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Using Latent Class Analysis to Identify Sophistication Categories of Electronic Medical Record Systems in U.S. Acute Care Hospitals

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Abstract

Many believe that electronic medical record systems hold promise for improving the quality of health care services. The body of research on this topic is still in the early stages, however, in part because of the challenge of measuring the capabilities of electronic medical record systems. The purpose of this study was to identify classes of Electronic Medical Record (EMR) system sophistication in hospitals as well as hospital characteristics associated with the sophistication categories. The data used were from the American Hospital Association (AHA) and the Health Information Management and Systems Society (HIMSS). The sample included acute care hospitals in the United States with 50 beds or more. We used latent class analysis to identify the sophistication classes and logistic regression to identify relationships between these classes and hospital characteristics. Our study identifies cumulative categories of EMR sophistication: ancillary-based, ancillary/data aggregation, and ancillary-to-bedside. Rural hospital EMRs are likely to be ancillary-based, while hospitals in a network are likely to have either ancillary-based or ancillary-to-bedside EMRs. Future research should explore the effect of network membership on EMR system development.

Keywords

Electronic Medical Records; Electronic Health Records; Hospitals; Diffusion of Innovation

INTRODUCTION

Electronic Medical Record (EMR) Systems have the potential to facilitate the sharing of information across health care providers, reduce care delivery errors by replacing handwritten orders with computer entry, support tasks that are subject to human error, and provide decision support to prevent adverse reactions and increase adherence to evidence-based guidelines (L. Burke & Weill, 2009). Unfortunately, a recent study found that only 1.5% of U.S. hospitals, not including those run by the Veterans Health Administration, have comprehensive electronic record systems in all clinical units, and only 10.9% have basic systems (Jha et al., 2009).

Historically, much of the discussion about realizing the potential for efficiency and quality gains has centered on individual applications that comprise EMR systems, such as

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The authors have no conflict to report for this study.

computerized provider order entry (CPOE) or electronic medication administration (EMAR). However, this approach overlooks the inter-relationships among component applications. For example, while CPOE can reduce delays in medication administration by improving efficiency of medication orders to the pharmacy, it has limited benefit in terms of improving charting accuracy when the medication is dispensed to the patient. A system that includes both CPOE and EMAR has greater potential for improving care quality by reducing delays in administration and increasing charting accuracy (FitzHenry et al., 2007). A focus on individual EMR components provides an incomplete picture of hospital EMR capabilities because it ignores the implications of system sophistication.

Whereas it is well documented that EMR system capabilities vary across hospitals (Furukawa et al., 2008; HIMSS Analytics, 2006b; Li et al., 2008), “there is no consensus on what functionalities constitute essential elements necessary to define an electronic health record in a hospital setting” (Jha et al., 2009). There are conceptual models that identify aspects of sophistication (Paré & Sicotte, 2001/10), prescriptive models that specify pathways to developing more sophisticated systems (HIMSS Analytics, 2006b), and studies employing expert panels to identify required electronic health record system functionalities (Jha et al., 2009). However, we have found only one study that statistically derives a measure of EMR capabilities using data regarding actual EMR system components in U.S. hospitals (Blavin, Buntin, & Friedman, 2010). Blavin et al. (2010) developed a continuous variable to score EMR systems based on the number of EMR components that the hospital had adopted. We propose latent class analysis (LCA) not as a substitution to their approach but, instead, as a complementary method of understanding sophistication of EMR systems. Specifically, we believe LCA is useful for grouping hospitals’ EMR systems into clusters (or classifications) of sophistication.

The purpose of this study is to further understand the state of EMR systems in U.S. hospitals. Specifically, the study addresses the following questions: (1) Can a useful measure of hospital EMR sophistication be developed empirically using latent class analysis (LCA)? (2) If so, is the sophistication level of hospital EMR systems associated with other hospital characteristics? Given the push for health care delivery organizations to adopt EMR systems, as illustrated by the Meaningful Use incentive program (Centers for Medicare & Medicaid Services, 2010), developing methods for objectively measuring EMR system sophistication is important and should prove useful for future research that analyzes impacts of EMR systems on the quality and efficiency of patient care.

Conceptual Framework

The definition of an electronic medical record (EMR) provided by the Health Information Management & Systems Society (HIMSS) is useful for operationalizing the components of an EMR system:

> An application environment composed of the clinical data repository, clinical decision support, controlled medical vocabulary, order entry, computerized provider order entry, pharmacy and clinical documentation applications. This environment supports the patient’s electronic medical record across inpatient and outpatient environments, and is used by healthcare practitioners to document, monitor, and manage health care delivery within a care delivery organization (CDO). The data in the EMR is the legal record of what happened to the patient during their encounter at the CDO and is owned by the CDO” (HIMSS Analytics, 2006a).

In addition to clarifying the necessary components, this definition also highlights the inherent complexity of EMR systems as a collection of technologies that standardize data, house data, shape work processes, and communicate information between various units or departments.

Sophistication is a useful concept for thinking about the complexity of EMR systems. One definition of sophistication in the context of clinical information systems is “the diversity of technological devices and software applications used to support patient management and patient care [and] clinical support … as well as the extent to which computer-based applications are integrated [via] electronic and automatic transfer of information” (Paré & Sicotte, 2001/10). Given that highly sophisticated EMR systems may offer the greatest potential benefit, it would be useful to identify what constitutes sophistication in EMR systems. The concept of “technology clusters” (i.e., “one or more distinguishable elements of technology that are perceived as being closely interrelated”) (Rogers, 2003) has been used in previous research as a guide for conceptually categorizing clinical, administrative, and strategic information systems capabilities in health care organizations (Bhattacherjee et al., 2007; Burke et al., 2002; Burke & Menachemi, 2004; Menachami et al., 2006; Wang et al., 2005). In the present study, the technology clusters are components within the EMR system itself that have been statistically identified and comprise categories of EMR system sophistication.

METHODS

This is a cross-sectional study using 2006 HIMSS Analytics data (updated 1/2/07) and American Hospital Association (AHA) 2006 data. The HIMSS dataset contains survey data from 32,911 health care organizations of various types, of which 3,271 are acute care hospitals with 50 or more beds, which was the unit of analysis for this study. We included only hospitals with 50 or more beds due to a large amount of missing data in the HIMSS dataset for hospitals with fewer beds. Given that these smaller hospitals are not included in our analysis, results cannot be generalized to this group. The HIMSS data were linked to the American Hospital Association data to obtain hospital characteristics. Since Medicare ID was used as the linking variable, it was necessary to drop hospitals in the HIMSS data for which there was no Medicare ID reported, reducing the number of acute care hospitals in the study from 3,271 to 2,529. (See Table I.)

To develop a composite measure of EMR sophistication, we identified thirteen IT components from the HIMSS Analytics model for which we could find indicators in the dataset: laboratory information system, pharmacy management system, radiology information system, controlled medical vocabulary (CMV), clinical data repository (CDR), order entry, nursing documentation, picture archiving communication systems (PACS), computerized provider order entry (CPOE), clinical decision support system (CDSS), electronic medication administration (EMAR), barcode or radio frequency identification (RFID), physician documentation. Determining the presence of an EMR component in a given EMR system is not straightforward in the HIMSS data because hospitals report one of seven status categories for all of the components, with the exception of PACS which is reported either as either “current” or “planned.” Due to some debate about what constitutes a complete implementation, we ran sensitivity analyses using different criteria for the presence of a particular IS component. In the end, we used a lenient definition of the presence of a component (i.e., those reporting “live and operational,” “installation in process,” “to be replaced,” and “contracted/not yet installed” because it yielded the highest posterior probabilities for the final latent class model.

After identifying the thirteen potential composite measures, we performed latent class analysis (LCA) (Lanza & Collins, 2011) using randomly selected split samples to validate the EMR sophistication categories identified. LCA can be used to identify clusters of cases from a sample or population based on responses to multiple categorical survey items and must be interpreted to identify the best fitting model. Each subject is assumed to belong to one and only one category, and the category membership is assumed to affect subject responses to multiple items of interest to the researcher (Vermunt, 2008). LCA estimates two probabilities: the prevalence of each category (i.e., latent class) and the probability given the particular latent class membership that a subject will provide a particular response to an observed variable (Thompson, 2006), that is, the thirteen IT components in this study.

Prior to conducting the analysis, it was unknown how many classes would emerge and whether the classes would be interpretable in the context of EMR system sophistication. Models with two through five classes were identified for both split samples (n = 1,261 and n = 1,268) to assess the best fit. Likelihood ratio chi-square (G^2), Akaike's Information Criterion (AIC), and Bayesian Information Criterion (BIC) were used in the assessment, with smaller G^2, AIC, and BIC values indicating a better fit. Interpretability of the classes and the probability of a hospital belonging to a particular class were also considered, as classes with near-zero likelihood of membership are not useful for analytic purposes.

After identifying the best fitting model of EMR sophistication classes on the split samples, we ran LCA on the full data set (n=2,529) with covariates. This approach uses multinomial logistic regression as used by Lanza et al. (2007) to identify relationships between hospital characteristics and membership in a given EMR sophistication class. Results are reported for each covariate with *p* values to assess statistical significance of each hospital characteristic variable and odds ratios to represent effect size of each characteristic on EMR sophistication class membership.

RESULTS

Results of the latent class analysis on the thirteen EMR component variables were consistent across three starting values and the two samples (i.e., random split sample). Based on (1) the likelihood ratio chi-square (G^2), AIC, and BIC values, (2) stability of Rho parameter estimates, (3) the size of the distributed probabilities of class membership, and (4) and the interpretability and usefulness of the classes, the three-class model provided the best overall fit. Whereas the four-class and five-class models generally yielded better (i.e., lower) G^2 and AIC values than the three-class model, the BIC value for the three-class model was preferable. Furthermore, the results of the three-class model could be interpreted more clearly as meaningful classes (Lanza et al., 2007) than those of the four-class model. After validating the three-class model using split samples, we completed the remainder of the analysis using the full dataset (n = 2,529).

With respect to the thirteen EMR components, there was a wide range of adoption among the hospitals in this study. Frequencies of the thirteen EMR component variables, upon which the sophistication classes were based, demonstrate substantial variation in terms of adoption levels by hospitals (See Table II). Controlled medical vocabulary was the least frequently adopted component (13.76% of hospitals), with pharmacy management system being the most commonly adopted (99.29%). Notably, in addition to the pharmacy management system, the vast majority of hospitals in the sample also indicated adoption of a laboratory information system, radiology information system, and order entry.

While the frequencies illustrate a range of adoption levels, they do not indicate how the components cluster together to form sophistication classes. Rho estimates, the probabilities of each particular EMR component conditional on the given latent-class membership (Lanza et al., 2007), were utilized for interpretation of the sophistication class characteristics.

Components with conditional probabilities of 0.60 or higher for a given class were considered components of that class. (See Table III.)

Defining Classes of EMR Sophistication

Analysis of the Rho estimates suggests a cumulative progression in sophistication across the classes. Each latent class was assigned a label to represent the progression: ancillary-based EMR sophistication, ancillary/data-aggregation, and ancillary-to-bedside systems. Hospitals in the ancillary-based class tend to have a laboratory system (0.95), pharmacy system (0.98), radiology system (0.81), and order entry (0.82) in place. These ancillary-based systems tend not to have any other components, with all other items having no greater than a 0.3 probability of being in place. Based on the Gamma parameter estimates, approximately 14% of the hospitals can be expected to fall into this class.

Results indicate that approximately 45% of the hospitals in the sample have ancillary/data-aggregation EMR sophistication, which means having all the ancillary-based level components – laboratory system, pharmacy system, radiology system, and order entry—plus clinical data repository (CDR) and clinical decision support system (CDSS) capabilities (0.83 and 0.72 probability, respectively).

Approximately 42% of the hospitals have ancillary-to-bedside EMR systems, which are comprised of all six components found in the ancillary/data-aggregation class, in addition to nursing and physician-oriented components not likely to be found in ancillary/data-aggregation systems: nursing documentation (0.97), electronic medication administration (0.89), computerized provider order entry (0.78), physician documentation (0.68), and picture archiving and communication systems (0.61).

To assess the reliability of the EMR sophistication class assignment for hospitals, the mean posterior probabilities of class membership were analyzed. The posterior probabilities for a given hospital indicate the probability of the hospital being classified in each of the sophistication classes of the model given the hospital's responses on the thirteen EMR component indicators. For a perfect fit, hospitals categorized to a class would have a mean posterior probability of 1.0 for that class and 0 for other classes. In our study, the mean posterior probabilities suggest good latent classification : 0.86 for Class 1 hospitals in Class 1, 0.88 for Class 2 hospitals in Class 2, and 0.99 for Class 3 hospitals in Class 3. (See Table IV.)

In summary, the laboratory information system, pharmacy management system, radiology information system, and order entry appear to be foundational systems found in nearly all hospitals in the sample. EMR systems that tend to have just these four components can be considered to have an ancillary-based level of sophistication. Ancillary/data-aggregation systems tend to have these as well as clinical data repository and clinical decision support systems. Ancillary-to-bedside systems have high probabilities of having the six components of the ancillary/data-aggregation system, plus the nursing and physician-oriented components: nursing documentation, electronic medication administration record, computerized provider order entry, physician documentation, and picture archiving and communication systems. Two of the thirteen system components included in the study—controlled medical vocabulary (CMV) and barcoding/RFID—did not have a high probability of being present in any of the three classes of infrastructures.

Hospital Characteristics and EMR Sophistication

After validating the sophistication categories using LCA on the split samples, we used logistic regression on the full dataset to address the second research question: Is the sophistication level of hospital EMR systems associated with other hospital characteristics?

Characteristics analyzed were geographic region (i.e., AHA region code), urban/rural, hospital size (number of staffed beds), ownership (for-profit, not-for-profit, and government), teaching status, and network affiliation. Table V shows the p values and odds ratios for each of the hospital characteristics with respect to membership in the ancillary-to-bedside EMR sophistication class and the ancillary-based EMR sophistication class. The ancillary/data-aggregation EMR sophistication class was used as the reference group since it is the largest of the three classes in terms of percentage of hospitals. Notably, only two of the characteristics did not reach statistical significance: teaching status and government ownership, both present in a relatively small number of the hospitals (11% and 12%, respectively).

Hospital Characteristics and EMR Sophistication Class Membership

Hospital size, measured by the number of staffed beds, has a substantial relationship with membership in the ancillary-based class. Specifically, smaller hospitals are much more likely to fall into the ancillary-based EMR system class than the ancillary/data-aggregation class (odds ratio = 0.42). Hospital size does not substantially differentiate the ancillary-to-bedside EMR class from the ancillary/data-aggregation class, however (odds ratio = 1.02).

Ownership status appears to have a strong correlation to EMR capabilities. Specifically, not-for-profit hospitals are much less likely to fall into the ancillary-based EMR class than the ancillary/data-aggregation class (odds ratio = 0.22). Not-for-profit status is not a substantial differentiator between ancillary-to-bedside EMR systems and ancillary/data-aggregation systems, however (odds ratio = 1.07).

Rural hospitals are more likely to fall into the ancillary-based EMR class than the ancillary/data-aggregation class (odds ratio = 1.3) and less likely to fall into the ancillary-to-bedside class than the ancillary/data-aggregation class (odds ratio = 0.7). The geographic region variables were included in the model as controls to reduce the possibility of spurious findings for the urban/rural variable and therefore not intended for interpretation.

Hospitals participate in networks to coordinate and promote services in the community. Networks are alliances or contractual obligations among organizations that do not share ownership, which is a distinction from health systems, which have unified ownership (Bazzoli, Shortell, Dubbs, Chan, & Kralovec, 1999). The AHA network measure has been used in other studies that classify networks (Bazzoli et al., 1999) and evaluate impacts of networks (Burgess, Carey, & Young, 2005). In our study, hospitals in a network are substantially more likely to fall into either the ancillary-to-bedside EMR class (odds ratio = 1.5) or the ancillary-based EMR class (odds ratio = 1.4) than the ancillary/data-aggregation class. The reason for this effect is not immediately clear. Specifically, it is not known whether certain networks are comprised of hospitals with ancillary-to-bedside EMR systems and other networks are comprised of hospitals with ancillary-based EMR systems, or whether the EMR capabilities vary across hospitals within the same network.

In summary, hospitals in the ancillary-based EMR sophistication class are more likely than those in the ancillary/data-aggregation class to be small, for profit, members of a network, and located in a rural area. Hospitals in the ancillary-to-bedside EMR sophistication class are more likely than those in the ancillary/data-aggregation class to be members of a network and in an urban area.

DISCUSSION

As momentum for EMR adoption continues to increase, it becomes even more important to understand these systems as clusters of technologies instead of individual technologies in order to help ensure that potential benefits are realized. While recommendations about pathways for EMR system development are helpful, we must recognize that most hospitals are not starting from scratch in their EMR system development. Current capabilities and past experiences with technologies will influence future technology adoption and implementation. Therefore, having information about the state of hospitals' EMR infrastructures is important for planning future system development.

The latent class model identified in this analysis supports the idea of levels of EMR sophistication, a finding that is consistent with other studies, such as DesRoches et al. (2008) and the HIMSS Analytics EMR Adoption Model (DesRoches et al., 2008; HIMSS Analytics, 2006b). In fact, our results indicate clusters of EMR components that are quite similar to the HIMSS Analytics model. However, we identify 3 broad categories of sophistication, whereas the HIMSS model identifies 8 levels with finer granularity. We believe our study complements these other studies by exemplifying latent class analysis as an alternative method for identifying sophistication categories. Furthermore, our study finds that the controlled medical vocabulary (CMV) component is not an element of any of the three sophistication categories, which implies that it is a more advanced capability than represented by the HIMSS model, which places it in stage 2 of its 7-stage model. Again, a strength to the LCA approach is that it identifies the categories empirically based on reported EMR capabilities, so results are not determined by expert opinions of sophistication or policy requirements for EHRs (e.g., to achieve Meaningful Use incentives).

Furthermore, while our study did not directly measure levels of integration (i.e., how well-integrated the components are), results imply that the extent of integration across departments increases as system sophistication increases, which is consistent with other information systems literature (Paré & Sicotte, 2001/10). For example, the "ancillary-based" latent class is comprised of four components, three of which are housed within one department: laboratory, radiology, or pharmacy. These silos of components within the ancillary-based class suggest that a significant barrier to achieving the ancillary/data-aggregation class of EMR is the integration of component systems across departmental boundaries.

The presence of clinical data repository (CDR) and clinical decision support (CDSS) in the ancillary/data-aggregation level of EMR sophistication illustrates a movement beyond ancillary services into clinical data aggregation and decision support capabilities. Despite integration beyond the ancillary-based level of sophistication, the ancillary/data-aggregation class does not include components that most directly involve the activities of nurses and physicians, such as electronic medication administration (EMAR) and computerized provider order entry (CPOE). Along these lines, it is possible that the CDSS capability present in the ancillary/data-aggregation class is lower-level support, such as error checking for drug-drug interactions that typically takes place in the pharmacy, rather than guidance on treatment protocols (Davis, 2007). Since the data used included only one measure of CDSS, it is not possible to make this distinction with any certainty, which is a limitation of the study. In other words, while the study captures variation in EMR system sophistication based on the presence of individual components, it is not able to account for variation in functionality within individual components. This limitation may have resulted in higher percentages of hospitals reporting CDSS capability than in studies that measure specific decision support capabilities (e.g., Jha et al., 2009).

There are a few other study issues and limitations that could have contributed to higher percentages of EMR adoption reported in this study than in other studies. First, there is not a standard measure of EHR "implementation" in the literature. HIT implementation processes are often fluid and iterative (Hartswood et al., 2003; Heeks, 2006); therefore, studies vary in their approach for determining whether a particular component has been implemented. We used a lenient set of criteria for implementation status, as discussed above in the methods section, and hospitals reporting the presence of an EMR component in this study were only required to have the component implemented in one or more clinical units, which may not capture comprehensive use of the EMR (Jha et al., 2009; Blavin et al., 2010). However, due to the age of the data, this lenient definition of implementation may reflect more current levels of sophistication as components that were under contract in 2006 may now be installed. Furthermore, the data in this study included only acute care hospitals with more than 50 beds. This criterion for inclusion was needed due to the amount of missing data for smaller hospitals. However, it is possible that including smaller hospitals in the sample would reduce the percentage of hospitals falling into more advanced sophistication categories.

The final limitation that may contribute to higher percentages of adoption is that the latent class analytic method develops categories based on probabilities of individual cases having the defined combination of characteristics (i.e., EMR components) for its assigned class. However, not every case in a given class has a 1.0 probability for each component. In other words, some cases in a given class may not have all the components associated with being a member of the class. (See Table III.) The assigned class is the best fit for the individual case, but the cases in the classes are not perfectly uniform. In summary, due to the higher rates of adoption found in our study, it seems prudent to further compare results using different methods and datasets across studies.

Finally, the age of the data used in this study is a limitation. However, a key contribution of the study is demonstrating how latent class analysis can be used to understand sophistication of EMRs. Future research should employ the LCA method to analyze more recent hospital EMR data and with other sources of hospital EMR data in addition to HIMSS Analytics since EMR adoption rates vary over time and across studies (Dullabh, Katsh, Sondheimer, & Stromberg, 2011). Given the Meaningful Use incentive program through the Centers for Medicare and Medicaid Services, one would expect a substantial change in sophistication across the hospital EMR landscape. LCA offers potential for exploring such changes over time, that is, the evolution of EMR systems. While the levels of sophistication identified in the study imply the possibility of a cumulative progression, the cross-sectional approach is not sufficient for claiming such a progression actually occurs. A longitudinal analysis is needed to confirm whether hospitals are progressing through the sophistication levels and, if so, the amount of time such a progression tends to take. This is a question for future research. Not only should future work determine whether hospitals increase their EMR sophistication over time, but also whether (or how) the essence (i.e., EMR components) of the EMR sophistication classes change over time.

The latent class approach also could be used in future studies that identify relationships between EMR system sophistication and quality and patient safety measures. Mixed results in the literature on EMR usage and health care quality and cost (Chaudhry et al., 2006; Goldzweig et al., 2009; Karsh et al., 2010; Buntin et al., 2011) may be due, at least in part, to variation in the sophistication of EMR systems across health care delivery organizations. Longitudinal studies that differentiate between EMR sophistication levels could help clarify the impact that EMR systems have on service delivery and patient outcomes. Also, it is important to note is that the sophistication labels used in this study (i.e., ancillary-based, ancillary/data-aggregation, and ancillary-to-bedside) are relative only to the hospital EMR components in this study. What is an acceptable level of sophistication is not clear. More needs to be known about the relationships between EMR sophistication, quality, cost indicators, and contextual factors before such judgments can be made.

With respect to contextual factors, latent class analysis could prove to be a useful method for understanding not only sophistication of EMR systems, but also the environment for EMR use. In other words, LCA could be used to model configurations of EMR components with organizational, financial, and operational factors, which would yield multidimensional categorizations that better explain the environment in which the EMR is used. Since EMRs are tools for care delivery embedded within organizational cultures and workflows, these multidimensional categorizations would likely lead to better information about factors affecting quality and cost of care delivered than do analyses of EMR sophistication alone.

Two hospital characteristics in this study are important for understanding influences on EMR sophistication: rural vs. urban and network membership. Hospitals in rural areas are lagging behind others in EMR sophistication. Further research should clarify the reasons for this disparity and the impacts on care for rural patients. These hospitals may need additional support and/or incentives to promote the adoption and implementation of ancillary-to-bedside EMR systems. With respect to networks, results indicate a bifurcation of sophistication; that is, members of networks tend to have either ancillary-based or ancillary-to-bedside systems, not ancillary/data-aggregation. This is a key finding because it raises the question of whether EHRs are better able to facilitate patient care coordination in some networks as compared to others. Future research should clarify the extent to which network characteristics influence the homogeneity of EMR sophistication of member hospitals.

In conclusion, many hospitals in the U.S. are lacking the EMR components that most directly affect the activities of nurses and physicians, and nearly all are lacking a controlled medical vocabulary (CMV). These capabilities are directly relevant to the Centers for Medicare & Medicaid Services (CMS) incentives for meaningful use of electronic health records, which requires use of the EMR at the bedside (e.g., e-prescribing) and the exchange of patient information across health care delivery organizations (Centers for Medicare & Medicaid Services, 2010). Furthermore, hospitals are proceeding with the development of EMR systems without the benefits of standardized terminology CMVs offer. Perhaps, this is due to a belief that CMVs are most critical for interoperability across systems in different organizations, and hospitals have been more focused primarily on developing systems to suit their internal needs. If so, the inclusion of CMV in EMR systems in the U.S. may increase substantially, given the CMS meaningful use requirements for sharing information electronically between providers. In fact, hospital EMR systems may have progressed since the collection of data used in this study. Nevertheless, it appears that we still have a long way to go before the vision of EMR meaningful use is attained in U.S. acute care hospital settings.

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Table I

Comparison of Sample Hospitals to AHA Hospitals with 50+ Beds

Hospital Characteristic	**AHA (n=4,359)**		**HIMSS (n=2,529)**	
# of Beds				
• Less than 100	1341	30.8%	476	18.8%
• 100–299	2089	47.9%	1360	53.8%
• 300 or More	929	21.3%	693	27.4%
Teaching	366	8.4%	285	11.3%
Network				
• Yes	1217	27.9%	846	40.0%
• No	2124	48.7%	1282	60.0%
• Missing data	1018	23.4%		
Not-for-profit	2387	54.8%	1709	67.6%
Government	173	4%	311	12.3%
Rural	1214	27.9%	640	25.3%
Region New England	213	4.9%	124	8.0%
Region Mid Atlantic	537	12.3%	377	14.9%
Region South Atlantic	782	17.9%	538	21.2%
Region East North Central	646	14.8%	435	17.2%
Region East South Central	371	8.5%	190	7.5%
Region West North Central	429	9.8%	203	8.0%
Region West South Central	545	12.5%	311	12.3%
Region Mountain	285	6.5%	114	4.5%
Region Pacific	492	11.3%	235	9.3%
Region Other	59	1.4%	2	.08%

Table II

Frequencies of EMR Component Capabilities (in percentages)

EMR Component	Yes	No	Missing
Pharmacy Mgt System	99.29	0.4	0.32
Laboratory Info System	98.3	0.83	0.87
Order Entry	96.6	3.16	0.24
Radiology Info System	95.14	3.56	1.3
Clinical Data Repository	80.74	18.9	0.36
Clinical Decision Support	68.33	31.32	0.36
Nursing Documentation	59.51	38.63	1.86
EMAR	58.32	41.44	0.24
PACS	49.98	50.02	0
Computerized Provider Order Entry	45.04	54.61	0.36
Physician Documentation	34.12	63.7	2.17
Barcode/RFID	22.46	74.77	2.77
Controlled Med Vocabulary	13.76	82.21	4.03

Table III

Components of the EMR Sophistication Classes

EMR Component	Ancillary-based	Ancillary + data aggregation	Ancillary-to-bedside
Laboratory Info System	0.9507	0.9962	1.0000
Radiology Info System	0.8089	0.9843	0.9920
Pharmacy Mgt Sys	0.9794	0.9974	1.0000
Controlled Medical Vocabulary	0.0209	0.0621	0.2738
Clinical Data Repository	0.1975	0.8349	0.9836
Nursing Documentation	0.1241	0.4069	0.9712
EMAR	0.3010	0.3902	0.8875
Order Entry	0.8226	0.9845	0.9984
Clinical Decision Support	0.0798	0.7159	0.8509
Computerized Provider Order Entry	0.0295	0.2792	0.7771
Physician Documentation	0.0458	0.1328	0.6787
PACS	0.2091	0.4899	0.6057
Barcode/RFID	0.2559	0.1265	0.3362

Table IV

Mean Posterior Probabilities by Class

	Class 1	**Class 2**	**Class 3**
Class 1	0.86	0.06	0.00
Class 2	0	0.88	0.12
Class 3	0	0	0.99

Table V

Hospital Characteristics and Odds Ratios for EMR Sophistication

Hospital Characteristic	Ancillary-to-bedside EMR	Ancillary-based EMR	p-Value
# of Staffed Beds (standardized)	1.0271	0.4211	0.0000
Teaching	1.5006	1.1126	0.1324
Network	1.5332	1.4077	0.0025
Not-for-profit	1.0758	0.2128	0.0000
Government	0.8233	0.5251	0.0846
Rural	0.7087	1.3095	0.0058
Region NE	1.4333	0.16	0.0034
Region Mid Atlantic	1.5789	0.3045	0.0000
Region SE:	1.3239	0.4381	0.0085
Region Mid West	1.0136	0.2642	0.0046
Region Central	2.4168	0.8788	0.0005
Region S Central	2.0701	0.9074	0.0033
Region S West	1.973	0.2456	0.0002
Region West	3.0048	2.504	0.0004

Note: Ancillary/data-aggregation is the reference category for the odds ratios