ANNUAL REVIEWS

Annual Review of Public Health

The Digitization of Patient Care: A Review of the Effects of Electronic Health Records on Health Care Quality and Utilization

Hilal Atasoy,[1] Brad N. Greenwood,[2] and Jeffrey Scott McCullough[3]

[1]Department of Accounting, Temple University, Philadelphia, Pennsylvania 19122, USA; email: hilal.atasoy@temple.edu

[2]Carlson School of Management, University of Minnesota, Minneapolis, Minnesota 55455, USA; email: wood@umn.edu

[3]Department of Health Management and Policy, University of Michigan, Ann Arbor, Michigan 48109-2029, USA; email: jemccull@umich.edu

Annu. Rev. Public Health 2019. 40:487–500

First published as a Review in Advance on December 19, 2018

The *Annual Review of Public Health* is online at publhealth.annualreviews.org

https://doi.org/10.1146/annurev-publhealth-040218-044206

Each author contributed equally to this article.

Keywords

electronic health records, EHR, clinical care quality, medical costs, adoption, machine learning

Abstract

Electronic health records (EHRs) adoption has become nearly universal during the past decade. Academic research into the effects of EHRs has examined factors influencing adoption, clinical care benefits, financial and cost implications, and more. We provide an interdisciplinary overview and synthesis of this literature, drawing on work in public and population health, informatics, medicine, management information systems, and economics. We then chart paths forward for policy, practice, and research.

INTRODUCTION

Clinicians and scholars have long sought to understand how electronic medical records could be used to facilitate and improve patient care. Hospitals began to adopt information technology (IT) as early as the 1960s, and yet only during the past decade has electronic health record (EHR) adoption become widespread. The digitization of patient records opens rich possibilities for medical professionals: in particular, search capabilities to instantly access and process patient data, automated reminders to avoid medication errors, improved information sharing across the medical team, and increased transparency by ensuring both complete and legible documentation of the patient's condition. In this article, we provide a retrospective on the voluminous empirical work examining the effects wrought by EHRs. In doing so, our goal is twofold: first, to provide a base of understanding regarding empirical knowledge of the effects of EHRs; and second, to chart paths forward for research that supports improved health technology policy and to propose research questions relating to the design of EHRs and the use of digital health information.

We do so in five sections. First, we define EHRs and provide a brief overview of their adoption and meaningful use, as well as the mechanisms through which EHRs may influence quality. Second, we review the literature measuring the relationship between EHRs and quality at both a local level and a national level. Third, we discuss studies of EHRs and the efficiency or cost of health care. Fourth, we discuss some of the unanticipated consequences of EHR utilization. Finally, we conclude by discussing the need for greater health information exchange and how EHRs may serve as platforms for data-driven innovation and may be ideal for the application of big data methods.

Defining EHRs

The EHR is, at its core, a digitized medical chart. Deriving value from this technology requires a broad array of functions that gather, manage, and share digital health information. This information can then be exploited to support medical decision making and operations (23, 52). Ideally, information gathering begins before a patient encounter, retrieving records from other providers or past patient encounters. This, and other information, is then updated at the beginning of the patient's interaction with the physician or nursing staff; additional data—such as lab values, images, and progress notes—are added as the encounter progresses. These data could, ideally, be made portable so they may be shared with other providers or accessed via patient portals.

EHRs may also serve as a platform for decision support. Established clinical guidelines or best medical practices may be operationalized within the EHR software. Algorithms can, for example, check for drug allergies or drug–drug interactions. Treatment guidelines may be embedded within the EHR, utilizing patient-level data to prompt providers with suggestions or raise flags regarding potentially risky interventions. These capabilities depend on detailed patient information and a provider interface at the point of care.

The Adoption of EHRs

Broadly speaking, the literature on the dissemination and implementation of EHRs can be grouped into three distinct but related streams: direct assessments of the level of adoption, assessments of policy- and hospital-level factors that may accelerate or stymie the diffusion and use of EHRs, and assessments of the hospital- and physician-level degree of EHR utilization.

As might be expected, initial investigations of EHR adoption were motivated mostly from the observation that, despite the many benefits of EHR, limited adoption was witnessed [see Ford et al. (33) for a meta-analysis of this work]. Estimates suggest that prior to the Health

Information Technology for Economic and Clinical Health (HITECH) Act, fewer than 10% of hospitals (and fewer than 20% of physicians) were using these systems (55). The HITECH Act of 2009, signed into law under President Obama, was meant to change this pattern of slow adoption by subsidizing adoption costs, changing reimbursement rules, and providing technical support. The HITECH Act further emphasized the adoption of decision support capabilities and utilization at the point of care, formally referred to as "meaningful use." Jha et al. (56, 57), for example, note that prior to the HITECH Act, less than 2% of hospitals met the criteria of meaningful use (with rural, public, and smaller hospitals lagging behind their larger, urban competitors). Key administrative barriers to adoption included capital and maintenance costs, along with physician resistance to change (22, 84) or a simple lack of exposure to the systems (23).

The HITECH Act leveraged approximately $30 billion in incentives for the adoption and meaningful use of EHRs (55). These funds subsidized the cost of adoption for clinics and hospitals while penalizing late adopters by reducing Medicare reimbursement growth. The adoption and meaningful use of EHRs greatly increased following the HITECH Act (3). Recent estimates suggest that basic EHR adoption increased drastically following the HITECH Act (1), with nearly 90% adoption of basic EHR (39). This conclusion remains contentious as some studies suggest that EHR adoption was rising naturally and that most adoption would have occurred without the HITECH Act (28, 81).

Researchers have also explored the broader determinants of EHR adoption. Angst et al. (9), for example, argue that social contagion by neighboring organizations can strongly influence diffusion. Others argue that tacit barriers, such as the absence of a business case (101), or conflicting policies, such as state medical privacy laws (82), may decrease EHR adoption. Other scholars have noted that EHR interoperability remains a challenge, particularly across vendors, and that information sharing is rare despite government investment in information exchanges (39). Researchers have argued that privacy can be a critical concern during EHR adoption decisions (8) and have suggested that EHRs are often neglected by users if they lack logical or physical accessibility to the physician (49). The extant literature further suggests that it is critical to focus on cultural, rather than technological, change during implementation, ensure that clinical champions are empowered, and provide sufficient training (26).

Mechanisms for Changing Quality

Quality improvement is one of EHR's most widely heralded benefits. EHRs may improve patient safety and clinical outcomes through a variety of mechanisms. We first discuss clinical decision support, which is arguably the most emphasized mechanism in the health informatics and policy literature. We then discuss how EHRs may improve clinical communication and information management. Finally, we conclude by exploring less direct mechanisms, such as care coordination.

Medical errors are a widespread problem with serious repercussions for patient morbidity and mortality (50, 51, 86). Decision support algorithms may identify and prevent errors. The most common decision support systems are designed to prevent medication errors. These systems may check for drug allergies, drug–drug interactions, and drug dosing errors. At the same time, clinical decision support may be applied to a broad range of functions. Prespecified order sets, such as common postoperative monitoring and care, may help implement care guidelines and minimize deviation from best practices (89, 112). These guidelines may recommend a series of screenings, tests, and medications to improve diagnosis and treatment.

The complex nature of clinical medicine creates numerous opportunities for miscommunication. EHRs may improve clinical communication. Consider a simple medication prescription in an inpatient environment. This process requires, at a minimum, communication and coordination among the physician, pharmacist, and nursing staff. A comprehensive EHR can resolve communication errors (even simple ones stemming from handwriting legibility) by connecting ordering physicians with pharmacists, who fill the prescriptions, and nurses, who administer prescriptions to patients.

EHRs may also improve information management, which is particularly relevant for patients with multiple comorbidities or those that require extensive monitoring and testing. Diagnosing and monitoring these conditions require large quantities of clinical information. EHRs may help capture and organize these data, thus expediting and improving treatment decisions.

Lastly, EHRs may reduce fragmentation across disparate providers and care settings. Individual providers often focus on a single facet of care and cannot always interact in real time or seamlessly share medical records. This siloed information, which is difficult to share across providers, leads to fragmentation. It is intuitive that data input and access should be seamless across a diverse set of providers. EHRs are an essential tool for coordinating providers' activities. Improved care coordination can reduce errors, avoid duplicative tests, and enhance medical decision making. These systems may be particularly valuable when patient care requires multiple specialists or transitions in care settings.

Benefits of EHRs on Care Quality

There is a large empirical literature on the relationship between EHRs and health care quality. Below, we begin with an overview of this literature. We then address three topics: the impact of decision support systems on quality, how other mechanisms (e.g., communications and information management) impact quality, and evidence from studies using large longitudinal databases of EHR adoption to study quality.

Empirical evidence of the impact of EHRs on quality emerged in the 1990s (13, 20, 90). The focus and findings of the early literature (about 1995 to 2010) were notably mixed; many studies observed no significant relationship (20). More recent research provides stronger support for the notion that EHRs improve quality. Buntin et al. (18), in an examination of articles between 2007 and 2010, found that 62% of studies yielded unambiguously positive consequences from EHR systems, while an additional 30% reported mixed results with positive overall findings. Jones et al. (60) updated this analysis, finding that 56% of articles reported unambiguously positive consequences; an additional 21% had positive, albeit mixed, findings through 2013. Other reviews examined the effects of EHR and clinical decision support systems in emergency departments (EDs) (15) and intensive care units (91). Evidence again suggests beneficial effects for both emergency medicine and intensive care unit patients but emphasizes the limitations of the existing empirical evidence.

Particularly strong evidence indicates that decision support systems improve patient safety for medication prescribing (18–20, 60). In such research, scholars have found that EHRs with decision support capabilities decrease rates of both drug–drug interactions (100, 102) and medication errors (36). Dosage error reductions have further been achieved through automated dosage calculators (103), as well as improved medication adherence (61) and reduced medication overuse (73).

The impact of decision support systems goes beyond medication prescribing. Early research suggests that electronic prompting can improve preventive care for a variety of conditions, ranging from the reception of Papanicolaou smears to the administration of the influenza vaccine (12). Further work finds that decision support systems have improved cardiovascular risk assessment in primary care settings (108). These systems have been used to implement evidence-based care guidelines and to disseminate time-sensitive clinical information (19, 20, 60). More recently, decision support algorithms have been combined with electronic surveillance technology to provide clinical alerts, leading to significantly improved inpatient sepsis management and significantly reduced sepsis mortality (72).

EHRs also improve the communication and management of clinical information for both providers and patients. EHRs have, for example, been shown to reduce prescribing errors, even in the absence of decision support systems. These systems may obviate simple communication errors, such as those that stem from poor handwriting. They may also improve the clarity of complex orders, facilitate provider access to health information (65, 79, 98), and raise patient satisfaction by increasing the clarity of instructions for postacute recovery (62). Some evidence even indicates that patient portals are associated with improved screening (78, 110); however, the evidence from both observational studies and randomized controlled trials (RCTs) remains mixed (21, 40).

Quality Estimates Using Large Longitudinal Data Sources

It is difficult to extrapolate from the above studies to the national value of health IT. Most studies have analyzed a single provider organization and usually focus on user-developed systems (60). Evidence of selection bias in EHR adoption (88) and its effects on quality (74) further complicate the issue. Early EHR adopters often provided higher-quality care than did providers who opted not to adopt EHRs. Studies that ignored this selection process would have overestimated the impact of EHRs on quality. A growing number of studies address these issues using national data that follow EHR adoption and patient outcomes longitudinally, commonly employing a difference-in-difference (i.e., provider fixed effects) strategy to address selection bias in technology adoption. Using such national data along with causal identification strategies can improve both internal and external validity. Challenges still exist as multiprovider EHR databases may not capture important heterogeneity in the technical capabilities of either EHR systems or their use within organizations.

Further studies have examined the relationship between EHR adoption and patient safety. Early research on process quality measures found no effect or small effects of EHRs (58, 74). These studies suggest that the benefits of EHRs for patient safety are low for the average hospital. Other studies using patient-level administrative claims data found modest patient safety improvements following hospital EHR adoption (6, 88). Similar results have been found using EHR adoption data in an ambulatory setting (75), and more recent studies using newer data have found larger patient safety gains (34, 48).

Researchers have also sought to directly measure the relationship between EHR adoption and outcomes such as mortality. Miller & Tucker (83), for example, found that EHR adoption averted 16 neonatal deaths per 1,000 live births. Other studies using Medicare data found no effect of EHR adoption on mortality for the average patient (6, 76). McCullough et al. (76), however, found that EHRs reduced mortality by more than 1 death per 100 admissions among very high severity patients. This effect is concentrated almost entirely among patients with comorbidities requiring coordination across multiple clinical specialties and for those requiring extensive monitoring and information management.

Finally, two notable papers evaluated the effects of EHR adoption under the HITECH Act. Physician EHR adoption was found to avert 3.2% of ambulatory care-sensitive hospital admissions (68). Hospitals' adoption and meaningful use were also associated with improved process adherence and higher patient satisfaction (4).

EFFICIENCY AND COST IMPLICATIONS OF EHRs

In addition to clinical care outcomes, EHR systems can affect the cost and efficiency of health care organizations and the health system as a whole. EHRs can automate existing processes, improve management of medical practices and chronic care, and facilitate integration and communication within and across health care organizations. These mechanisms can then translate into reduced costs and improved productivity.

From a policy perspective, EHR systems have gained attention as a potential remedy for the rising costs of US medical care. Investigations of costs generally consider two measures: providers' operational costs and costs of care to health insurers. Hillestad et al. (45) use results from previous studies to extrapolate the net cost savings of EHR adoption, accounting for the initial implementation costs. They estimate that EHR implementation could lead to more than $81 billion of net cost savings annually across the United States. These benefits are argued to arise from improvements in care efficiency, patient safety, and management of chronic diseases; although some scholars have subsequently argued that the assumptions of such work, e.g., that EHRs can replace a physician's clerical staff, are unrealistic (99). Similar to the research in the space of care quality, initial estimates of the cost benefits of EHRs are derived mostly from single-site studies, but large national studies have begun to build on this work. Dranove et al. (27) study newer and relatively advanced EHRs and find no significant decrease in costs on average. In fact, operational costs have been observed to rise after EHR adoption in some cases, especially for more advanced EHR systems. This effect, however, is attenuated if hospitals are located in geographical areas that are more IT-industry intensive (27). The findings of Dranove et al. (27) suggest the importance of complementary labor and IT resources in successful EHR implementations.

The effects on the costs to Medicare are also mixed; they increased with EHR implementations in earlier periods (1998–2005) (6) but decreased after the HITECH Act. Lammers & McLaughlin (67), for example, estimate a savings of $3.8 billion in Medicare expenditures between 2010 and 2013. These differing results suggest that the effects are often idiosyncratic to the organization and that not all organizations are able to absorb the hefty implementation and maintenance costs of EHR systems to realize cost reductions (59).

In addition to considering direct costs, investigators should recognize potential efficiency and productivity gains that EHRs may help to realize. Scholars in this space have analyzed the impacts of EHRs on efficiency using operational performance measures and economic production functions. Commonly used operational financial measures include return on assets (i.e., net income divided by total assets) and net patient revenue. In many cases, EHR adoption improves these metrics (80), especially via improved patient flow (25) and business process redesign (24). Gains in efficiency and productivity from EHRs have further been estimated using a production function approach. These models measure the relationship between value-added output and IT inputs while holding constant the contribution of other inputs, e.g., labor and capital. Using this method, studies have found moderate gains in efficiency and productivity from EHR investments (69); larger benefits have been observed in facilities that invest in workplace organizations that complement IT (46).

Finally, EHR implementations are often part of a broad organizational transformation, where the financial effects may not be observable in short-term operational data. In such cases, the valuation of the hospital within financial markets can offer a viable proxy of the organization's financial health. Market values incorporate direct accounting measures such as costs, profits, and assets, as well as other information available to investors. They can also reflect the current and expected future value of the organization. Kohli et al. (63), for example, find that health IT investment increases firm value in the long term, and the effects on market value are larger compared with the effects on accounting variables. Thus, it is not clear whether EHRs impact access to capital markets, as they are found to have insignificant effects on bond credit ratings (77). One important limitation of the market value approach is that it is restricted to publicly traded health care organizations. Understanding the broader financial impacts of EHR systems would require going beyond these large public providers.

UNINTENDED CONSEQUENCES OF EHRs

Researchers are also beginning to take note of EHRs' unanticipated consequences. These might be new uses of, or efficiencies from, EHR adoption but may also include difficulties with the adoption and implementation of information systems. These difficulties include disruption of organizational workflows (44, 93), tool failure (109), maintenance issues in keeping best practices current (96), user resistance to change (23, 56), and others very much idiosyncratic to the hospital context.

New ways of digitally capturing medical data may also be used for billing purposes. EHRs may, for example, better document comorbidities to justify higher reimbursement rates from payers to providers. Many insurers pay higher reimbursement rates for patients with more severe complications or comorbidities; thus, better documentation may improve charge capture. In this case, EHRs may raise short-run medical expenditures but could improve long-run efficiency. These systems might also be misused either by manipulating data input or by processing data inappropriately in order to upcode claims. Upcoding results from distorted incentives and artificially inflating the overall cost of care born by the insurer and society. It is empirically challenging to distinguish more accurate charge capture from inefficient upcoding, as both lead to a higher reported patient complexity with more expensive medical claims. Empirical evidence is mixed: Adler-Milstein & Jha (2) find no change in case mix index following EHR adoption, whereas two other studies (38, 70) find that patient severity increases following EHR adoption. Gowrisankaran et al. (41) have found that EHRs led to higher codes for medical, but not surgical, claims, following the 2007 Medicare payment reform. This change increased the difficulty of documenting complications and appears to have increased EHRs' value for billing. Gowrisankaran et al. do not, however, find that the increase in documented severity is correlated with the financial returns to improved documentation. This finding suggests that EHRs might improve billing accuracy rather than increase fraudulent billing.

Further work on the unanticipated effects of EHRs has included the ability of EHRs to expedite legal proceedings (92), to increase or change the hospital's retention of human capital (42), and to reduce regional network externalities of costs driven from EHRs (10).

Paths Forward: Health Information Exchange

The benefits of EHR systems' capabilities are often limited if data cannot be passed to other providers outside the boundary of the clinic or hospital (107). This issue is especially important because most current EHR systems have limited interoperability and cannot communicate directly with each other. One proposed remedy for this concern is health information exchanges (HIE), where members can share information even if their EHR systems are not compatible. The HITECH Act had a relatively small effect on both interoperability and information exchange (2, 39).

Literature discussing the impacts of HIEs has generally focused on the ability of these technologies to eliminate duplicate tests and procedures if the necessary information is available to different providers. Some studies have found that hospital HIE adoption reduced redundant testing and imaging [e.g., CT scans and ultrasounds (11, 66)], and visit-level HIE use decreased ED-originated admissions, readmissions, future encounters, length of stay, and number of procedures in non-ED visits (35).

The diffusion of HIEs has remained stagnant despite their policy significance (4, 47, 106). Scholars have proposed several reasons for this lack of adoption. Health care providers may lack the incentives to share medical information. Providers may, for example, engage in information blocking, i.e., strategically withholding information, if they believe they might lose patients (5). EHR vendors may also design systems that are incompatible with other vendors to increase consumer "lock in" and increase the cost of switching to other vendors. Security and privacy concerns are also critical, and the lack of standardized data protocols across different organizations can deter HIE utilization (30, 111). Finally, providers may not think an HIE is helpful in most circumstances (29). Some researchers (95) and surveys of physician attitudes (111) suggest that the additional information provided by an HIE is often unnecessary and that the systems are sufficiently cumbersome that physicians are deterred from accessing HIEs.

Given the limited adoption and interoperability in this space, we believe significant opportunities exist to uncover potential catalysts to affect change, from both a research perspective and a policy perspective. The network properties of software interoperability and information exchange participation suggest that markets are especially vulnerable to failure, and government action may be appropriate. Potential policies include introducing interoperability standards, providing direct subsidies for HIE adoption and use (similar to those provided by the HITECH Act), and changing reimbursement systems to provide better incentives for information sharing.

Paths Forward: Data Analytics

The widespread adoption of EHRs creates a framework for collecting and analyzing health data. These systems provide a platform for data analytics, which may yield long-run gains in health care quality and efficiency. As with other platform technologies, large gains may take some time to manifest (17). Exploiting the digital infrastructure and data captured by EHRs is especially important, given the ongoing innovations in machine learning and artificial intelligence.

Machine learning and artificial intelligence differ drastically from conventional decision support systems. Traditional decision support algorithms are based on the explicit coding of expert knowledge (87). Machine learning and artificial intelligence instead learn patterns from data and discover information that might otherwise have gone unnoticed (85), an ability that increases with data availability. Furthermore, these statistical tools are incredibly flexible and can therefore be applied to a wide range of problems. Machine-learning tools were commercially applied first to traditional prediction tasks such as measuring insurance risks and financial forecasting, but they are now used for a wide range of tasks that were not always viewed as predictive. Notable examples include search, driving, translation, image recognition, etc. (7). There is a similarly wide variety of applications in health care. Recent studies show how machine learning may be applied to problems that have long been viewed as statistical prediction problems, including risk adjustment (94) and severity measurement (16). Machine-learning tools have also used medical image analysis and medical diagnosis (31, 43, 71), tasks not conventionally seen as statistical prediction problems.

The combination of EHR data and machine-learning tools may soon make personalized and evidence-based medicine a meaningful reality. While RCTs, the causal gold standard, yield compelling evidence with strong internal validity, it is important to recognize the limitations of such approaches (32, 105). RCTs are rarely designed or scaled to address the variation faced by patients and providers. In response to this problem, the US Food and Drug Administration increasingly emphasizes the need for real-world evidence to guide the approval and use of treatments (37, 53, 97). EHR data and machine-learning tools may be used to better understand the consequences of medical decisions. Thus, the application of such tools in medicine is a nontrivial empirical problem as naïve applications of machine learning can produce biased treatment effects (14). Nevertheless, there exists a large and growing literature on causality for machine learning (14, 104); although these approaches will never supplant clinical trials, they may provide valuable complementary evidence.

Emerging opportunities in unsupervised machine learning may yield seismic shifts in how knowledge is generated and discovered (54). Two critical concerns, which may be solved by the emergence of unsupervised learning, are the ability to generalize beyond the average patient who participates in an RCT and the ability to extract information from broader sets of results across multiple RCTs. With regard to patient generalization, one consistently highlighted concern is that the typical patient in most RCTs is an older American white male. To the extent that treatment effects may be heterogeneous across subpopulations (based on comorbidities, race, gender, etc.) (64), important opportunities exist to synthesize information from extant studies and understand how differential effects may manifest across overrepresented and underrepresented groups. Emerging initiatives such as Watson Oncology are testaments to this potential, albeit far from realized, benefit. By synthesizing information across thousands of patients and trials simultaneously, these systems may be able to mine new medical data rapidly without needing to execute potentially costly RCTs.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

LITERATURE CITED

1. Adler-Milstein J, DesRoches CM, Kralovec P, Foster G, Worzala C, et al. 2015. Electronic health record adoption in US hospitals: progress continues, but challenges persist. *Health Aff.* 34:2174–80
2. Adler-Milstein J, Jha AK. 2014. No evidence found that hospitals are using new electronic health records to increase Medicare reimbursements. *Health Aff.* 33:1271–77
3. Adler-Milstein J, Jha AK. 2017. HITECH Act drove large gains in hospital electronic health record adoption. *Health Aff.* 36:1416–22
4. Adler-Milstein J, Lin SC, Jha AK. 2016. The number of health information exchange efforts is declining, leaving the viability of broad clinical data exchange uncertain. *Health Aff.* 35:1278–85
5. Adler-Milstein J, Pfeifer E. 2017. Information blocking: Is it occurring and what policy strategies can address it? *Milbank Q.* 95:117–35
6. Agha L. 2014. The effects of health information technology on the costs and quality of medical care. *J. Health Econ.* 34:19–30
7. Agrawal A, Gans J, Goldfarb A. 2016. The simple economics of machine intelligence. *Harvard Business Review* Nov. 17. **https://hbr.org/2016/11/the-simple-economics-of-machine-intelligence**
8. Angst CM, Agarwal R. 2009. Adoption of electronic health records in the presence of privacy concerns: the elaboration likelihood model and individual persuasion. *MIS Q.* 33:339–70
9. Angst CM, Agarwal R, Sambamurthy V, Kelley K. 2010. Social contagion and information technology diffusion: the adoption of electronic medical records in US hospitals. *Manag. Sci.* 56:1219–41
10. Atasoy H, Chen P-Y, Ganju K. 2017. The spillover effects of health IT investments on regional healthcare costs. *Manag. Sci.* 64:2473–972
11. Ayabakan S, Bardhan I, Zheng ZE, Kirksey K. 2017. The impact of health information sharing on duplicate testing. *MIS Q.* 41:1083–103
12. Balas EA, Boren SA, Brown GD, Ewigman BG, Mitchell JA, Perkoff GT. 1996. Effect of physician profiling on utilization. Meta-analysis of randomized clinical trials. *J. Gen. Intern. Med.* 11:584–90
13. Bates DW, Leape LL, Cullen DJ, Laird N, Petersen LA, et al. 1998. Effect of computerized physician order entry and a team intervention on prevention of serious medication errors. *JAMA* 280:1311–16

14. Belloni A, Chernozhukov V, Hansen C. 2014. High-dimensional methods and inference on structural and treatment effects. *J. Econ. Perspect.* 28:29–50
15. Bennett P, Hardiker NR. 2016. The use of computerized clinical decision support systems in emergency care: a substantive review of the literature. *J. Am. Med. Inform. Assoc.* 24:655–68
16. Bergquist SL, Brooks GA, Keating NL, Landrum MB, Rose S. 2017. *Classifying lung cancer severity with ensemble machine learning in health care claims data*. Presented at Machine Learning for Healthcare Conference, Boston, Aug. 18–19
17. Brynjolfsson E, McAfee A. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: Norton
18. Buntin MB, Burke MF, Hoaglin MC, Blumenthal D. 2011. The benefits of health information technology: a review of the recent literature shows predominantly positive results. *Health Aff.* 30:464–71
19. Campanella P, Lovato E, Marone C, Fallacara L, Mancuso A, et al. 2016. The impact of electronic health records on healthcare quality: a systematic review and meta-analysis. *Eur. J. Public Health* 26:60–64
20. Chaudhry B, Wang J, Wu S, Maglione M, Mojica W, et al. 2006. Systematic review: impact of health information technology on quality, efficiency, and costs of medical care. *Ann. Intern. Med.* 144:742–52
21. Coughlin SS, Williams LB, Hatzigeorgiou C. 2017. A systematic review of studies of web portals for patients with diabetes mellitus. *mHealth* 3:23
22. Cutler DM, Feldman NE, Horwitz JR. 2005. US adoption of computerized physician order entry systems. *Health Aff.* 24:1654–63
23. DesRoches CM, Campbell EG, Rao SR, Donelan K, Ferris TG, et al. 2008. Electronic health records in ambulatory care—a national survey of physicians. *N. Engl. J. Med.* 359:50–60
24. Devaraj S, Kohli R. 2000. Information technology payoff in the health-care industry: a longitudinal study. *J. Manag. Inform. Syst.* 16:41–67
25. Devaraj S, Ow TT, Kohli R. 2013. Examining the impact of information technology and patient flow on healthcare performance: a Theory of Swift and Even Flow (TSEF) perspective. *J. Oper. Manag.* 31:181–92
26. DeVore SD, Figlioli K. 2010. Lessons premier hospitals learned about implementing electronic health records. *Health Aff.* 29:664–67
27. Dranove D, Forman C, Goldfarb A, Greenstein S. 2014. The trillion dollar conundrum: complementarities and health information technology. *Am. Econ. J. Econ. Policy* 6:239–70
28. Dranove D, Garthwaite C, Li B, Ody C. 2015. Investment subsidies and the adoption of electronic medical records in hospitals. *J. Health Econ.* 44:309–19
29. Eden KB, Totten AM, Kassakian SZ, Gorman PN, McDonagh MS, et al. 2016. Barriers and facilitators to exchanging health information: a systematic review. *Int. J. Med. Inform.* 88:44–51
30. Edwards A, Hollin I, Barry J, Kachnowski S. 2010. Barriers to cross-institutional health information exchange: a literature review. *J. Healthc. Inform. Manag.* 24:22–34
31. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, et al. 2017. Dermatologist-level classification of skin cancer with deep neural networks. *Nature* 542:115–18
32. Feinstein AR, Horwitz RI. 1997. Problems in the "evidence" of "evidence-based medicine." *Am. J. Med.* 103:529–35
33. Ford EW, Menachemi N, Peterson LT, Huerta TR. 2009. Resistance is futile: but it is slowing the pace of EHR adoption nonetheless. *J. Am. Med. Inform. Assoc.* 16:274–81
34. Freedman S, Lin H, Prince J. 2018. Information technology and patient health: analyzing outcomes, populations, and mechanisms. *Am. J. Health Econ.* 4:51–79
35. Frisse ME, Johnson KB, Nian H, Davison CL, Gadd CS, et al. 2011. The financial impact of health information exchange on emergency department care. *J. Am. Med. Inform. Assoc.* 19:328–33
36. Fritz D, Ceschi A, Curkovic I, Huber M, Egbring M, et al. 2012. Comparative evaluation of three clinical decision support systems: prospective screening for medication errors in 100 medical inpatients. *Eur. J. Clin. Pharmacol.* 68:1209–19
37. Galson S, Simon G. 2016. *Real-world evidence to guide the approval and use of new treatments*. Discuss. Pap., Natl. Acad. Med., Washington, DC

38. Ganju KK, Atasoy H, Pavlou PA. 2016. *Do electronic medical record systems inflate Medicare reimbursements?* Res. Pap. 16-008, Fox Sch. Bus., Temple Univ.
39. Gold M, McLaughlin C. 2016. Assessing HITECH implementation and lessons: 5 years later. *Milbank Q*. 94:654–87
40. Goldzweig CL, Orshansky G, Paige NM, Towfigh AA, Haggstrom DA, et al. 2013. Electronic patient portals: evidence on health outcomes, satisfaction, efficiency, and attitudes: a systematic review. *Ann. Intern. Med.* 159:677–87
41. Gowrisankaran G, Joiner KA, Lin J. 2016. *Does health IT adoption lead to better information or worse incentives*? NBER Work. Pap. 22873
42. Greenwood B, Ganju K, Angst CM. 2017. Just what the doctor ordered? Physician mobility after the adoption of electronic health records. *Acad. Manag. Proc.* 2017:11853
43. Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, et al. 2016. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA* 316:2402–10
44. Hefter Y, Madahar P, Eisen LA, Gong MN. 2016. A time-motion study of ICU workflow and the impact of strain. *Crit. Care Med.* 44:1482–89
45. Hillestad R, Bigelow J, Bower A, Girosi F, Meili R, et al. 2005. Can electronic medical record systems transform health care? Potential health benefits, savings, and costs. *Health Aff.* 24:1103–17
46. Hitt LM, Tambe P. 2016. Health care information technology, work organization, and nursing home performance. *ILR Rev*. 69:834–59
47. Holmgren AJ, Patel V, Adler-Milstein J. 2017. Progress in interoperability: measuring US hospitals' engagement in sharing patient data. *Health Aff.* 36:1820–27
48. Hydari MZ, Telang R, Marella W. 2017. Saving patient Ryan—Can advanced electronic medical records make patient care safer? *Manag. Sci.* **http://dx.doi.org/10.2139/ssrn.2503702**
49. Ilie V, Van Slyke C, Parikh MA, Courtney JF. 2009. Paper versus electronic medical records: the effects of access on physicians' decisions to use complex information technologies. *Decis. Sci.* 40:213–41
50. IOM (Inst. Med.). 2000. *To Err Is Human: Building a Safer Health System*. Washington, DC: Natl. Acad. Press
51. IOM (Inst. Med.). 2001. *Crossing the Quality Chasm: A New Health System for the 21st Century*. Washington, DC: Natl. Acad. Press
52. ISO (Int. Organ. Stan.). 2008. *Electronic health record definition, scope, and context*. ISO/TC 215 Tech. Rep., Int. Organ. Stand., Geneva
53. Jarow JP, LaVange L, Woodcock J. 2017. Multidimensional evidence generation and FDA regulatory decision making: defining and using "real-world" data. *JAMA* 318:703–4
54. Jensen PB, Jensen LJ, Brunak S. 2012. Mining electronic health records: towards better research applications and clinical care. *Nat. Rev. Genet.* 13:395–405
55. Jha AK. 2010. Meaningful use of electronic health records: the road ahead. *JAMA* 304:1709–10
56. Jha AK, DesRoches CM, Campbell EG, Donelan K, Rao SR, et al. 2009. Use of electronic health records in U.S. hospitals. *N. Engl. J. Med.* 360:1628–38
57. Jha AK, DesRoches CM, Kralovec PD, Joshi MS. 2010. A progress report on electronic health records in US hospitals. *Health Aff.* 29:1951–57
58. Jones DA, Shipman JP, Plaut DA, Selden CR. 2010. Characteristics of personal health records: findings of the Medical Library Association/National Library of Medicine Joint Electronic Personal Health Record Task Force. *J. Med. Libr. Assoc.* 98:243–49
59. Jones SS, Heaton PS, Rudin RS, Schneider EC. 2012. Unraveling the IT productivity paradox—lessons for health care. *N. Engl. J. Med.* 366:2243–45
60. Jones SS, Rudin RS, Perry T, Shekelle PG. 2014. Health information technology: an updated systematic review with a focus on meaningful use. *Ann. Intern. Med.* 160:48–54
61. Karlsson LO, Nilsson S, Bång M, Nilsson L, Charitakis E, Janzon M. 2018. A clinical decision support tool for improving adherence to guidelines on anticoagulant therapy in patients with atrial fibrillation at risk of stroke: a cluster-randomized trial in a Swedish primary care setting (the CDS-AF study). *PLOS Med*. 15:e1002528

62. Kazley AS, Diana ML, Ford EW, Menachemi N. 2012. Is electronic health record use associated with patient satisfaction in hospitals? *Health Care Manag. Rev.* 37:23–30
63. Kohli R, Devaraj S, Ow TT. 2012. Does information technology investment influence a firm's market value? A case of non-publicly traded healthcare firms. *MIS Q*. 36:1145–63
64. Kudenchuk PJ, Maynard C, Martin JS, Wirkus M, Weaver WD. 1996. Comparison of presentation, treatment, and outcome of acute myocardial infarction in men versus women (the Myocardial Infarction Triage and Intervention Registry). *Am. J. Cardiol.* 78:9–14
65. Kuperman GJ, Teich JM, Gandhi TK, Bates DW. 2001. Patient safety and computerized medication ordering at Brigham and Women's Hospital. *Jt. Comm. J. Qual. Improv.* 27:509–21
66. Lammers EJ, Adler-Milstein J, Kocher KE. 2014. Does health information exchange reduce redundant imaging? Evidence from emergency departments. *Med. Care* 52:227–34
67. Lammers EJ, McLaughlin CG. 2017. Meaningful use of electronic health records and Medicare expenditures: evidence from a panel data analysis of US health care markets, 2010–2013. *Health Serv. Res.* 52:1364–86
68. Lammers EJ, McLaughlin CG, Barna M. 2016. Physician EHR adoption and potentially preventable hospital admissions among Medicare beneficiaries: panel data evidence, 2010–2013. *Health Serv. Res.* 51:2056–75
69. Lee J, McCullough JS, Town RJ. 2013. The impact of health information technology on hospital productivity. *RAND J. Econ.* 44:545–68
70. Li B. 2014. *Cracking the codes: Do electronic medical records facilitate hospital revenue enhancement?* Work. Pap., Kellogg Sch. Manag., Northwest. Univ., Evanston, IL
71. Madabhushi A, Lee G. 2016. Image analysis and machine learning in digital pathology: challenges and opportunities. *Med. Image Anal.* 33:170–75
72. Manaktala S, Claypool SR. 2017. Evaluating the impact of a computerized surveillance algorithm and decision support system on sepsis mortality. *J. Am. Med. Inform. Assoc.* 24:88–95
73. McCullough JM, Zimmerman FJ, Rodriguez HP, Bell DS, Torrens PR. 2014. Impact of clinical decision support on receipt of antibiotic prescriptions for acute bronchitis and upper respiratory tract infection. *J. Am. Med. Inform. Assoc.* 21:1091–97
74. McCullough JS, Casey M, Moscovice I, Prasad S. 2010. The effect of health information technology on quality in US hospitals. *Health Aff.* 29:647–54
75. McCullough JS, Christianson J, Leerapan B. 2013. Do electronic medical records improve diabetes quality in physician practices? *Am. J. Manag. Care* 19:144–49
76. McCullough JS, Parente ST, Town R. 2016. Health information technology and patient outcomes: the role of information and labor coordination. *RAND J. Econ.* 47:207–36
77. McEvoy D, Barnett ML, Sittig DF, Aaron S, Mehrotra A, Wright A. 2018. Changes in hospital bond ratings after the transition to a new electronic health record. *J. Am. Med. Inform. Assoc.* 25:572–74
78. McInnes DK, Shimada SL, Rao SR, Quill A, Duggal M, et al. 2013. Personal health record use and its association with antiretroviral adherence: survey and medical record data from 1871 US veterans infected with HIV. *AIDS Behav*. 17:3091–100
79. Meisenberg BR, Wright RR, Brady-Copertino CJ. 2014. Reduction in chemotherapy order errors with computerized physician order entry. *J. Oncol. Pract.* 10:e5–9
80. Menachemi N, Burkhardt J, Shewchuk R, Burke D, Brooks RG. 2006. Hospital information technology and positive financial performance: a different approach to finding an ROI. *J. Healthc. Manag.* 51:40–58
81. Mennemeyer ST, Menachemi N, Rahurkar S, Ford EW. 2016. Impact of the HITECH Act on physicians' adoption of electronic health records. *J. Am. Med. Inform. Assoc.* 23:375–79
82. Miller AR, Tucker C. 2009. Privacy protection and technology diffusion: the case of electronic medical records. *Manag. Sci.* 55:1077–93
83. Miller AR, Tucker CE. 2011. Can health care information technology save babies? *J. Political Econ.* 119:289–324
84. Miller RH, Sim I. 2004. Physicians' use of electronic medical records: barriers and solutions. *Health Aff.* 23:116–26

85. Mullainathan S, Spiess J. 2017. Machine learning: an applied econometric approach. *J. Econ. Perspect.* 31:87–106
86. NPSF (Natl. Patient Saf. Found.). 2015. *Free from Harm: Accelerating Patient Safety Improvement Fifteen Years After to Err Is Human*. Boston: NPSF
87. Obermeyer Z, Emanuel EJ. 2016. Predicting the future—big data, machine learning, and clinical medicine. *N. Engl. J. Med.* 375:1216
88. Parente ST, McCullough JS. 2009. Health information technology and patient safety: evidence from panel data. *Health Aff.* 28:357–60
89. Payne TH, Hoey PJ, Nichol P, Lovis C. 2003. Preparation and use of preconstructed orders, order sets, and order menus in a computerized provider order entry system. *J. Am. Med. Inform. Assoc.* 10:322–29
90. Pestotnik SL, Classen DC, Evans RS, Burke JP. 1996. Implementing antibiotic practice guidelines through computer-assisted decision support: clinical and financial outcomes. *Ann. Intern. Med.* 124:884–90
91. Prgomet M, Li L, Niazkhani Z, Georgiou A, Westbrook JI. 2017. Impact of commercial computerized provider order entry (CPOE) and clinical decision support systems (CDSSs) on medication errors, length of stay, and mortality in intensive care units: a systematic review and meta-analysis. *J. Am. Med. Inform. Assoc.* 24:413–22
92. Ransbotham S, Overby EM, Jernigan MC. 2016. *Electronic trace data and legal outcomes: the effect of electronic medical records on malpractice claim resolution time*. Res. Pap. 2016-052, Scheller Coll. Bus., Ga. Inst. Technol., Atlanta
93. Read-Brown S, Hribar MR, Reznick LG, Lombardi LH, Parikh M, et al. 2017. Time requirements for electronic health record use in an academic ophthalmology center. *JAMA Ophthalmol.* 135:1250–57
94. Rose S. 2016. A machine learning framework for plan payment risk adjustment. *Health Serv. Res.* 51:2358–74
95. Ross SE, Schilling LM, Fernald DH, Davidson AJ, West DR. 2010. Health information exchange in small-to-medium sized family medicine practices: motivators, barriers, and potential facilitators of adoption. *Int. J. Med. Inform.* 79:123–29
96. Shah SD, Cifu AS. 2018. From guideline to order set to patient harm. *JAMA* 319:1207–8
97. Sherman RE, Anderson SA, Dal Pan GJ, Gray GW, Gross T, et al. 2016. Real-world evidence—what is it and what can it tell us? *N. Engl. J. Med.* 375:2293–97
98. Shulman R, Singer M, Goldstone J, Bellingan G. 2005. Medication errors: a prospective cohort study of hand-written and computerised physician order entry in the intensive care unit. *Crit. Care* 9:R516–21
99. Sidorov J. 2006. It ain't necessarily so: the electronic health record and the unlikely prospect of reducing health care costs. *Health Aff.* 25:1079–85
100. Smithburger PL, Buckley MS, Bejian S, Burenheide K, Kane-Gill SL. 2011. A critical evaluation of clinical decision support for the detection of drug–drug interactions. *Expert Opin. Drug Saf.* 10:871–82
101. Song PH, McAlearney AS, Robbins J, McCullough JS. 2011. Exploring the business case for ambulatory electronic health record system adoption. *J. Healthc. Manag.* 56:169–82
102. Sönnichsen A, Trampisch US, Rieckert A, Piccoliori G, Vögele A, et al. 2016. Polypharmacy in chronic diseases–Reduction of Inappropriate Medication and Adverse drug events in older populations by electronic Decision Support (PRIMA-eDS): study protocol for a randomized controlled trial. *Trials* 17:57
103. Terrell KM, Perkins AJ, Hui SL, Callahan CM, Dexter PR, Miller DK. 2010. Computerized decision support for medication dosing in renal insufficiency: a randomized, controlled trial. *Ann. Emerg. Med.* 56:623–29
104. Van der Laan MJ, Rose S. 2011. *Targeted Learning: Causal Inference for Observational and Experimental Data*. New York: Springer Sci. Bus. Media
105. Ventegodt S, Andersen NJ, Brom B, Acup D, Merrick J, DE Greydanus. 2009. Evidence-based medicine: four fundamental problems with the randomized clinical trial (RCT) used to document chemical medicine. *Int. J. Adolesc. Med. Health* 21:485–96
106. Vest JR. 2009. Health information exchange and healthcare utilization. *J. Med. Syst.* 33:223–31
107. Walker J, Pan E, Johnston D, Adler-Milstein J, Bates DW, Middleton B. 2005. The value of health care information exchange and interoperability. *Health Aff.* 24:W5

108. Wells S, Furness S, Rafter N, Horn E, Whittaker R, et al. 2008. Integrated electronic decision support increases cardiovascular disease risk assessment four fold in routine primary care practice. *Eur. J. Cardiovasc. Prev. Rehabil.* 15:173–78
109. Wright A, Ai A, Ash J, Wiesen JF, Hickman T-TT, et al. 2018. Clinical decision support alert malfunctions: analysis and empirically derived taxonomy. *J. Am. Med. Inform. Assoc.* 25:496–506
110. Wright A, Poon EG, Wald J, Feblowitz J, Pang JE, et al. 2012. Randomized controlled trial of health maintenance reminders provided directly to patients through an electronic PHR. *J. Gen. Intern. Med.* 27:85–92
111. Wright A, Soran C, Jenter CA, Volk LA, Bates DW, Simon SR. 2010. Physician attitudes toward health information exchange: results of a statewide survey. *J. Am. Med. Inform. Assoc.* 17:66–70
112. Zhang Y, Padman R, Patel N. 2015. Paving the COWpath: learning and visualizing clinical pathways from electronic health record data. *J. Biomed. Inform.* 58:186–97