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Electronic Health Record Incentive Program Demonstrates Adoption Association with Improved Care

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Abstract

This study used Meaningful Use (MU) payment information as a proxy for electronic health record (EHR) adoption linked to Centers for Medicare and Medicaid (CMS) data indicating quality to demonstrate the association of EHR adoption with improved care. The CMS quality indicators used were comprised of data from the value-based purchasing (VBP) program, readmission reduction program, and hospital compare mortality data. Results showed a positive association of EHR adoption with the VBP data, which most closely aligns the MU achievement period with the quality measure period. Readmission and mortality data showed negative and neutral associations, respectively, with a less aligned timeframes. In addition, descriptive analysis was performed to characterize hospitals meeting the MU criteria, changes from year one to year two of the program, and a computation of providers that met in the first year and failed to meet the second year. Descriptive analysis shows large increase in MU achievement in year 2, especially for rural hospitals. The analysis also shows there is a greater than 30 percent drop-off rate of hospitals that met in year 1 and were unable to reach achievement in year 2.

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Chapter 1 - Introduction

Introduction

Efforts to enhance Electronic Health Record (EHR) adoption are supported by the Health Information Technology for Economic and Clinical Health Act (HITECH) of 2009. Under the HITECH Act, incentive payments up to $27 billion dollars over ten years will be made to eligible providers and hospitals that demonstrate adoption of EHR systems. The EHR incentive program known as meaningful use (MU), seeks to improve quality, safety and effectiveness of care. (US, 2011)

Despite such large amounts of money and resources committed toward improving care, the impact of increased EHR adoption is not clearly known. A review of literature provides evidence to support the concept that EHR adoption will improve care. However, literature can also be found indicating increased EHR has no impact on improving care. Some evidence even suggests EHR adoption can have a detrimental impact on the quality of care. The results from multiple studies show conflicting and inconsistent results and create doubt whether the goals of MU will be realized.

Earlier studies have often been based on older data, used survey response data to measure EHR adoption, or used a narrow definition with respect to EHR functionality. Considering the highly dynamic nature of EHR adoption in today's healthcare environment, earlier conclusions may no longer be as applicable. In order to strengthen the evidence of the key question as to whether EHR adoption improves care, current data is required.

This study considers MU incentive program results to measure adoption in the acute care hospital setting and uses recent data to evaluate quality. By considering whether MU incentive was achieved, a strong binary indicator of EHR implementation and adoption is attained, eliminating some variability of EHR adoption seen in previous studies. The analysis of the incentive program and quality measures originates with data published by the CMS. The VBP program, initiated in October 2012, consists of a composite score for each hospital related to quality and presents a consistent measure of quality. (US, 2013a) In addition, readmission reduction program data published in late 2012 and most recent hospital mortality data provide the opportunity to analyze the impact of meeting MU criteria as it relates to current quality indicators. Further exploration of the characteristics of hospitals meeting MU and the changes from 2011 to 2012 are included in the analysis and discussion.

Background

In 2004, then President Bush announced the formation of the Office of the National Coordinator for Health Information Technology (ONC). (US, 2013b) The goal of widespread technology adoption by healthcare providers and hospitals within ten years was established. In 2009, the Obama administration took the additional step of creating the EHR incentive program, under the HITECH Act. The incentive program transitions into a penalty program for providers and hospitals that have not adopted technology and demonstrated its use in its later years. The justification for the program is largely based on the idea that increasing EHR adoption results in improved care with respect to higher quality, greater efficiency and lower costs. (US, 2011)

The initial requirements to meet meaningful use and the subsequent first years of the program have been met with some debate. A key issue with the program is the conflicting evidence in literature as to whether EHR adoption actually results in the anticipated improvements.

Studies suggesting improvement in care associated with EHR adoption and studies showing no associated improvement have been equally criticized. Critique often includes the limitations of the study design. Studying the impact of EHR adoption does not lend itself to a stronger study design such as a randomized trial. Due to the limitations, any factors that can strengthen the results should be explored. One weakness of previous work relates to how EHR adoption is measured and to what level of granularity. Using the achievement of meeting MU criteria as an indicator of EHR adoption provides a more strict researcher-independent definition. Additional descriptive information can be gathered by reviewing the changes and characteristics of hospitals that met MU in 2011 and 2012.

Purpose of the Study

The purpose if this study is to show the association of EHR adoption as measured by meeting MU criteria in acute care hospitals with hospital compare mortality rates, VBP factor and readmission reduction program data. The data for MU achievement for 2011 and 2012 also provides information about the hospitals that are reaching the incentive and changes that took place from the first to second year of the program.

Significance of the Study

This study seeks to add to the evidence of whether EHR adoption results in improved care. A central theme of the HITECH program is that adoption will result in improvements in health care with respect to quality, efficiency and costs. Other studies have been completed that use national hospital quality data. However, no other studies that associate the payment results of MU program with quality measures have been noted. The study has potential to provide stronger evidence today and provide a new perspective on evaluating EHR adoption in the future.

Research Questions

The study seeks to show if EHR adoption is associated with improved care. By comparing the means of quality variables using two-tailed independent t-tests from a group of hospitals that met MU in 2011 and did not, the study seeks to determine if there is a statistically significant difference in the mean results. Additionally, the MU Paid 2012 and non-paid will be evaluated for the selected quality variables. Additional descriptive information regarding the characteristics of hospitals that met MU in 2011 and 2012 is reviewed.

Definition of Key Terms

Electronic Health Records (EHR) – computerized health record that meets the criteria established by ONC as certified-EHR

HITECH – Act approved in 2009 that includes EHR incentive program

Hospital Compare Data – CMS data made available to the public to compare hospital quality metrics

Independent t-test – statistical test performed to compare the mean of two groups. Also referred to as t-test. Demonstrates the ability to reject NULL hypothesis based on level of significance

Meaningful Use (MU) – EHR incentive program established by HITECH

Readmission Reduction Program – CMS program to award or penalize hospitals based on number of readmissions. Medicare payment adjustments went into effect in fiscal year 2013.

Value-based Purchasing (VBP) – CMS program to award or penalize hospitals based on a composite factor derived from select hospital compare measures

Limitations

The primary study objective uses data measured at a single point of time to evaluate the association of meeting MU with quality measures. This cross-sectional analysis prevents causal conclusions from being formed. The results cannot definitively show that meeting MU which demonstrates EHR adoption is the cause of any observed differences in mean quality scores.

The measurement timeframe of some of the data being used also potentially weakens the study results. The readmission reduction program and the 30 day mortality rates used in the study both are based on CMS data from July 2008 through June 2011. The older data pre-dates the major federal push to reduce readmissions and the start of the incentive program. Ideally, detail hospital compare data would be available and would allow the analysis to be done over a time period more closely related to the time periods associated with MU achievement period.

The time frame of the readmission and mortality caused some concern about whether the evaluation of MU 2012 and the readmission and mortality measures should be included in the study. However, excluding this data, especially since it leads to contrary results may have been viewed as biased toward showing EHR adoption improves care. With this consideration in mind, the negative and neutral results of the readmission and mortality data associated with MU 2012 achievement were included in the analysis.

Another factor related to timing of data and measuring adoption is that 2011 was the first year for the MU incentive program. However, hospitals that met MU in 2011 may have had EHR systems for several years. Therefore, conclusions reached by comparing MU paid in 2011 versus quality may be a reflection of the quality measure scores after a number of years of EHR usage. Without data regarding the length of time the hospitals used EHR systems, the conclusions cannot be used to predict future impact as EHR adoption rate increases. With knowledge of the length of EHR implementation known, the study could estimate how long it will take to see improvements in other measures areas.

The unknown time it takes for EHR adoption to impact quality creates some uncertainty about the optimal time frame of quality measures that should be used in assessing the relationship between EHR adoption and quality. Articles have noted that EHR implementation may take some time before there is an impact on care. (DesRoches, 2010) This concept suggests the time frame of quality measures to most accurately reflect impact of EHR adoption should be from post-implementation, potentially several years after. This may suggest that MU 2012 achievement would more appropriately be used to compare to quality measure data collected in 2013 or later.

The use of the composite mortality index that was calculated from an average of the mortality rate for heart failure, heart attack, and pneumonia has not been validated. If there were any missing values, the average was calculated from the remaining. Depending on which value was missing, this may have an impact on the results.

Another limitation relates to the nature of the MU program. Providers attest to meeting the criteria through a CMS website. Critics have argued that the program exposes itself to false claims of meeting MU that will result in payments to organizations and providers that fell short. Any inaccurate reported information with respect to meeting the criteria would weaken the study conclusions.

In studies which use a binary value for EHR adoption, it is possible that the organization has only marginally adopted the EHR. In the statistical analysis, the organization would be included with other EHR adopting organizations, potentially creating a level of error. When using the meeting of MU as a proxy for EHR adoption, essentially the opposite influence can occur. It is possible that an organization meets most of the MU criteria, but not all. This organization would be included in the statistics as not having an EHR, and could potentially create some level of inaccuracy.

Chapter 2: Literature Review

Overview

Recent literature was reviewed to build a foundation of information about the current state of research related to EHR adoption and improved quality. Studies selected for inclusion were categorized by negative, neutral or mixed, and positive conclusions along with applicable setting. Included in the reviewed articles were primary studies, systematic reviews, and commentary articles. All articles selected for inclusion were published in 2005 or later.

Study Selection

Initially, searches were performed on MEDLINE for ‘electronic health records’ and ‘quality’, along with similar terms, ‘quality improvement’ and ‘improved care’. Records were returned with abstract and examined to determine if the study topic was directly applicable to EHR adoption and improved care. Studies were selected for further review if concepts demonstrated in the study were generally applicable to broader health care and related to MU. Some topics, such as EHR impact in a long-term care setting, were excluded because long-term care is not included in the MU incentive program. A second MEDLINE search was performed using ‘meaningful use’ and ‘quality improvement’. Following the searches, articles that were potential matches were carefully reviewed. Literature articles that were related to EHR adoption and improved patient care and applicable to the MU program were included in the review.

A second source of articles was Google Scholar. Searches were performed using the same terminology. Articles were first screened by title then possible matches were further examined for inclusion. In addition, only articles that originated from peerreviewed journals were included in the review. The Google Scholar search provided a much larger result set that becomes increasingly less related to the search terms as the reader progresses through the returned results. Based on this information, only the initial topic-related pages of search results were examined for applicability and inclusion.

Following the searches, included articles were reviewed and references used in the articles were also considered for inclusion in this review. The goal of the search was not to systematically measure the quantity of articles that report a positive or negative impact of EHR adoption, but to identify a body of knowledge on the topic as defined by recent literature.

For purpose of this review, improved care includes the components reducing costs, improving effectiveness, and improving quality. The studies reviewed were classified as having a positive impact on care if any or all of the improved care characteristics were predominant results. Most studies included in the review consider the improvement of quality as it relates to EHR adoption.

Studies Showing Negative Impact

Ambulatory

Using 2003 and 2004 data from 50 family practices, Crosson demonstrated that patients receiving diabetes care according to accepted guidelines was lower in practices that had an EHR compared to practices that did not. The patients were selected randomly and examined by retrospective chart review. The status of EHR adoption was acquired by survey. The study noted limitations due to the cross-sectional nature of the data originally collected for a different purpose. Additionally, the binary nature of EHR usage and the accuracy of documentation and chart review are limiting factors. (Crosson, 2007)

Hospital

An additional negative impact study examined the costs and quality of national hospital data from 2003 to 2007, along with the level of computerization. The cost and quality data was obtained from CMS existing data repository. The level of computerization was based on Healthcare Information and Management Systems Society (HIMSS) survey data. The key finding of the study is the correlation of increased costs with hospitals that had increased computerization. This conclusion is contrary to the MU program objectives to apply technology to reduce healthcare costs. (Himmelstein, 2010)

Studies Showing No Impact or Mixed Results

Studies showing no impact or mixed results include both the ambulatory and hospital domains. Two of the ambulatory studies were based on National Ambulatory Medical Care Survey (NAMCS) data.

Ambulatory

Using 2003-2004 NAMCS data, Linder determined that higher EHR adoption was not associated with higher quality. Specific measures evaluated showed a range of results for quality measures. The study did not differentiate functional features or different levels of EHR adoption. Further study limits were introduced by the NAMCS data, which relies on accuracy of coding and self-reported EHR status. (Linder, 2007)

Using data from a 2005-2007 data from the IMPROVE HF initiative, Walsh compared compliance with care guidelines for heart failure patients and use of EHR. The study found only modest improvements of compliance for EHR sites compared to non-EHR sites. Limits of the study include dependence on chart review. Also, the data was cross-sectional in nature, which prevents a cause-effect conclusion. (Walsh, 2010)

Also in the ambulatory domain, Keyhani used 2005 NAMCS data and found no correlation between EHR component functionality and quality of care for patients with high blood pressure or chronic disease. EHR elements considered were physician notes, reminders, computerized physician order entry (CPOE), and ordering of tests. A key limitation of the study is the cross-sectional nature of the data source, limiting causal conclusions. Keyhani suggested additional research to examine length of EHR adoption and impact over time. (Keyhani, 2008)

Zhou addressed the issue of length of time of EHR usage compared with quality. The results showed no impact of EHR adoption length of time related to quality. The data was based on a statewide EHR adoption survey from 2005 linked to claims data for the quality component. (Zhou, 2009)

Romano considered a specific EHR feature, Clinical Decision Support (CDS) and the relationship to quality in the ambulatory setting. The study used NAMCS data from 2005-2007 and found no consistent association with higher quality when an EHR with CDS functionality was used. One of the strengths of the study is the national level of the data used in the analysis versus other studies that have used data from a single institution. Romano also suggested the use of randomized trials to gain a better understanding of EHR impact. (Romano, 2011)

Crosson demonstrated in 2012 that diabetic patients faired no better when providers used an EHR versus paper in meeting three key treatment guidelines. In the diabetes improvement program, the results of patients treated by providers using paper records were better than or comparable to those treated providers using EHRs. A suggested mechanism of the observed results is due to the failure of providers to adopt new workflows that take advantage of EHR capabilities, especially related to CDS. The authors concluded that the Regional Extension Centers (REC), created to assist provider adoption, need to focus on effective use and integration of technology in order to ensure the MU program improves care in the primary care setting. (Crosson, 2012)

McCormick analyzed ordering practices of physicians when electronic access to results was available to determine if the proposed saving of EHR influencing a reduction of duplicate testing is observed in practice. The authors examined imaging results and lab results and found there is no correlation between having electronic access and reduction in ordering of further tests. For imaging, they found ordering increased when electronic access was provided to previous results. The study notes the limitations of not accounting for providers that may be ordering for their own self-interest or other differences in ordering practice. Also, the potential benefit to the patient was not included in the analysis. A key conclusion the author reaches is that the estimates of savings from EHR adoption need to be verified with data. (McCormick, 2012)

Hospital

In the hospital setting, Jones used Hospital Compare Data from 2003-2006 for quality combined with HIMSS EHR adoption data. Hospitals with increased EHR adoption showed improvement for some measures, but no improvement for others. The small number of confounding factors that were considered in the analysis limited the study. Also, the details of EHR adoption did not specify the level of success associated with the implementation. (Jones, 2010)

DesRoches examined the relationship between EHR adoption and improved quality in hospital in a 2010 publication. The analysis used 2008 survey data to determine

EHR adoption and used a 2009 release of process of care measures from the Hospital Quality Alliance (HQA) to determine quality. The results of the study showed there were minimal improvements in hospitals with EHR functionality versus non-EHR hospitals with respect to both improved quality and efficiency. The cross-sectional nature of the data was noted as a potential limitation of the study. Additionally, the author explored other potential contributing factors to the lack of evidence to show EHR adoption improves quality. The potential that the improvement from EHR adoption may not be seen for years or until more hospitals reach adoption was included in the discussion. The results suggest the need to examine not just adoption, but the way EHR systems are used to ensure EHR use leads to improvements. (DesRoches, 2010)

A more recent study by Kazley, looked at CPOE adoption at hospitals related to quality. The study used data from the HQA linked to HIMSS CPOE adoption data. Some specific measures showed small improvements for hospitals with CPOE. However, a single quality measure also showed a negative correlation to CPOE. The study did not account for varying degrees of CPOE usage at different hospitals. (Kazley, 2011)

Studies Showing Positive Impact

Studies that showed positive impact of EHR adoption were also based on hospital and ambulatory settings. The studies showed a broad range of positive impacts from minor to more significant.

Ambulatory

Sequist performed a randomized trial to evaluate impact of CDS for patients with diabetes and coronary artery disease. Multiple practices were randomized to either provide care as usual or be presented electronic reminders for care guidelines. Results showed only a small number of measures actually improved when reminders were used. The response by physicians that was largely positive, suggested the reminders would have a positive impact. (Sequist, 2005)

Baron suggested that use of EHR technology to improved quality is possible but requires more than just technology. In this study, along with using an EHR to manage care, patient reminders were mailed and significant investment in educating physicians demonstrated improved quality. The study was limited to only a small physician practice, but the goal of a 10% increase in mammography rates was achieved. (Baron, 2007)

Persell performed a pre-implementation versus post-implementation (pre-post) analysis of quality measures related to changes in EHR pop-up reminders. The changes involved enabling pop-ups that were closely aligned with accepted care guidelines. The study showed improved quality results over a period of time following the EHR enhancement. There are some limits as the practice already had an established EHR and quality improvement initiatives were underway prior to the change to pop-ups. Nevertheless, the potential value of the EHR functionality was demonstrated. (Persell, 2011)

In a recent study involving a 2009-2010 regional quality initiative, Cebul demonstrated that practices using an EHR had improved quality of care for diabetes patients compared to non-EHR practices. The authors evaluated the difference between the study results and other studies showing no improved care. A key difference identified was the timeframe of the data used in NAMCS-based studies compared to more recent data in this study. Limits of the study included influences from the voluntary participation and submission of data. Suggested additional research included pre-post evaluations of EHR use and quality improvement. (Cebul, 2011)

A study by Poon linked Healthcare Effectiveness Data and Information Set (HEDIS) and EHR features obtained through survey. The study found consistent results with other studies that EHR adoption was not associated with higher quality when considering EHR usage as a binary variable. However, when evaluating EHR features, they found a positive association between quality and certain EHR components, including problem list, visit notes, and incorporation of radiology results. The authors concluded that EHR adoptions focused on the right elements could have a positive impact on care. (Poon, 2010)

An additional randomized trial of diabetes care related to use of CDS was performed in 2006-2007. The regional study by O'Connor showed an improvement of care associated with the use of CDS for diabetes patients. Limits of the study included the strong baseline position that existed prior to the intervention and the inability to explain why the use of CDS improved care. (O'Connor, 2010)

In a 2012 article, Hebel performed retrospective analysis of the volume of test ordering related to whether an internal Health Information Exchange was in use at a large health organization. The study found a significant decrease in the quantity of tests ordered when information from previous testing was readily available. The reduction in tests ordered analysis was as high as 50%. (Hebel, 2012)

Hospital

In the hospital setting, Amarasingham performed a cross-sectional analysis of 72 hospitals comparing quality data to level of clinical information technology. The level of automation was determined through use of survey data and was combined with statewide reporting of costs and outcomes. The study found that hospitals with higher level of clinical technology had fewer complications, lower mortality, and lower costs. The limits of the study include the narrow focus of functionality that was evaluated and correlated with higher quality. Also, the results were applicable to only the 72 hospitals included in the study and may not translate to all populations. (Amarasingham, 2009)

An additional hospital study by Elnahal demonstrated that hospitals with the top ten percent quality scores were more likely to have adopted EHR technology. He study was based on a 2009 survey. Limits of the study include the self-reported and cross-sectional nature of the data used in analysis. (Elnahal, 2011)

Tables 1 and 2 summarize the ambulatory and hospital research studies included in the review.

Table 1: Comparison of Ambulatory EHR Adoption-Improved Care Research

Year Publish	Author	EHR Adoption	Quality Measurement	Comments	Primary Findings
2007	Crosson	Self-reported survey	2003 - 2004; chart review; random cases	Diabetes guidelines not followed	Negative
2007	Linder	Self-reported survey	2003 - 2004; NAMCS data	Did not consider levels of EHR function	Neutral
2010	Walsh	Self-reported; confirmed by site visits	Compliance to guidelines	IMPROVE HF initiative	Mixed results
2008	Keyhani	Select EHR functionality	2005 NAMCS data	Notes, reminders, CPOE, test ordering	Neutral
2009	Zhou	Statewide survey	2005 claims data	Length of EHR adoption	Neutral
2011	Romano	Self-reported survey	2005 - 2007 NAMCS data	Clinical decision support only	Neutral
2012	Crosson	Self-reported	Compliance to guidelines for diabetes	Random limited grouping	Neutral
2012	McCormick	Self-reported survey	2008 NAMCS; Reduction of duplicate tests	National representative sample	Mixed results
2005	Sequist	Randomized; prospective	Care guidelines	Use of CDS in random trial	Positive
2007	Baron	Single practice initiative	Rate of mammography	Improved by 10%; also included mailings	Positive
2011	Persell	Single practice; pre-post	Compliance to care guidelines	Use of CDS; pop-ups	Positive
2011	Cebul	Self-reported; voluntary participation	Compliance to care guidelines	Diabetes care	Positive
2010	Poon	Survey	HEDIS data	Some measures influenced	Positive
2010	O’Connor	Single practice random trial	Compliance care guidelines	Diabetes; strong baseline	Positive
2012	Hebel	Single organization	Volume of tests ordered	Up to 50% reduction	Positive

Table 2: Comparison of Hospital EHR Adoption-Improved Care Research

Year Publish	Author	EHR Adoption	Quality Measurement	Comments	Primary Findings
2010	Hummelstein	HIMSS survey	2003 - 2007 CMS cost and quality data	Increased costs with computerization	Negative
2010	Jones	HIMSS survey	2003 - 2006 CMS quality data	-	Mixed results
2010	DesRoches	2008 survey	2009 HQA process of care	EHR adoption may take time to influence quality	Neutral
2011	Kazley	HIMSS survey	HQA quality data	CPOE functionality only	Mixed results
2009	Amarasingham	Survey data	Complications; mortality; costs	Limited to 72 hospitals	Positive
2011	Elnahal	Self-reported	HQA data	High quality more likely to have EHR functionality	Positive

Systematic Reviews

Several systematic reviews published over the last few years were also examined for further insight into the variable results of studies relating EHR adoption to improved patient care. These are presented here in order of publication.

In 2005, Garg looked at controlled trials using CDS in an attempt to characterize studies that showed improvement. The review found that CDS improved care in 64% of the studies that were included. The review also suggested that existing studies generally had not included workflow design and more research was needed into understanding the mechanism of improvement. (Garg, 2005)

In 2006, Chaudry published a systematic review of articles from 1995 to 2004 and found the majority of demonstrated evidence of EHR adoption improving care was related to four early adopter institutions. In this article, Chaudry suggested that while these institutions have demonstrated improved care through technology, the results might not be applicable to other organizations. (Chaudry, 2006)

In 2008, Dexheimer looked specifically at randomized trials and CDS systems. The review found that randomized trials were performed infrequently. The trials that have been done have generally shown modest improvement of care when using CDS. (Dexheimer, 2008)

In 2009, Goldzweig examined costs and benefits of EHR adoption in an updated systematic review. Since the previous work, the review found an increase in the number of patient-oriented tools. Also, a greater number of organizations are contributing to the literature. Finally, the review identified a continued lack of cost benefit data for EHR adoption. (Goldzweig, 2009)

In the most recent systematic review, Buntin performed an update to the Chaudry and Goldzweig reviews. The results of this review showed that 92% of studies published from 2007 to 2010 indicate positive impact of EHR adoption. The review noted the possibility of publication bias factoring into this observation. An additional limitation is that all included studies are treated equally. (Buntin, 2011)

Commentary and Supporting Literature

The commentary articles that are included in this review represent both MU and EHR adoption. Opinions that support and criticize MU are included. In the area of EHR adoption, articles that are critical of earlier studies are included. Also included are letters sent to journals in response to included primary research articles. The letters highlight the strong debate that is ongoing in today' changing environment.

Meaningful Use

Hussain presented his position that MU is flawed because it does not represent the interests of providers. The article explained that when the incentive dollars are no longer available, the return on investment for EHR adoption is lacking. Hussain further suggested an alternative approach to increasing adoption that is 'bottom-up' oriented from the providers needs and adds features one by one. (Hussain, 2011)

In response to Hussain, Baron identified flaws in the bottom up approach as they would not promote the use of standards, but continue to support individual tastes. Without standardization, the interoperability issues between caregivers would not be resolved. Baron further noted that patients are the benefactors of standardized data that can be shared. (Baron, 2011)

In another 2011 article, Classen discussed EHR adoption and the inconsistent results of past studies related to improved quality. Classen noted the potential unintended impact on commercial EHR vendors to break their usual release routine in order to meet demands of MU. The article also notes that some early adopters that developed in-house EHR solutions are turning to commercial packages due to maintenance challenges. These early adopters are the same institutions that demonstrated EHR value as discussed by Chaudry. (Classen, 2011)

Jha identified underlying information about the MU initiative in a 2010 publication. The article discussed the high bar set by the MU program for providers and hospitals to achieve incentives. The speed at which the MU program requires adoption is noted as a concern. The article described the challenge and still developing knowledge base associated with EHR implementation practices (Jha, 2010)

In a 2011 published article, Abbett considers EHR functionality that could aid in quality improvement (QI) initiatives. The authors take the position that the existing MU stage 1 quality requirements, which only enforce capability to electronically measure a set of defined quality metrics, fall short of the full potential of EHR to support QI efforts. The authors suggest significantly more effort needs to be put into understanding work flows and processes and ensuring EHR systems support a broader range of functionality. CDS and specialized alerts are discussed. The authors conclude that the MU criteria alone are not enough to deliver on the promise of health information technology (HIT). (Abbett, 2011)

Letters to Journals

In correspondence published in December 2011, Koppel offers criticism of previous work by Cebul which demonstrated the positive association of diabetes care with use of EHRs. Koppel argues that the study design failed to account for preexisting trends, and suggested the article would not be strong enough evidence to be included in other systematic reviews. Koppel asks “Are we so desperate to believe EHRs are our key solution that we accept reports with such weak methodologies?” The authors replied to the letter by clarifying a couple of items and explaining preexisting baseline data was not available. The response also notes the ability to improve the evidence with randomized trials. However, it is unlikely to be carried out in today’s environment. (Koppel, 2011)

In 2012, Gordon responded to McCormick’s article noting that opposite conclusions were reached by Hebel in another recently published study relating order reduction with EHR use. Gordon noted that to view EHR for a single aspect of improvement, reduction of orders, was a limited viewpoint. The letter states the position that EHR technology is needed for improvements today and into the future and that additional study is warranted with a broader scope.

Table 3 summarizes the systematic reviews, commentary articles, and letters that are included in the review.

Table 3: Systematic Reviews, Commentary, and Letters

Year Publish	Author	Summary
2005	Garg	CDS improved care; little focus on workflow and understanding mechanism of improvement
2006	Chaudry	Most improvement associated with 4 early adopters; Results may not be generalizable
2008	Dexheimer	Randomized trials were infrequent; Show modest improvement
2009	Goldzwieg	Examined costs and benefits as evidence is lacking; New organizations contributing to data.
2011	Buntin	92% of studies 2007-2011 show positive association of EHR adoption and quality; Noted possibility of publication bias.
2011	Hussain	MU is flawed; Return on investment is lacking long term; provider needs are under-served
2011	Baron	Response to Hussain; Provider-focused would detract from standardization and limit interoperability
2011	Classen	Inconsistent results of EHR adoption; EHR vendors are negatively impacted by MU; Move away from in-house EHR packages
2010	Jha	High bar set by MU; Speed of program is a concern; EHR implementation is a developing discipline
2011	Abbett	MU falls short with respect to quality improvement efforts; Need greater focus on workflows and processes
2011	Koppel	Letter; Critical of Cebul article describing improved adherence to diabetes care guidelines study; Claim study design was flawed
2012	Gordon	Letter; Critical of McCormick and reinforcement of Hebel findings related to ordering of tests; Must take a comprehensive look at EHR impact

EHR Adoption Considerations

In a 2007 publication, Lobach discussed the unique challenges associated with researching EHR adoption. Lobach noted that in order to accurately study EHR adoption, researchers must consider the impact of failed implementation attempts. The variable degrees of success in deploying systems would add to accuracy of study information. As part of implementing systems, the training component should also be considered. The degree to which users are able to perform functions and ease of use are factors in implementation success. Lobach suggested there is a need for assessment tools to measure these factors along with evaluation of additional defined parameters in the clinical setting. The article identified the need for better study design to accurately evaluate the impact of EHR adoption. It is noted that a blind randomized trials would not be feasible. The potential of confounding factors for pre-post implementation studies is discussed. (Lobach, 2007)

In 2010, Karsh discussed fallacies and realities in HIT. Karsh suggested the current path of adoption would not be successful in reaching goals. The article discussed the lack of an FDA-style safety oversight of EHR implementations. EHR software is identified as being of poor quality and poor usability. The author identified other challenging characteristics that are unique to implementing EHR systems. (Karsh, 2010)

A 2011 publication by Mohan challenged the conclusions of the Romano study that indicated no association between EHR adoption and quality using NAMCS data. Mohan believes the data used was not purposed for evaluating the impact of EHR and is not as accurate as possible. In addition, Mohan contends the use of 2005-2007 data is simply out of date. The article suggests more recent data would show stronger correlation of EHR adoption with improved quality. (Mohan, 2011)

Jha provided an assessment of EHR adoption in hospitals based on 2010 survey results taken at the time the initial MU final rule was being finalized, published in 2011. They sought to identify the number of hospitals that have EHR, how many intended to apply for MU incentives based on belief they could meet the requirements, and what the major barriers are holding back others. The results showed continued increase in EHR adoption especially among non-profit, larger teaching hospitals mainly associated with urban areas. Up to two thirds of hospitals planned to apply for the incentives, although the availability of core functionality demonstrated progress would be needed. Only 4.4% had full list of core functions available. (Jha, 2011)

In a 2012 publication, DesRoches reviewed the most recent data on hospital EHR adoption in the light of the MU program based on 2011 survey data. Although less rigorous than meeting MU criteria, the survey was used as a proxy standard to assess ability of hospitals to meet MU. Despite survey non-response limitations, the study showed that there has been a substantial increase in the number of hospitals with EHRs. The results also showed a widening gap between the adoption rates of hospitals with different characteristics. Hospitals that have adopted EHRs are most likely to be large teaching institutions, generally in the northeast. Small, rural non-teaching facilities continued to adopt EHR at a slower rate. (DesRoches, 2012)

Wolf examined the EHR adoption rates of providers that are not eligible for the MU incentive program, such as long-term, rehabilitation, and psychiatric facilities. The analysis was performed using 2009 survey data from AHA to determine EHR adoption.

The finding is that the rates of adoption at the ineligible facilities is less than half that at eligible hospitals. The reasons behind the low adoption included a lack of perceived benefits and underserved market by EHR vendors. The authors noted the potential impact to the overall health system if a large segment does not adopt technology required to exchange information. (Wolf, 2012)

Topaz examines the debate around the impact of EHR adoption on outpatient quality in a 2012 publication. The author notes that study design is a major factor that has weakened the conclusions of some efforts and has led to critique from other authors. The ability to measure EHR adoption and the use of limited quality indicators has led to specific criticism for studies reviewed. The author suggests further research with stronger study design. The article also suggests including more than just process of care measures in the analysis of quality. (Topaz, 2012)

In a 2012 publication, Harle discussed the six key quality components identified by the Institute of Medicine and the current status of research evidence to support each of the objectives. The authors noted there is stronger evidence to suggest EHR adoption can improve patient safety and effectiveness of care. However, the literature is weaker in showing increased efficiency with use of EHR systems. Even though the authors support the EHR incentive investment, they suggest additional research in several under-investigated domains. (Harle, 2012)

Table 4 details the articles associated with EHR adoption that were included in the literature review section.

Table 4: EHR Adoption Considerations; Commentary and Research

Year Publish	Author	Summary
2007	Lobach	Failed implementations and training should be considered; Identified need for better study design evaluating impact of EHRs
2010	Karsh	Question ability to meet national goals of EHR adoption; Identify the need for FDA-style oversight
2011	Mohan	Challenged conclusions reached by Romano; Use of 2005-2007 data is out of date and not intended for EHR study
2011	Jha	Survey to hospitals related to MU intent; Showed increased adoption and intent to meet MU criteria, especially non-profit large teaching hospitals
2012	DesRoches	Approximated ability to meet MU based on survey data; Study showed increased EHR adoption, but increased adoption gap between large urban and small rural hospitals
2012	Wolf	Examined facilities not eligible for MU; Found low adoption rates
2012	Topaz	Outpatient quality and EHR adoption examined; Study design has weakened conclusions; Need to improve design and increase scope of quality measures identified
2012	Harle	Discussed six key Institute of Medicine objectives; EHR adoption can improve care and safety; Evidence showing improvement in efficiency is weaker

Why Such Discrepancy in Study Results?

There are several factors that may be contributing to the inconsistent results of studies that examine EHR adoption and improved care. The timeframe of the data used in the analysis is a factor. In addition, assessing EHR adoption is very complex with a high degree of variability. The ability to develop a study design that is optimal for evaluating EHR impact is difficult. Lastly, the measurement of improved care is not straightforward.

The timing factor of the study data is supported by the evolution of systematic reviews included in this review. The earliest review suggests just over half of articles show positive EHR impact, while the most recent review suggests almost all of the articles as showing positive impact. The arguments made by Mohan appear to be valid by considering the studies included in this review. The studies that showed mixed results or no impact used data that is older than data used in the positive impact studies. Considering the speed of implementation required to meet the MU program requirements, the EHR environment is undergoing change. This further validates the need to use the most up to date data available to accurately assess the impact of EHR systems.

The complexity and variability of successful EHR adoption is an additional factor that contributes to inconsistent study results. Several of the reviewed articles included only a binary variable for the status of EHR adoption. With such a high degree of variability between the success levels, combining data from different level adoption can lead to invalid data analysis. One method to correct for this potential was demonstrated by studies that considered individual EHR functionality. However, even within a single EHR feature such as CPOE, the rate of use of the systems by clinicians can vary.

Grouping disparate data to be statistically evaluated as a single group weakens the conclusions.

The design of studies that seek to characterize the impact of EHR is also an important consideration. Studies showing no impact or mixed results were often retrospective statistical evaluations of quality and survey data, not intended to measure EHR adoption. Studies showing positive impact introduced pre-post evaluations and random trials along with statistical retrospective analysis.

The definition of quality used in the various studies differed greatly. In many cases, existing quality registries such as HEDIS or NAMCS were used to evaluate quality. While these data registries are widely accepted, they were not developed in the context of measuring HIT adoption. In order to consistently evaluate the impact of EHR adoption, a common definition of improved care would reduce the variability.

Suggested Research Considerations

In order to overcome the issues identified in the studies reviewed, future study designs need to account for potential variability of EHR adoption. If multiple organizations were to be compared, use of an assessment tool to evaluate EHR status would enhance reliability of results. An alternative design that only includes a single organization with a single level of EHR adoption would also eliminate the ambiguity introduced by this factor but also have more limited applicability.

An additional factor to improve the past research involves planning and collecting data specifically for the purpose of evaluating EHR adoption related to patient care improvement. This would eliminate the weakening of the conclusions by using data for purposes it was not originally intended for.

As noted in the systematic review section, only a small number of randomized trials are performed in the study of EHR adoption. Designing trials that are based on randomization would help to strengthen the conclusions. While pre-post studies may not be as solid as random trials, they would still be of higher value than retrospective data analysis driven studies. Use of standardized quality measures is an additional factor that can also lead to stronger study conclusions and less room for critique.

Summary

As the review articles show, studies evaluating EHR adoption and improved care have shown variable results. Contributing to the variability, are the use of data from different time frames, the use of data that was collected for alternative goals, and the lack of accounting for variability in EHR adoption. In addition, the nature of studying EHR impact makes study design a challenge.

Healthcare professionals have expressed doubt and identified potential flaws in the MU program. Other practitioners have expressed strong support of the program. The MU program is intended to improve the quality of care and reduce costs. In order to gain a clearer understanding if these goals can be met, stronger research on the impact of EHR adoption is needed.

Chapter 3: Methods

Methodology

The study methods and data that were analyzed are described in the following section. The study used publicly available data from CMS to measure the quality factor and EHR adoption factor. A hospital directory with attributes of interest was constructed and linked to the source data. Statistical analysis was performed to compare the mean value of specific groups, looking for statistical significant differences between means. Additional descriptive hospital information was developed from the listing of hospitals the met MU criteria in the first and second year of the program.

Research Design

The study uses a cross-sectional design to compare the mean measures of quality of two groups at specific points in time. The first group is made up of acute care hospitals that were paid for meeting MU criteria in 2011. The second group is made up of acute care hospitals that did not meet the MU criteria in 2011. Thus, the dependent variable in the testing is MU paid, a binary value. The independent variable is the selected quality indicator used. The analysis was repeated using the same quality data and evaluated against meeting MU in 2012. Additional divisions of the paid and non-paid groups were performed using common hospital attributes. Further descriptive information was derived by examining the characteristics of hospitals that met MU in 2011 and 2012, along with an examination of the changes from year to year.

Population and Sample Design

The population included in the study was limited by the data in the VBP and readmission reduction data. CMS calculated and published the factors for these measures for all acute care hospitals in the U.S. In total there were 3,428 hospitals included in the analysis.

Data Collection

Study source data was downloaded from a variety of internet sources. CMS was the source of hospitals that were paid for MU in 2011 and 2012. CMS was also the source of latest version of hospital compare data used. The VBP and readmission reduction information was downloaded from a summary listing provide by Kaiser Permanente. (Kaiser, 2012) These values were evaluated against similar data from CMS and found to be consistent with CMS and more conveniently formatted for analysis. The hospital directory information was obtained by using the free hospital lookup information available from the American Hospital Association (AHA) at www.aha.org. Supplemental information was obtained from American Hospital Directory (AHD) website, www.ahd.com. The full set of data was loaded into a SQL relational database.

Data Analysis

Data manipulation was performed to prepare the data for import into a statistical software package. Detail description of the data source files and assignment of values is described further in the section.

The list of hospitals that were paid for meeting MU used in this analysis was made available by CMS in late 2012. The list included payment information for hospital fiscal year 2011 and 2012. The federal hospital fiscal year runs from October 1 through the following September 30. In order to receive payments for MU, the hospital would have had to attest to meeting the criteria via the CMS registration and submission process. Meeting MU criteria meant that the hospital met all the functional core objectives and five out of ten menu objectives. Some measures require a threshold of compliance must be met. Other measures are a binary indication that a particular functionality is enabled within the EHR software. The EHR software must also be certified according to a process and criteria described by CMS. A key consideration in this study is the structure of the MU program. In the first year, providers are required to meet the criteria and submit an attestation for 90 days worth of data. In order to meet the MU criteria in the second year, a full 365 days of data compliance is required. (US, 2011)

The hospital compare data used in this analysis was last updated in January 2013. Hospital compare is a consumer-oriented website that makes it possible for patients to compare hospitals side by side with respect to a number of quality indicators. Three measures of 30-day mortality from the hospital compare data were used, heart attack mortality, heart failure mortality, and pneumonia mortality. The timeframe for the collection of the data CMS used to calculate the mortality rate is from July 2008 through June 2011. A composite average was developed for the mortality score. If one or more of the mortality values was not available in the hospital compare, the remaining measures were averaged. Each of the values was treated equally as there was no weighting used when determining the composite mortality score. Hospitals with no available mortality score were eliminated from the analysis.

The VBP program adjusts payments from services billed to CMS by a reduction or addition of up to 1 percent for fiscal year 2013. Hospitals with the highest reduction will lose nearly 1 percent of Medicare billing. Hospitals with highest reward will gain up to 1 percent on top of Medicare billing. The VBP adjustment factor that is in effect for fiscal year 2013 was made available by CMS during the fourth quarter of 2012. (US, 2013b)

The VBP adjustment factor for 2013 is based on specific hospital compare measures that were selected by statistical analysis to show reliability of the indicators. The full list of measures used can be found in Table 1. The measures used to calculate the VBP adjustment factor cover two domains, select process of care measures and patient survey measures. The VBP data was measured from July 2011 through March 2012. (US, 2013b)

Table 5: Component Measures of the VBP Factor

Clinical Process of Care Measures	
Measure ID	Measure Description
Acute Myocardial Infarction (AMI)	
AMI-7a	Fibrinolytic Therapy Received Within 30 Minutes of Hospital Arrival
AMI-8a	Primary Percutaneous Coronary Intervention (PCI) Received Within 90 Minutes of Hospital Arrival
Heart Failure (HF)	
HF-1	Discharge Instructions
Pneumonia (PN)	
PN-3b	Blood Cultures Performed in the Emergency Department Prior to Initial Antibiotic Received in Hospital
PN-6	Initial Antibiotic Selection for Community-Acquired Pneumonia (CAP) in Immunocompetent Patient
Healthcare-associated Infections (SCIP – Surgical Care Improvement Project)	
SCIP-Inf-1	Prohylatic Antibiotic Received Within One Hour Prior to Surgical Incision
SCIP-Inf-2	Prophylatic Antibiotic Selection for Surgical Patients
SCIP-Inf-3	Prophylatic Antibiotic Discontinued Within 24 Hours After Surgery End Time
SCIP-Inf-4	Cardiac Surgery Patients with Controlled 6:00 a.m Postoperative Serum Glucose
Surgeries	
SCIP-Card-2	Surgery Patients on a Beta Blocker Prior to Arrival That Received a Beta Blocker During Perioperative Period
SCIP-VTE-1	Surgery Patients with Recommended Venous Thromboembolism Prophylaxis Ordered
SCIP-VTE-2	Surgery Patients Who Received Appropriate Venous Thromboembolism Prophylaxis Within 24 Hours Prior to Surgery to 24 Hours After Surgery
Survey Measures	
HCAHPS	Hospital Consumer Assessment of Healthcare Providers and Systems Survey

The readmission reduction program also applies a Medicare adjustment payment factor of up to one percent penalty or bonus beginning in fiscal year 2013. The readmission payment adjustment factor is based on hospital compare readmission data. The factor is calculated based on a combination of achieving low readmission rates and improving readmission rates as compared to baseline data. The readmission measures that are included in determining the composite score are the 30 day readmission rates for heart failure, heart attack, and pneumonia from the hospital compare dataset. The timeframe used for determining the readmission rate adjustment factor is the same as was used in hospital compare mortality rates, from July 2008 to June 2011. (US, 2013c)

Hospital attributes were imported and recorded in a database table. The attribute used in the analysis are described here. Hospital ownership was derived from the Hospital Compare dataset. The source data values for hospital ownership were condensed into four categories based. Teaching status was added and was considered a binary value for purposes of the analysis, not differentiating between major and minor teaching facilities. The source of the teaching status was mainly the AHA directory lookup, with supplemental from information from the AHD directory hospital lookup tool. In constructing the hospital directory, the teaching status of six hospitals was not found. These hospitals were grouped with non-teaching hospitals in the analysis.

An additional hospital attribute categorized as hospitals as either urban or rural. The source of the classification was the AHA directory lookup. The directory construction effort failed to categorize 170 hospitals (5%). The last hospital attribute to be considered in the analysis was the bed size. The bed size information was obtained from the AHA directory and AHD directory, where possible. The bed size data for 27 hospitals was not found. These unknown bed size hospitals were excluded from analysis involving the bed size. The hospitals were grouped into three categories based on bed size, small (1-99 beds), medium (100-399 beds), and large (>= 400 beds).

Using relational database tools, the analysis data was prepared by linking the source data based on the unique CMS identifier. The hospital compare data, VBP, readmission reduction data all contained the hospital identifier. A linkage between the hospital directory and the CMS identifier was constructed to be able to group the data by the attributes of teaching status, setting (urban or rural), and bed size.

To permit statistical analysis, data was formatted into analysis groups as described. This data was then imported into the statistical tool to permit calculation of means using independent t-tests. Statistical independent t-tests were performed separately on each quality indicator used and then by attribute groupings for both the MU paid 2011 and 2012 hospitals.

The resulting means and indications which represent statistically significant differences was evaluated to add to the evidence of whether EHR adoption as measured by MU achievement is related to improved care.

The t-tests were evaluated using a priori alpha value of 0.01. That is, in order to reject the null hypothesis that the two groups being evaluated have equal means, the calculated p-value must be less than 0.01. This significance would indicate there is a difference between the means of the two groups and the difference is not caused by chance alone in 99% of the cases. The confidence interval used for the testing was set at 99%.

Summary of Methods

In summary, data sources were identified and imported to construct analytical dataset using standard relational database tools. The attributes of the analyzed hospitals were constructed from multiple sources. The data sources were linked to the hospital directory using a unique CMS identifier. Data was exported for use with statistical software, performed using independent t-tests to compare means. VBP factor, mortality rate composite, and readmission reduction factor associated with MU achievement for 2011 were evaluated with and without grouping of the results by hospital attributes. Additionally, MU achievement for 2012 was evaluated with and without hospital attribute grouping. Additional analysis was done identifying attributes of hospitals meeting MU criteria in 2011 and 2012 and the change from year to year.

Chapter 4: Results

Overview of Results

The results of the comparison of means were assembled in tables according to the dependent and independent variable being compared. The overall analysis including all samples was listed first and the attribute groupings were included in each table. The groups appear with ownership group listed first, followed by teaching binary grouping, then urban/rural grouping and finally hospital bed size. Each of the three dependent variables, MU paid 2011, MU paid 2012, and MU paid in both 2011 and 2012, was evaluated against the three independent quality indicators. The VBP factor table summary is followed by the readmission reduction factor, then the mortality composite score for each MU paid variable. Preceding each set of tables relating to a single MU payment group, a short description identifying the means that showed significant differences within the limit were noted. The descriptive analysis section follows the comparison of means. The summary of the descriptive analysis precedes the tables that summarize the descriptive data results.

MU Paid in 2011 versus Not Paid in 2011

In the VBP factor analysis, the mean for hospitals paid in 2011 differed significantly from non-paid (α=0.01). The significant differences were seen through many of the grouping of attributes as well. In all cases where significance was demonstrated, the mean was higher for paid hospitals than non-paid. Within the ownership grouping, significant differences were demonstrated for the non-profit and proprietary owners. Both teaching and non-teaching means showed significant differences. Also showing significance difference was the urban hospital grouping.

Within bed size breakdown, there were significant findings for the medium and large hospital groups. The VBP means and P values are shown in Table 6.

The readmission factor analysis for 2011 payment showed mixed results of means. Contrary to the findings for VBP, the non-paid hospitals mostly showing higher means. However, none of the metrics resulted in significant differences within the limits. The readmission means and P values are shown in Table 7.

The mortality variable means were also mixed. The comparison for rural hospitals showed a lower mean for paid hospitals that had a low P value, but not within the limits. None of the results in this section showed significant difference between the groups. The mortality means and P values are shown in Table 8.

Table 6: Mean VBP Factor Associated with MU Paid/Not Paid in 2011

		MU Paid 2011	MU Not Paid 2011	P value
All Acute Care Hospitals		0.0753 (N=651)	0.0028 (N=2777)	< 0.001
Grouping by Ownership				
	Government	-0.0160 (N= 105)	-0.0381 (N=518)	0.444
	Non-profit	0.0616 (N=374)	-0.0086 (N=1669)	< 0.001
	Physician	0.3533 (N=3)	0.2080 (N=20)	0.493
	Proprietary	0.1573 (N=169)	0.0660 (N=570)	< 0.001
Grouping by Teaching Status				
	Teaching	0.0592 (N=216)	-0.0320 (N=861)	< 0.001
	Non-teaching	0.0832 (N=435)	0.0184 (N=1916)	< 0.001
Grouping by Setting				
	Urban	0.0963 (N=472)	0.0039 (N=1874)	< 0.001
	Rural	0.0097 (N=151)	-0.0004 (N=761)	0.648
	Uncategorized	0.0746 (N=28)	0.0046 (N=142)	0.155
Grouping by Bed Size				
	Small (1-99 beds)	0.0600 (N=194)	0.0555 (N=944)	0.840
	Medium (100-399)	0.0950 (N=352)	-0.0191 (N=1463)	< 0.001
	Large (>=400 beds)	0.0339 (N=103)	-0.0535 (N=345)	< 0.001

Table 7: Mean Readmission Factor Associated with MU Paid/Not Paid in 2011

		MU Paid 2011	MU Not Paid 2011	P value
All Acute Care Hospitals		-0.2967 (N=651)	-0.2744 (N=2777)	0.133
Grouping by Ownership				
	Government	-0.2364 (N=105)	-0.2552 (N=518)	0.409
	Non-profit	-0.3166 (N=374)	-0.2793 (N=1669)	0.057
	Physician	0.000 (N=3)	-0.0300 (N=20)	0.558
	Proprietary	-0.2955 (N=169)	-0.2862 (N=570)	0.745
Grouping by Teaching Status				
	Teaching	-0.3091 (N=216)	-0.2677 (N=861)	0.098
	Non-teaching	-0.2906 (N=435)	-0.2775 (N=1916)	0.476
Grouping by Setting				
	Urban	-0.2814 (N=472)	-0.2597 (N=1874)	0.194
	Rural	-0.3343 (N=151)	-0.3098 (N=761)	0.456
	Uncategorized	-0.3514 (N=28)	-0.2799 (N=142)	0.35
Grouping by Bed Size				
	Small (1-99 beds)	-0.2860 (N=194)	-0.2251 (N=944)	0.033
	Medium (100-399)	-0.2876 (N=352)	-0.2962 (N=1463)	0.654
	Large (>=400 beds)	-0.3536 (N=103)	-0.3282 (N=345)	0.521

Table 8: Mortality Composite Associated with MU Paid/Not Paid in 2011

		MU Paid 2011	MU Not Paid 2011	P value
All Acute Care Hospitals		12.75 (N=608)	12.79 (N=2524)	0.507
Grouping by Ownership				
	Government	12.71 (N=99)	12.87 (N=479)	0.286
	Non-profit	12.72 (N=352)	12.76 (N=1596)	0.575
	Physician	-	-	-
	Proprietary	12.84 (N=157)	12.82 (N=443)	0.856
Grouping by Teaching Status				
	Teaching	12.60 (N=202)	12.70 (N=819)	0.299
	Non-teaching	12.83 (N=406)	12.83 (N=1705)	0.944
Grouping by Setting				
	Urban	12.75 (N=437)	12.68 (N=1689)	0.352
	Rural	12.74 (N=146)	13.03 (N=734)	0.021
	Uncategorized	12.82 (N=25)	12.78 (N=101)	0.893
Grouping by Bed Size				
	Small (1-99 beds)	12.63 (N=174)	12.57 (N=744)	0.631
	Medium (100-399)	12.90 (N=332)	12.95 (N=1427)	0.528
	Large (>=400 beds)	12.46 (N=102)	12.61 (N=343)	0.304

MU Paid in 2012 versus Not Paid in 2012

In the VBP factor evaluation for 2012 paid hospitals versus unpaid, there were mixed results when comparing the means. None of the computed metrics demonstrated significant difference of means within the limit. The means and P values for VBP factor and MU paid 2012 are shown in Table 9.

Within the readmission factor, means were lower for hospitals not paid in 2012 versus hospitals that were paid for all of the scenarios that showed significant differences. The overall comparison showed a significant difference of means as did several attribute groups. In the ownership breakdown, government, non-profit, and proprietary owners showed significant differences. Both teaching and non-teaching groups showed significant differences between paid and non-paid means within the limit. Within the urban, rural, uncategorized settings, all groups showed significant differences. When grouping by hospital size, small and medium groups showed significant differences. These results are displayed in Table 10.

The mortality composite analysis showed mixed results of means, as some paid means were lower and some non-paid means were lower. There were no significant differences observed in the mortality analysis. Table 11 shows the mortality results.

Table 9: Mean VBP Factor Associated with MU Paid/Not Paid in 2012

		MU Paid 2012	MU Not Paid 2012	P value
All Acute Care Hospitals		0.0168 (N=1601)	0.0163 (N=1827)	0.954
Grouping by Ownership				
	Government	-0.0427 (N=263)	-0.0284 (N=360)	0.481
	Non-profit	0.0025 (N=972)	0.0058 (N=1071)	0.763
	Physician	0.2971 (N=7)	0.1963 (N=16)	0.516
	Proprietary	0.0935 (N=359)	0.0806 (N=380)	0.520
Grouping by Teaching Status				
	Teaching	-0.0109 (N=506)	-0.0161 (N=571)	0.900
	Non-teaching	0.0296 (N=1095)	0.0310 (N=1256)	0.712
Grouping by Setting				
	Urban	0.0244 (N=1081)	0.0209 (N=1265)	0.124
	Rural	-0.0074 (N=447)	0.0096 (N-465)	0.319
	Uncategorized	0.0527 (N=73)	-0.0114 (N=97)	0.738
Grouping by Bed Size				
	Small (1-99 beds)	0.0491 (N=497)	0.0618 (N=641)	0.448
	Medium (100-399)	0.0122 (N=867)	-0.0054 (N=948)	0.437
	Large (>=400 beds)	-0.0407 (N=228)	-0.0259 (N=220)	0.132

Table 10: Mean Readmission Factor Associated with MU Paid/Not Paid in 2012

		MU Paid 2012	MU Not Paid 2012	P value
All Acute Care Hospitals		-0.3168 (N=1601)	-0.2452 (N=1827)	< 0.001
Grouping by Ownership				
	Government	-0.3068 (N=263)	-0.2120 (N=360)	0.001
	Non-profit	-0.3168 (N=972)	-0.2583 (N=1071)	< 0.001
	Physician	-0.0300 (N=7)	-0.0244 (N=16)	0.881
	Proprietary	-0.3299 (N=359)	-0.2491 (N=380)	0.001
Grouping by Teaching Status				
	Teaching	-0.3222 (N=1095)	-0.2430 (N=1256)	< 0.001
	Non-teaching	-0.3053 (N=506)	-0.2501 (N=571)	0.006
Grouping by Setting				
	Urban	-0.2966 (N=1081)	-0.2363 (N=1265)	0.004
	Rural	-0.3545 (N=447)	-0.2747 (N=465)	0.001
	Uncategorized	-0.3864 (N=73)	-0.2203 (N=97)	< 0.001
Grouping by Bed Size				
	Small (1-99 beds)	-0.2986 (N=497)	-0.1866 (N=641)	< 0.001
	Medium (100-399)	-0.3200 (N=867)	-0.2713 (N=948)	0.002
	Large (>=400 beds)	-0.3502 (N=228)	-0.3173 (N=220)	0.322

Table 11: Mortality Composite Associated with MU Paid/Not Paid in 2012

		MU Paid 2012	MU Not Paid 2012	P value
All Acute Care Hospitals		12.76 (N=1543)	12.80 (N=1589)	0.394
Grouping by Ownership				
	Government	12.77 (N=252)	12.90 (N=326)	0.279
	Non-profit	12.72 (N=956)	12.79 (N=992)	0.263
	Physician	11.10 (N=2)	11.12 (N=4)	0.975
	Proprietary	12.87 (N=333)	12.76 (N=267)	0.35
Grouping by Teaching Status				
	Teaching	12.64 (N=498)	12.72 (N=523)	0.297
	Non-teaching	12.82 (N=1045)	12.84 (N=1066)	0.726
Grouping by Setting				
	Urban	12.69 (N=1040)	12.70 (N=1086)	0.874
	Rural	12.91 (N=437)	13.05 (N=443)	0.139
	Uncategorized	12.82 (N=66)	12.75 (N=60)	0.759
Grouping by Bed Size				
	Small (1-99 beds)	12.60 (N=450)	12.57 (N=468)	0.752
	Medium (100-399)	12.91 (N=862)	12.96 (N=897)	0.434
	Large (>=400 beds)	12.51 (N=227)	12.64 (N=2180)	0.264

MU Paid for Both 2011 and 2012 versus Not Paid for Both Years

In the VBP factor analysis, for all cases which showed significant differences, the mean for the paid group was higher than the non-paid group. The overall analysis, including all hospitals, showed significant difference of means. With the ownership grouping, non-profit and proprietary groups demonstrated significant differences. Both teaching and non-teaching groups showed significant differences of means. For bed size, the medium and large groups demonstrated significant differences. The means and P values are shown in Table 12.

In the readmission factor analysis, the means were lower for non-paid hospitals in the scenarios where significance was observed. The overall analysis showed a significance difference of means between the paid and non-paid groups. Also, the non-profit ownership group showed a significant difference of means. Several of the calculations for other groups resulted in a fairly low P value, however, none within the limit of significance. Table 13 shows the results of the readmission values.

The mortality composite analysis continued to show no significant differences along with mixed results as shown in Table 14.

Table 12: Mean VBP Factor Associated with MU Paid/Not Paid in Both 2011 and 2012

		MU Paid 2011 and 2012	MU Not Paid 2011 and 2012	P value
All Acute Care Hospitals		0.0801 (N=450)	0.0069 (N=2978)	< 0.001
Grouping by Ownership				
	Government	-0.0341 (N= 64)	-0.0345 (N=559)	0.991
	Non-profit	0.0532 (N=238)	-0.0022 (N=1805)	0.001
	Physician	0.3533 (N=3)	0.2080 (N=20)	0.493
	Proprietary	0.1690 (N=145)	0.0669 (N=594)	< 0.001
Grouping by Teaching Status				
	Teaching	0.0446 (N=138)	-0.0222 (N=939)	0.001
	Non-teaching	0.0958 (N=312)	0.0204 (N=2039)	< 0.001
Grouping by Setting				
	Urban	0.0946 (N=331)	0.0107 (N=2015)	< 0.001
	Rural	0.0278 (N=97)	-0.0019 (N=815)	0.283
	Uncategorized	0.0923 (N=22)	0.0048 (N=148)	0.156
Grouping by Bed Size				
	Small (1-99 beds)	0.0794 (N=139)	0.0531 (N=999)	0.299
	Medium (100-399)	0.0950 (N=242)	-0.0111 (N=1573)	< 0.001
	Large (>=400 beds)	0.0274 (N=68)	-0.0443 (N=380)	0.007

Table 13: Mean Readmission Factor Associated with MU Paid/Not Paid in Both 2011 and 2012

		MU Paid 2011 and 2012	MU Not Paid 2011 and 2012	P value
All Acute Care Hospitals		-0.3256 (N=450)	-0.2716 (N=2978)	0.002
Grouping by Ownership				
	Government	-0.2861 (N= 64)	-0.2481 (N=559)	0.381
	Non-profit	-0.3626 (N=238)	-0.2760 (N=1805)	0.001
	Physician	0.0000 (N=3)	-0.0300 (N=20)	0.558
	Proprietary	-0.2891 (N=145)	-0.2882 (N=594)	0.975
Grouping by Teaching Status				
	Teaching	-0.3358 (N=138)	-0.2672 (N=939)	0.022
	Non-teaching	-0.3211 (N=312)	-0.2736 (N=2039)	0.024
Grouping by Setting				
	Urban	-0.3052 (N=331)	-0.2573 (N=2015)	0.013
	Rural	-0.3779 (N=97)	-0.3062 (N=815)	0.071
	Uncategorized	-0.4018 (N=22)	-0.2753 (N=148)	0.134
Grouping by Bed Size				
	Small (1-99 beds)	-0.3083 (N=139)	-0.2253 (N=999)	0.015
	Medium (100-399)	-0.3215 (N=242)	-0.2904 (N=1573)	0.180
	Large (>=400 beds)	-0.3804 (N=68)	-0.3257 (N=380)	0.238

Table 14: Mortality Composite Associated with MU Paid/Not Paid in Both 2011 and 2012

		MU Paid 2011 and 2012	MU Not Paid 2011 and 2012	P value
All Acute Care Hospitals		12.78 (N=433)	12.78 (N=2699)	0.938
Grouping by Ownership				
	Government	12.67 (N=61)	12.86 (N=517)	0.307
	Non-profit	12.72 (N=234)	12.76 (N=1714)	0.698
	Physician	-	-	-
	Proprietary	12.91 (N=138)	12.80 (N=462)	0.343
Grouping by Teaching Status				
	Teaching	12.65 (N=133)	12.68 (N=888)	0.752
	Non-teaching	12.83 (N=300)	12.83 (N=1811)	0.955
Grouping by Setting				
	Urban	12.80 (N=317)	12.68 (N=1809)	0.131
	Rural	12.69 (N=95)	13.02 (N=785)	0.032
	Uncategorized	12.83 (N=21)	12.78 (N=105)	0.84
Grouping by Bed Size				
	Small (1-99 beds)	12.64 (N=126)	12.58 (N=792)	0.617
	Medium (100-399)	12.95 (N=239)	12.94 (1520)	0.914
	Large (>=400 beds)	12.42 (N=68)	12.60 (N=377)	0.294

Descriptive Analysis

The group composite information is described in the following section. The ownership grouping is made up of predominantly non-profit hospitals comprising nearly 60% of the hospitals. The next largest ownership group is proprietary ownership. Teaching hospitals comprise approximately 31% of hospitals. The grouping by setting showed over 68% of hospitals classified as urban. The bed size grouping shows nearly 52% of hospitals were classified as medium, with 33% classified as small. Table 15 shows the summary of the descriptive analysis for group compositions, MU paid 2011 and MU paid 2012.

With respect to MU in 2011 overall, nearly 19% of hospitals were paid. In the ownership attribute grouping, the highest percentage of payment for 2011 was seen in the proprietary grouping. The teaching groups showed nearly the same MU achievement as non-teaching with a slightly higher percentage at teaching hospitals. Twenty percent of urban hospitals achieved MU in 2011, while less than 17% of rural hospitals were paid. With respect to hospital size, large hospitals had the highest percent in 2011 at 23%. The small hospital group had the lowest rate at 17%.

MU payment data for 2012 showed an increase in achieving payment in all groups. The overall rate increased to over 46%. Within the ownership grouping, non-profit and proprietary groups achieved at over 47%, while the government owned hospitals had a rate of 42%. Both teaching and non-teaching hospitals rates were similar at nearly 46%. In the grouping by setting, the highest achievement rate of 49% was reached by rural hospitals. With respect to hospital size in 2012 payment, large hospitals continued to show the highest rate at nearly 51%.

The results when evaluating hospital characteristics that were paid for MU in both 2011 and 2012 show 13 % of hospitals overall achieved both payments. In the ownership grouping, the highest rate of nearly 20% was reached by the proprietary grouping. Teaching and non-teaching reached payment in both years at around 13%. Urban hospitals received payment at a rate of 14%, while rural hospitals had a rate of 11%. Large hospitals had the highest rate among the bed size group at over 15%. Table 16 presents these results in addition to the year by year analysis.

The change in percentage from MU 2011 to 2012 was also computed. Overall, there was nearly a 28% increase in percentage of hospitals paid in 2012 versus 2011. In the ownership grouping, the largest gains were seen in the non-profit group where there was a 29% increase. Non-teaching hospitals showed a slightly higher increase than teaching at 28%. Rural hospitals increased 32% from 2011 to 2012, the highest rate increase in the group by setting. The change was similar for hospital bed size groups, with a slightly higher change for medium hospitals.

An additional metric that was evaluated for the descriptive statistics was the percentage of hospitals that were paid for MU in 2011 but not paid in 2012. Overall, nearly 31% of hospitals that were paid in 2011 did not receive payment in 2012. Among hospital ownership grouping, 39% of government hospitals that were paid in 2011 did not receive payment in 2012. Teaching hospitals showed a 36% drop-off. In the grouping by setting, nearly 36% of rural hospitals that received payment in 2011 did not in 2012. Among the bed size grouping, large hospitals dropped off at nearly 34%.

Table 15: Attribute Group Composition and Percentage Paid for MU

		Composition	MU Paid 2011	MU Paid 2012
All Acute Care Hospitals		100 %	18.99 %	46.70 %
Grouping by Ownership				
	Government	18.17	16.85	42.22
	Non-profit	59.60	18.31	47.58
	Physician	0.67	13.04	30.43
	Proprietary	21.56	22.87	48.58
Grouping by Teaching Status				
	Teaching	31.42	20.06	46.98
	Non-teaching	68.58	18.50	46.58
Grouping by Setting				
	Urban	68.43	20.12	46.08
	Rural	26.60	16.58	49.01
	Uncategorized	4.96	16.47	42.94
Grouping by Bed Size				
	Small (1-99 beds)	33.20	17.05	43.67
	Medium (100-399)	52.95	19.4	47.77
	Large (>=400 beds)	13.07	22.99	50.89

Table 16: Change Year to Year and MU Paid for Both 2011 and 2012

		MU Paid Both 2011 and 2012	Change 2011 to 2012	Percent of MU 2011 not 2012
All Acute Care Hospitals		13.12	27.71	30.88
Grouping by Ownership				
	Government	10.27	25.37	39.05
	Non-profit	11.65	29.27	36.36
	Physician	13.04	17.39	0.00
	Proprietary	19.62	25.71	14.20
Grouping by Teaching Status				
	Teaching	12.81	26.92	36.11
	Non-teaching	13.27	28.08	28.28
Grouping by Setting				
	Urban	14.11	25.96	29.87
	Rural	10.63	32.43	35.76
	Uncategorized	12.94	26.47	21.43
Grouping by Bed Size				
	Small (1-99 beds)	12.21	26.62	28.35
	Medium (100-399)	13.33	28.37	31.25
	Large (>=400 beds)	15.18	27.90	33.98

Summary of Results

Analysis of MU payment in 2011 showed significant differences associated with the VBP factor. The paid group had a consistently higher mean in the VBP analysis. MU payments for 2012 showed significant differences with the readmission reduction factor. The non-paid group had consistently higher mean in the readmission analysis. The analysis for MU payment in both years showed some significant differences for both VBP and readmissions. The results means were mixed in the analysis for payment in both MU years.

The descriptive analysis shows characteristics of hospitals meeting MU for the permutations of MU payment years. Also, the change from year to year and the percentage of hospitals that dropped off from year one to year two provide further description of the analysis.

Chapter 5: Summary, Conclusions, and Recommendations

Overview of Section

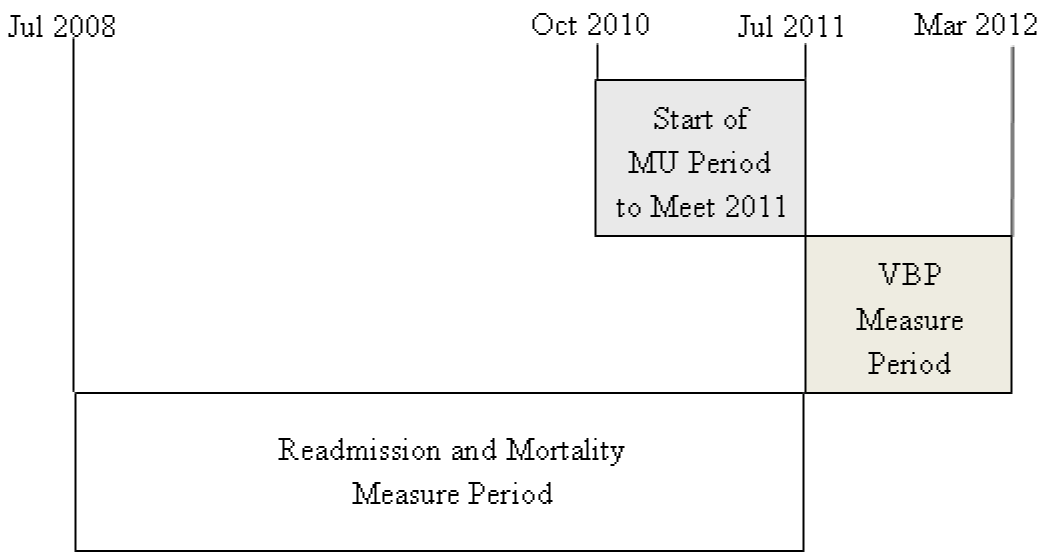
The conclusions reached from the study can be viewed as mixed results with respect to a whether EHR adoption improves care. The study did meet the goal of adding to and strengthening the data on the crucial issue. The strongest evidence produced by the analysis shows that hospitals meeting MU in the first year of the program had higher scores in the VBP adjustment. Data analysis from the readmission reduction program weakened that position, as it suggests EHR adoption hurts readmission rates. The analysis from the mortality data showed both MU and non-MU hospitals were equivalent. The strength of the VBP data and relative weakness of the readmission and mortality data relate to the measure timeframe used and will be discussed further.

The descriptive analysis provides insight into the characteristics of hospitals that are meeting MU. The change from year one to year two of the program demonstrates the increasing rate of EHR adoption that is sweeping the healthcare environment. The high rate of hospitals that have not been able to maintain MU in year two after meeting year one, provides an alert to policy makers and hospitals seeking to meet MU requirements.

Summary of Findings

The evaluation of MU paid in 2011 associated with the VBP factors suggests a strong positive association between EHR adoption and improved care. The timeframe of the data used in the VBP factor is from the final quarter of fiscal year 2011 and the first two quarters of fiscal year 2012. Essentially, the VBP factor was calculated from data obtained just after the MU evaluation period. This data shows the strongest correlation between the measure period and the MU achievement period based on timing of the MU period and VBP measure period. The VBP measure period is directly after the start of the period required to meet the first 90 days of MU achievement as shown in Figure 1.

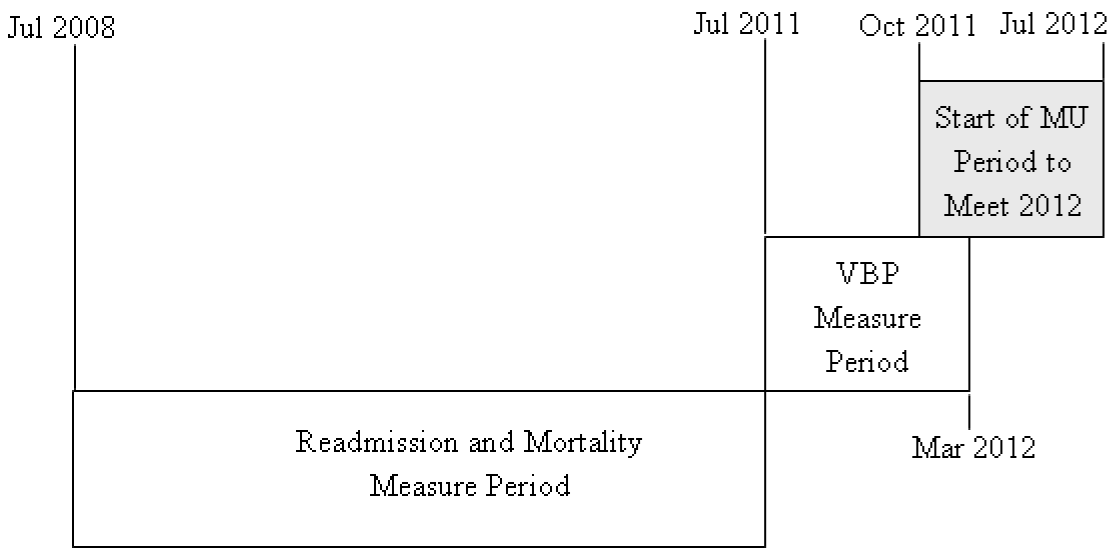
Figure 1: MU Measure for 2011 and Quality Measure Timeframes



However, it is unclear how long the hospitals meeting MU in 2011 have had EHR systems in place. It is likely that some, if not many of the hospitals had EHRs prior to the MU 2011 period. The improvement seen in the VBP measure may be a result of using an EHR for several years. Considering the tight timelines of the MU program relative to EHR implementation, the MU program left a small chance for hospitals to begin adoption when the final rules were announced and meet the 2011 requirements. The alignment of the readmission measure compared to MU 2011 period is also depicted in Figure 1.

The 2012 MU payment data shows a negative association between meeting MU and readmission reduction data. The conclusions drawn from this data are not as strong as the VBP conclusions due to the measure timeframe of the readmission data. First, the readmission factor was calculated from mid-2008 to mid-2011. Less focus of the readmission reduction was in place during the first part of the measure period. It would make more sense to compare meeting MU in 2012 with readmission data from after that time period. Using 2013 or 2014 data would more closely indicate the impact of having an EHR in place. Figure 2 depicts that much of the MU 2012 period is after the VBP measure period.

Figure 2: MU Measure for 2012 and Quality Measure Timeframes



The mortality data for all MU periods showed no differences between meeting and not meeting MU. This suggests there is no impact on improved care associated with EHR adoption. However, the mortality data shares the same timeframe as the readmission data. The same arguments weakening the readmission data due to timeframe apply to the mortality measure.

The descriptive analysis shows the makeup of hospitals when grouped by common attributes. Eight of ten hospitals are in either the non-profit or proprietary ownership groups. Approximately one third of hospitals are teaching facilities. Nearly 70% of hospitals are located in urban settings. Approximately half of hospitals are medium sized and one third is small. Only about one in eight hospitals is a large facility with 400 or more beds. These metrics can be useful when looking at which groups have varying adoption characteristics.

The first year of MU payments showed proprietary and non-profit hospitals had the highest achievement rates in the ownership groups. Teaching facilities and urban hospitals had somewhat higher achievement in the first year. The hospital size data also showed that large hospitals had the highest achievement rate and small hospitals had nearly 5% lower achievement.

The second year of MU payments showed a major increase in hospitals meeting MU compared to year one. Almost half the proprietary hospitals met MU in 2012. There was little difference in teaching versus non-teaching. In a dramatic shift from first year data, nearly half of rural hospitals met MU. Over 50% of large hospitals met MU in 2012 and small hospitals still had the lowest achievement among the hospital size groups.

The rate at which hospitals that met MU in 2011 and 2012 showed additional metrics describing the MU program. Proprietary hospitals had the highest rate among ownership groups. Despite impressive gains in the second year by rural hospitals, urban hospital still had the highest MU achievement level for both years. Large hospitals also had the highest level of achievement for meeting MU both years.

The change in each group from year to year showed the greatest increase in non-profits among the ownership group. There was only a small difference in change between teaching and non-teaching. Rural hospitals showed the largest increase in rate from year to year. Medium sized hospitals increased achievement of MU the most from year to year in the hospital size grouping.

The descriptive data analysis also showed the drop off from hospitals meeting year one to year two. Up to 40% of government owned hospitals meeting MU in 2011, failed to be paid for 2012. The drop off among non-profits was nearly as high, at over 36%. Teaching hospitals had a higher drop off rate than non-teaching. While rural hospitals showed the largest change in new adoption, they also showed the largest drop off of nearly 36%. Among hospital size groups, large hospitals showed the highest drop off rates.

The drop-off rates show the difficulty in meeting the MU criteria in the second year. Apparently, meeting the criteria for 365 days in the second year is difficult to maintain. This may suggest the changes to meet the program criteria in the first year are temporary. The adoption habits of providers may drop off after meeting the first 90 day period. This leads to the inability of hospitals to meet the second year criteria at an alarming rate of over 30%.

Conclusions

The primary conclusion of the study was that EHR adoption was demonstrated to be associated with improved care. The VBP data most closely aligns with the MU measurement period. While results show a strong indication that improvement can be seen with EHR adoption, the timing of when hospitals meeting MU in 2011 started using an EHR is unknown.

Other studies suggested the impact on care may take some time. (DesRoches, 2010) The positive results seen in the VBP analysis are aligned with results seen in previous work. Amarasingham showed a positive association of EHR adoption in a small cross-sectional study. (Amarasingham, 2009) Elnahal also demonstrated that the top hospitals with respect to quality tended to have EHRs in place. (Elnahal, 2011)

The readmission data, suggesting a negative association of care with EHR adoption resulted from data that is not as well aligned between the measure collection period and the MU period for 2012. The negative association of EHR adoption with care is a secondary conclusion of the study. The negative conclusion is weakened by the timeframe difference, yet there were statistically significant differences demonstrated.

The negative association is similar to previous work that was reviewed. Crosson noted a negative adherence to clinical guidelines for providers with EHRs in the ambulatory setting. (Crosson, 2007) Also, Kazely showed some negative association for a single measure in a study using HQA data. (Kazley, 2011)

The mortality data showed no impact of EHR adoption on improved care. This is also a secondary conclusion show in the study. The same timeframe challenges that weaken the readmission conclusion also weaken the conclusion drawn from the mortality data.

The neutral result is also similar to findings of other studies. Jones study which used hospital compare date from 2003 to 2006 also failed to show an impact of EHR adoption on quality. (Jones, 2010) Also, DesRoches showed minimal improvement in HQA data for hospitals that had EHRs in place. (DesRoches, 2010)

Overall, the findings in this study were the same as the literature reviewed, showing the full range of possibilities. There was some negative association observed, some neutral and some positive. Due to matching of timeframes, the strongest evidence is associated with the positive results from the VBP analysis.

The descriptive analysis of MU 2011 results in mainly consistent conclusions with previous research. Larger hospitals in urban setting had favorable contributions to meeting MU in 2011. In contrast to previous work, there was not a large difference between teaching and non-teaching hospitals. (DesRoches, 2012)

The descriptive analysis of MU 2012 showed results that were also partly consistent with other research and supported some new findings. The increase in EHR adoption and goal to reach MU criteria was identified in previous research. (Jha, 2011) Therefore, the increase in meeting MU and EHR adoption was consistent with other research. The results showing the greatest increase in rural hospitals is not consistent with previous research. (DesRoches, 2012) Rural hospitals may have been influenced by previous work suggesting they were lagging and responded by increasing their adoption rates.

The findings that almost one third of hospitals meeting MU in 2011 failed to meet in 2012 has not been discussed in previously identified research. This new finding that should garner the attention of both hospitals seeking to meet MU and policy makers. With this high of a drop-off rate, the idea that the MU program is moving very quickly with some unpredictable implications appears to be supported. (Jha, 2010)

Implications of the Study

The study results strengthen the evidence of EHR adoption association with improved care. However, the results do not completely settle the debate. Some validity to the rationale behind the MU program was demonstrated. At the same time, critics of the program would use the readmission and mortality data to counter the position.

The study did introduce a new way of measuring EHR adoption by the proxy of meeting MU. While the measure is not perfect, it does stand as a sensible way to eliminate some of the variability in measuring EHR adoption. In previous work, some studies classified a provider with a single function as having an EHR. One of the drawbacks of measuring EHR adoption by MU achievement is that the provider that meets all but one of the MU measures would be classified in the group representing non-payment and hence non-EHR.

The descriptive analysis provides insight to policymakers and healthcare professionals. Knowing what types of hospitals are achieving and not achieving MU may factor into future stages of the program. The large drop-off from year one to year two also suggests provider must be attentive to meeting the criteria, even after meeting the first year’s 90 day period.

Recommendations

CMS should provide hospital compare data at a more granular level. If the data was divided by fiscal year, the readmission and mortality rates for only the most recent year could have been evaluated. Evaluating one year versus three years of measure data may have changed the secondary conclusions of the study.

Also, CMS should be able to provide data to the public in a more timely fashion. The end date for data used for readmission and mortality was over 18 months old. CMS should work to provide this information so it can be analyzed when data is still most pertinent.

One of the most time consuming aspects of this study was construction of the hospital directory that included teaching status, urban or rural setting, and bed size. In order to support future non-funded research, this public data should be made available by CMS.

An additional way the data could have been evaluated would be to segregate providers meeting the first stage of MU in 2012 from those that met in 2011. In the analysis of MU 2012, these were grouped together. By separating them, further consideration to the impact of EHR adoption over time may have been observed.

Going forward, improved data released in a more timely fashion with continued evaluation of achieving MU criteria as a research indicator could help to settle the question as to whether EHR adoption improves care.

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