

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

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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.

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