet continues to be an important platform to empower people and to reach consumers with behavior change applications to address major public health challenges such as obesity, mental health and substance abuse. This burgeoning area is now complemented by research and development of smartphone-based mobile apps for consumers, which enable self-tracking and motivational support. Early validation studies are emerging that show mobile phones can be used as sensory tools (e.g., to measure physical activity [45] or depression [46]), or as a food diary tool [47]. When combined with behavior change approaches and what has been called "active assistance technologies" [48], these tools represent a powerful and effective way to increase population health, for example in the field of physical activity [49, 50]. However, many existing applications available today have been described as not grounded in evidence [50, 51] or as not having a strong theoretical foundation [52, 53]. A recent systematic review on the theoretical basis of behavior change applications concluded "that the effectiveness of Internet-based interventions is associated with more extensive use of theory (in particular the theory of planned behavior), inclusion of more behavior change techniques, and use of additional methods of interacting with participants (especially text messages)." [53]. Non-usage and drop-out attrition of participants [54] remains a substantial problem for randomized trials in the area, and there is now an increasing evidence-base on which factors predict and increase usage and adherence to web-based and mobile applications [55-59].

The number of high-quality randomized trials in this area has increased sharply, and appraisal and consolidation of the emerging evidence is required. A recently published extension of the CONSORT statement, CONSORT-EHEALTH [60] aims to improve the reporting of trials evaluating Web-based or mobile applications, as systematic reviews conducted in this area frequently decry reporting deficiencies such as not describing the intervention or its theoretical foundations in enough detail, or not measuring or reporting exposure to the intervention.

Evidence for Methods and Governance in Clinical Informatics

Health Information Technology Usability

As new HIT systems are developed, it is important to assess human factors components, including system usability. Compromised system usability for EHRs partially explains lower EHR adoption rates in specialty areas such as pediatric care [61]. Recommendations to increase EHR adoption rates include enhancing functionality for specialty care areas [62, 63], improving interoperability with other HIT [64], enhancing the ability to conduct research and quality improvement, reducing interference with workflow patterns [65], improving the organization of displayed information, streamlining login procedures [66], and decreasing documentation time [67]. EHRs were found in a systematic review by Poissant et al. to have mixed impacts on documentation time for nurses and increase work time for physicians, particularly when centrally located desktop workstations are used [68]. Documentation time would likely be decreased by streamlining data entry with simplified user interfaces and optimized default settings, improving the design of alerts and reminders, including avoiding hard stops [69] and increasing the positive predictive value of alerts [70].

Usability may also affect patient safety. One study by Han et al. found an unexpected increase in patient mortality following the introduction of an EHR with usability problems in a pediatric hospital [71, 72]. On the other hand, a later study by Longhurst et al. found a reduction in patient mortality based in large part on improvements in usability [73]. An emerging consensus is that both the system design [74] (EHR as designed) and the workflow implementation (EHR as implemented) affect patient safety. In order to improve the system design, guidelines for evaluating [75] and documenting [76] summative usability testing results have been published by the US National Institute of Standards and Technology. Likewise, the TURF (task, user, representation, and function) framework provides a set of objective measures for evaluating EHR usability as designed [77] and the SAFER (Safety Assurance Factors for Electronic Health Record Resilience) guides provide recommendations for proactive assessments of EHR usability focusing primarily on ensuring safety and effectiveness of EHRs as they are implemented [78]. For workflow implementation in pediatrics, recommendations were made to improve patient safety by reducing the risk of wrong patient errors, avoiding mode errors with weight-based dosing, and reducing delays for time-critical tasks for newborn patients [79].

For HIT systems designed for patients, additional usability issues have been found, particularly with interpreting medical terminology and graphed data [80], understanding drug-drug interaction alerts, and navigating complex login procedures. Older adult patients can have additional usability issues, such as limited vision when reading small font and giving up rather than using features that rely on interface exploration to get started [81].

Clearly, the evidence of the need for improved EHR usability is overwhelming and such improvements represent a significant challenge for informatics researchers in the coming years.

Data Mining, Text Mining, and Natural Language Processing

The international adoption of EHR systems has led to an unprecedented amount of clinical data available electronically [3, 82]. According to the US Centers for Disease Control and Prevention, more than 36 million hospital admissions and 1.3 billion ambulatory care visits are documented per year in the USA [83]. While mining EHR databases to facilitate medical research and improve clinical care is not a new area

of research [84], it has received increased attention with the recent emphasis on widespread EHR adoption [85].

Data mining, also known as knowledge discovery in databases (KDD), is a process to find previously unknown patterns in databases. Iavindrasana et al. reviewed the state-of-the-art practices in clinical data mining, focusing on methodological issues such as data cleaning, processing, and evaluation [86]. Early evidence demonstrated that data mining technologies can be applied to healthcare data to assess treatment effectiveness [87] and to improve healthcare management [88]. More recently, studies have shown that EHR data can be used to identify comorbidities using a data-driven statistical methodology [89], detect pharmacovigilance signals [90,91], and build predictive models for disease risks [92,93], surgery outcomes (94), and hospital admissions [95,96].

Clinical text is a major component of EHR data and it often contains rich information describing patients. Therefore text mining is inevitable when dealing with EHR data [96]. NLP technology, which can extract structured information from free text [97], has become an essential component and a top-ranked topic in clinical informatics [98]. Researchers have been actively developing advanced clinical NLP methods, represented by works such as the i2b2 NLP Challenges [99]. Strong evidence has shown the use of NLP in facilitating clinical and translational research based on EHR data. Murff et al. conducted a study among patients undergoing surgical procedures at VA medical centers and concluded that NLP analysis had higher sensitivity on identifying postoperative complications compared with discharge coding [100]. Another study by Elkin et al. also found that an NLP-based method that used the entire encounter note was more accurate than a model based only on the chief complaint field for a bio-surveillance system of influenza [101]. A number of studies have also used NLP for automatically extracting fine-grained phenotype information from EHRs and have shown great successes in genomic [102] and pharmacogenomic [103] studies that are based on EHR-linked biobanks. In addition to supporting medical research, NLP has been used in clinical settings as well, such as to supplement structured data for clinical decision support systems [104].

Overall, the evidence is very positive for the use of data mining, text mining, and NLP in highly focused domains designed to facilitate clinical and translational research, as well as patient care.

Privacy and Security

As HIT grows in scale and scope, it is also critical to ensure the trustworthiness of the system through robust privacy and security principles. These principles should be integrated into every step of the lifecycle of health information, from initial data collection, to the use of such information in primary care, to the reuse and dissemination of patient data for secondary endeavors.

At the point of health information collection, it is necessary to enable formal specification and management of policies. These policies enable organizations to specify how they intend to process health information, as well as enable patients to indicate how they want their information to be utilized. Recent research has shown how to model the system as access zones [105], integrate personally-controlled health records with health organization-controlled EHRs [106, 107], and control the flow of information to third-parties [108].

While such control structures can be formalized, there are many ways in which health information can be breached. For instance, health information may be insufficiently protected with weak encryption or passwords. Recent research demonstrated that in 14 of 15 password-protected files containing data from Canadian clinical trials sent over email, the passwords could be cracked using commercial password recovery systems [109]. Health information may also be exposed due to poor security principles. According to statistics from the Office for Civil Rights at the U.S. Dept. of Health and Human Services (HHS), there have now been over 500 breaches at healthcare providers involving more than 500 patients [110]. While breaches are not limited to medical information, a recent econometric analysis of breaches across industry sectors showed that a compromise of medical data increases the likelihood of a settlement by 31% [111].

Ensuring that threats originating from beyond a healthcare organization are appropriately addressed, insider threats still remain. The complexity and dynamic nature of primary care settings makes it difficult to define tight access controls while maintaining clinicians' access to the required data. As such, it has become important to develop and deploy auditing techniques to monitor access to, as well as utilization of, health information. It has been shown that machine learning frameworks can refine healthcare privacy officials' knowledge of suspicious behavior into classifiers for auditing purposes [112]. Additionally, unsupervised learning techniques have been suggested to explain accesses [113] and detect deviations from normal collaborative behavior [114]. Despite such advances, recent research suggests that certain open-source medical record systems have deficiencies which may hamper auditing efforts [115].

As health information is reused in secondary settings, it is recommended that such data be de-identified prior to dissemination. A software architecture for managing access to data at varying levels of de-identification has been put into practice by i2b2 [116]. Beyond their framework, there have been specific advances in various aspects of de-identification. Given that the majority of data generated in a healthcare setting is based in natural language, there continues to be a flurry of work in the development of new free text scrubbing technologies [117-119]. Moreover, there have been recent demonstrations that these technologies can be scaled beyond traditional English-speaking countries [120]. These technologies are now being ingrained in open-source technologies [121, 122]. Other open source de-identification technologies have been developed for a medical image toolkit in DICOM format [123].

Residual personal data stored as free text can leak information that can lead to re-identification. Thus, free text, or natural language, is still not shared on a wide basis. Rather, health information is shared in field-structured form, where it can be subject to generalization, perturbation, and suppression strategies that enable quantifiable confidentiality protections. Notably, such de-identification has enabled the dissemination of health data for machine

learning competitions [124] as well as clear demonstrations of how clinical data can be shared to support genotype association studies [125]. There remain concerns over health information and the potential for re-identification [126, 127]. Evaluations suggest that these risks vary [128], but several reviews have shown that there is a lack of re-identification attacks of de-identified data [129]. Nonetheless, to further mitigate risk, there has been movement to erect systems that enable queries against systems that return only aggregated results in local and described healthcare environments [130, 131].

Summary

Over the last several years, considerable progress has been made in demonstrating that various clinical informatics methodologies and applications improve the structure, process, or outcome of various facets of the healthcare system. Over the coming years, much more will be expected from the field. As we move past the "early adopters" in Rogers' diffusion of innovations' curve [132] through the "early majority" and into the "late majority," there will be a crucial need for methodologies and applications that have been rigorously demonstrated to work in multiple settings with different types of patients.

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