The Impact of EHR and HIE on Reducing Avoidable Admissions: Controlling Main Differential Diagnoses

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Abstract

Background
Many medical organizations have invested heavily in electronic health record (EHR) and health information exchange (HIE) information systems (IS) to improve medical decision-making and increase efficiency. Despite the potential interoperability advantages of such IS, physicians do not always immediately consult electronic health information, and this decision may result in decreased level of quality of care as well as unnecessary costs.

Methods
This study used a track log-file analysis of a database containing 281,750 emergency department (ED) referrals in seven main hospitals in Israel (the whole population in these hospitals). This database allowed us to evaluate the contribution of an EHR IS, as well as an HIE network, to decision-makers (physicians) by investigating whether EHR systems lead to improved medical outcomes in the complex and highly stressful environment of points of care in EDs, which are known for their tight time constraints and overcrowding. The impact of EHR IS and HIE network was evaluated by comparing decisions on patients classified by five main differential diagnoses (DDs).

Results
The results indicate that viewing medical history via EHR systems is associated with a sharp reduction in the number of possibly redundant admissions.

Among the DDs, we found information viewed most impactful for gastroenteritis, abdominal pain, and urinary tract infection in reducing readmissions within seven days, and for gastroenteritis, abdominal pain, and chest pain in reducing the single-day admissions rate. Both indices are key quality measures in the health system.

In addition, we found that interoperability (using external information provided online by health suppliers) contributed more to this reduction than local files, which are available only in the specific hospital.

Conclusions
Viewing medical history via an EHR IS and using HIE network components led to a reduction in the number of seven day readmissions and single-day admissions for all patients. Using patients' external medical history may imply a more thorough patient examination that can help eliminate unnecessary admissions. Nevertheless, in most instances physicians did not view medical history at all, probably due to the limited resources available in public medical facilities, combined with the stress of rapid turnover in ED units.

Keywords: medical decision analysis, electronic health record, health information exchange, medical informatics, interoperability, health maintenance organization, IS efficiency
Background

In recent years, the healthcare sector world-wide has been investing heavily in integrative and interoperable medical information systems, with the aim of improving the medical decision-making process and increasing its efficiency. However, the overall contribution of information technologies to the field is not always immediately apparent [1]. But clearly, lack of information may result in a decreased level of quality of care and unnecessary costs [2].

Health information technology and health information exchange (HIE) are increasingly viewed as key steps in overcoming the quality, safety and efficiency problems that plague U.S. health care delivery [3]. EHR and HIE networks coordinate the storage and retrieval of patient records from multiple health sources such as laboratories, other hospitals, specialized clinics, etc., thus providing vital historical medical information that is required for critical decision-making.

In the framework of this research, we aimed to understand the role that EHR and HIE networks can play in reducing the number of hospital readmissions and single day admissions. We examined the impact of medical information that is provided to a decision-maker in the highly stressful environment of an ED, with its complex conditions for providing medical care. Esquivel et al. [4], for instance, related unsatisfactory referral communication between primary care providers and specialists to the lack of attention on how the communication technology should fit with the social environment in which it is implemented.

Second, we explored the circumstances under which this information is most important with regard to main differential diagnoses (DDs) and information from external sources (interoperability).

The main objective of this research is to assess the impact of EHR IS and HIE network on physicians’ decision-making process in an ED environment by comparing the outcomes of five main DDs. One of the most significant decisions in an ED is whether to admit or discharge the patient. We examined whether EHR and HIE network could lead to decreases in redundant readmissions within a short period since a previous discharge. This is a widely used measure [5], as well as stated goal that is frequently expressed by care givers, hospital administrators, and policy makers [6].

If a patient is readmitted shortly after a hospital stay, this might indicate that the hospital discharged the patient without proper care or the right diagnosis. Alternatively, it may suggest that the patient did not follow the doctor’s instructions for various reasons, for example, because the prescribed medicine was costly, or lack of home care. However, readmission after a short time period might mean that the patient has a life threatening disease and needs to go to hospice care. In any case, a high rate of readmissions is an indication that the decision making process was faulty in some way. Recent policies seek to penalize doctors for high readmission rates, an indication of hospitals’ efforts to avoid such possibly redundant procedures [7]. Similarly, a report prepared for the US congress stated that short-term readmission reduction policies should be enacted to curb hospital costs and improve overall quality [8].

Hence we examined whether the proportion of single-day admissions fluctuates when patients’ medical history is inspected via EHR IS. We assumed that some single-day admissions are uncalled for, and could be prevented if a proper medical history was available. These scales have been used in previous studies in the field [9-12]. The
method of using subsets of several main differential diagnoses enabled us to compare more similar groups of patients.

This study focused on the main health maintenance organizations (HMO) in the state of Israel, one of the world’s largest non-governmental HMOs. This HMO serves over 3.8 million customers and employs more than 9,000 physicians and 26,000 other medical staff. The HMO operates seven general hospitals (all surveyed in this research), and many community clinics.

In 2004, the HMO deployed an EHR IS (analyzed here). The EHR IS retrieves data from many medical systems. This data retrieval architecture furnished a comprehensive, integrated and real time virtual patient record available at all points of care of the HMO. The system gathers historical patient data from the other healthcare information systems at the HMO’s hospitals and clinics. The data included patients’ demographics, chronic medication, adverse reactions, detailed lab and imaging results, past diagnoses, healthcare procedures etc. However, the examined interoperable system also collects two types of historical medical information - local and external - both of which can contribute to admission decisions. Local information is locally created data and reflects the integration between various units within a specific hospital, whereas external information refers to data created at different hospitals and other points of care, thus reflecting interoperability.

In terms of current policies, extensive data are available only to the HMO insured patients. Other HMO insured patients that visit one of the main HMO hospitals will only have local files; these include all the information that relates to previous encounters and hospitalizations at this hospital.

In addition, actual usage of the system at each of the seven hospitals was idiosyncratic because of differences in management policy relating to the system, electronic order entry in general, and the influence of other technologies on cooperation among physicians within each hospital. The database for this study covered 2004 to 2007 (after the EHR IS had been integrated into all hospitals).

Research Question

We examined the actual effect of the use of information provided by the system, locally and externally, at the point of care on the physicians' admission decisions. Our goal was to assess the way in which this information affected the process of decision-making, as well as to monitor the outcomes of decisions when EHR IS was viewed versus when it was not viewed. For this purpose we first studied the likelihood of (a) readmissions within a short period of time since an earlier discharge and (b) single day admissions, when physicians used the EHR IS compared to when physicians did not use the EHR IS. Then we compared the reduction in readmissions within seven days and single-day admissions when local information was viewed, versus when external medical information was retrieved (interoperability). Arendts et al. [13] showed that even small changes in admission rates can result in meaningful reductions in hospital occupancy and improve system capacity.

Research Hypothesis

In this section, we define the research hypotheses deriving from the research question. We aimed to discover the relationship between the use of EHR IS and the quality of medical decision-making.
Sox et al. [14] emphasized the importance of medical history to medical decisions (such as admission decisions). Walker et al. [15] argued that there is a relationship between viewing medical history and improved medical care performance including admission decisions. We used the seven day readmission measure as an indication of the accuracy of the initial admission decision. For instance, if an admitted patient was discharged and then returned in fewer than seven days and was again admitted, this may suggest either inappropriate early discharge or poor decision making concerning the requirements for of the earlier treatment [6, 16]. The first hypothesis is therefore:

**Hypothesis 1:** There is a negative relationship between viewing EHR IS and readmissions within seven days. This hypothesis was divided into two sub-hypotheses to capture the locality of information (external vs. local information):

- **Hypothesis 1a:** There is a negative relationship between viewing external information via EHR IS and readmissions within seven days.
- **Hypothesis 1b:** There is a negative relationship between viewing local information via EHR IS and readmissions within seven days.

In order to control for other time period of readmissions, we tested these hypotheses with readmissions within thirty days as well.

Similar to Hypothesis 1, we used single-day admissions to assess the appropriateness of the decisions made in the ED. We assumed that some of the single-day admissions were incorrect, and could be avoided given a proper medical history. The use of EHR has been suggested to be even more crucial during medical emergencies, where patients seldom go to the same hospital that treated them in the past [17]. This metric, which has been used in previous research [9-11] can provide information regarding the usefulness of EHR IS, as a complement to the analysis of seven day readmissions.

**Hypothesis 2:** There is a negative relationship between viewing EHR IS (including local or external information) and single-day admissions. This hypothesis was divided into two sub-hypotheses to capture the locality of information:

- **Hypothesis 2a:** There is a negative relationship between viewing external information via EHR IS and single-day admissions.
- **Hypothesis 2b:** There is a negative relationship between viewing local information via EHR IS and single-day admissions.

The logic behind hypothesis 3 was that viewing external medical history could be evidence of a more detailed examination, hence a better understanding of the patient’s condition, thus helping to avoid unnecessary admissions. Moreover, we expected medical staff to gain additional confidence after going through a patient’s medical record, thus allowing doctors to make a dismissal decision with a lower level of uncertainty.

**Hypothesis 3:** The effect of viewing external medical history on avoidable admissions (both readmissions and single-day admissions) will transcend that of viewing local information.

The hypotheses (above) were tested for selected frequent diagnoses: chest pain (CP), abdominal pain (AP), gastroenteritis (GE), urinary tract infection (UTI), pneumonia organism (PO). These frequent diagnoses were chosen by a panel of senior physicians in cooperation with the main HMO.
Method

The research method selected for this study was track log-file analysis, which incorporates various statistical tools. Log-files provide an objective and unbiased measure of system usage and are recommended for evaluating health IS [18]. See [19] for a review on health IT usability study methodologies. The log-files were based on data collected from 2005 to 2007 from seven main hospitals owned by the main HMO in Israel.

Log files have become a standard and essential part of large applications. Log files are commonly used for the purpose of software monitoring. It is not uncommon for log-files to be continuously generated, while occupying valuable storage space but they provide little or no value if they are never utilized to create value. The log-files in this study were restricted to the main DDs presented above (CP, AP, GE, UTI and PO).

The dependent variables

Readmission within seven days – Quantified whether a patient was readmitted to a hospital within seven days from the previous discharge for a closely related condition (coded 1), or otherwise (coded 0). This measure is widely used as a means of monitoring the efficacy of critical care pathways [5]. Studies have indicated that more than half of all readmission incidents could be avoided by implementing more efficient procedures [20, 21]. Furthermore, readmissions rates have also been used as a proxy for quality of care rendered during hospitalization [16, 22].

Single-day admission – Quantified whether a patient, as a result of the decision to admit, was admitted for a single day (coded 1) or for a longer period of time (coded 0). Existing scales have shown that such short-term admissions can be reduced using medical information [9, 10, 12]. The measurement scale for single day admissions filtered out patients who intentionally sought and received treatment involving single day admission. Only admissions from an ED to a specific hospital department were recorded and included. In addition, similar to many EDs around the world, hospitals in Israel maintain observation wards in which patients are supervised for a period of 12-24 hours. This period of observation was not included in the calculations.

The independent variables

Viewed medical history – The patients in our study were divided into two groups: patients whose medical history was viewed via the EHR IS and patients whose medical history was not viewed via the EHR IS. Vest [23] found that system access was not random, and that specific patient factors increased the odds of information access. Vest’s findings show that the more a person’s data were examined, the more likely that person was to have more emergency room visits and in-patient hospitalizations. The EHR IS provided full integrative information only on patients belonging to the main HMO, as specified in Table 1.

The term 'viewed medical history' refers to access to at least one of several medical history components in the EHR IS (see Table 1). This was measured as a dichotomous variable (1=history viewed; 0 if not).

Viewed Local Information: indicates examination of medical information available within the framework of local files available in a specific hospital. We coded the
variable 'Viewed local information' 1, if local information was viewed from the EHR IS, and 0: if local information was not viewed.

**Viewed External Information (Interoperability):** indicates the viewing of external integrative medical history, which was provided online by certain health suppliers. External information concerned only HMO patients for whom both local and external types of information were available. Coding was 1 if external information was viewed from the EHR IS and 0 if external information was not viewed.

**Health Maintenance Organization** – To control for major discrepancies in the quality and the amount of medical information between the main HMO patients and other HMO patients, a dichotomous variable was created (1— if the patient was a member of the main HMO, for whom full medical history was available via the EHR IS or 0— if the patient was a member of another HMO).

**Differential Diagnosis** – The DDs of ED referred patients were entered into the database using the WHO International Classification of Diseases (ICD/10) code. It should be noted that there could have been more than one DD per patient on a single referral. In this case we selected the main DD that was assigned by the physicians.

**ED Department** – This variable represented the specific type of unit where the patient was evaluated in the ED such as internal medicine or surgical.

**Hospital** – This variable represented the specific hospital where the patient was evaluated.

**Patient age** – Continuous variable representing the age of the patient.

**Patient gender** – Male/Female.

**Results**

We first present descriptive statistics regarding the distribution of ED referrals during the period of research. We then present statistical tests performed to measure the relationship between the research variables. Finally, we present the main findings regarding the track log-file analysis using multivariate regression analyses.

**Descriptive Statistics**

We present the data on referrals (consisting of admissions and discharges) from the seven hospitals chosen for the research. The log-file consisted of 281,750 samples of referrals. The names of the hospitals are not disclosed for reasons of confidentiality and privacy.

Figure 1 indicates that the majority of ED patients in the seven hospitals belonged to the main HMO (77.3% of the admitted patients and 72.93% of the discharged), and the remaining patients belong to various other HMOs.

Figure 2 presents the distribution of the admission and discharge decision rates by differential diagnoses, divided by type of medical history viewed.

According to Figure 2, the two main DDs in our study were chest pain (CP) and abdominal pain (AP), together amounting to approximately 78% of the entire population whose medical history was viewed.

It is clear that viewing external history did not take place very often. Viewing rates ranged from 11% for CP to 24% for UTI. In terms of the entire referral population,
external information was viewed in only 4.3% of the cases, compared to roughly 27% for viewing of local information.

Table 2 highlights a number of key variables that are implemented in the regression analyses, by HMO.

It is important to note that, patients’ medical history was viewed in only 31.18% of all hospital referrals. Hence, 68.82% of all referrals did not include any use of electronic medical history.

There was greater use of medical history for patients who were members of the main HMO, for whom more extensive data had been collected (data were examined in 32.7% of the main HMO cases compared to 26.68% for the remaining patients). Yet, even among members of the main HMO, the extent of use of medical history was not exceptionally high.

**Statistical Relationships between using EHR IS and the Dependent Variables**

The objective of this section was to explore statistical relationships between EHR IS implementation and the dependent variables.

Tables 3 and 4 show that for most DDs, there was a substantial decrease in the rates of both readmissions and single-day admissions when EHR IS was viewed.

The strongest decreases were observed for UTI, GE and AP. An exception was CP DD in which viewing of medical history had no effect on seven day readmissions.

**Results for the Multiple Regression Analysis**

The main findings regarding the track log-file analysis are summarized below. The results of each Table were analyzed separately. Additionally, the results are adjusted to age, gender, HMO, control variables for type of ED and control variables for type of hospital. Finally, we tested all the readmissions' hypotheses also in thirty days timeframe (in addition to the seven days) and we gained very similar results.

Table 5 shows that viewing external medical history via the EHR IS was consistently associated with a reduced number of seven day readmissions. When external medical history was viewed, the likelihood of seven day readmissions decreased by 74% for AP and by 69% for UTI (OR = 0.256 and 0.308 respectively). For all DDs taken together, there was a significant reduction of 48% (OR = 0.520) in seven day readmissions.

In addition, being a main HMO patient was positively correlated with higher odds for seven day readmission. This is not surprising, since the HMO owns all these hospitals, and it is likely that HMO patients will seek medical care at these hospitals more than patients belonging to other HMOs.

The results of Table 6 mirror those in Table 5. In general external medical history viewed via the EHR IS was positively and significantly correlated with reduced odds for single-day admissions. Viewing external medical history was associated with an impressive reduction of up to 35% in single-day admissions. Being a member of the main HMO was positively correlated with lower odds of single-day admission.

Tables 7 and 8 report these same analyses but for viewing local medical history via the EHR IS (rather than external medical history).
Similar to the external medical history findings, local history was associated with a significant reduction in readmissions across the board, ranging from 43% for PO (OR = 0.567) to 75% for both GE and UTI (OR = 0.249 and 0.246 respectively), and 72% for AP.

Table 7 also shows that HMO correlates with readmissions rates. Moreover, being an HMO member was positively correlated readmission. These correlations were not consistent across the DDs.

Table 8 shows that viewed local history was associated with a reduced number of single-day admissions. The largest reduction was again for GE, AP, and UTI with reduction of 22% (OR = 0.776), 38% (OR = 0.617), and 37% (OR = 0.633) respectively.

Additionally, it shows a consistent association of reduced single-day admissions for patients belonging to the main HMO.

Tables 5-8 examined external and local medical information independently. Tables 9 and 10 compare the two cases. These two regressions include a much smaller sample size (N = 40,030) because only cases in which information was viewed were included in the regression.

When contrasted with external medical information, viewed local medical history had a marginally significant association with an increased number of readmissions (OR = 1.272). We were not able to demonstrate this difference for the various DDs separately. We assessed that no significance was found for each DD due to small sample size. However, the direction of OR was kept solidly positive (OR range 1.149 to 1.393), except for PO DD (OR = 0.763), after controlling for all theory variables.

In Table 10, after contrasted with an external information, local medical history viewed had a significant association with increased number of single-day admissions (OR = 1.130) in comparison to external medical information. Again, this effect could not be found for the various DDs separately, probably due to the small sample size. Nevertheless, the direction of the association remained positive (OR range 1.024 to 1.149), except for UTI DD (OR = 0.883).

**Main Findings and Results**

Patient medical history was only viewed in 31.18% of all referrals to the ED via the EHR. Hence, 68.82% of all referrals did not involve any use of EHR IS. There was increased use of EHR IS for patients who were members of the main HMO, for whom more extensive data were collected and available for review.

Second, viewing local and external medical history via the EHR IS was positively associated with a reduced number of readmissions within seven days (hypothesis 1 supported) and single-day admissions (hypothesis 2 supported).

Third, GE, AP, and UTI DDs were found to have the highest association between EHR IS viewed and reduced number of seven day readmissions. GE, AP, and CP DDs had the highest association between EHR IS viewed and reduced single-day admission rates.

Finally viewing external medical history was more highly correlated with lower single-day admissions and seven day readmissions than local medical history (hypothesis 3 supported).
Discussion

Viewing medical history via an EHR IS relates to admission decisions and constituent for the reduction in the number of seven days readmissions and single-day admissions for all patients. The results suggest that short unnecessary admissions and readmissions, some of which may be caused by lack of viewing medical information, can be prevented in significant percentages, by using local and external medical history from EHR IS during the course of evaluation in the ED.

Findings also depict the higher effect demonstrated by external medical history, as compared with local medical history. External medical history examination implies a more thorough patient examination that can help avoid redundant admissions. Esquivel et al. [4] proposed that flexibility in the referral process is necessary for effective system use by staff. These findings, regarding interoperability, provide insight on the benefits of adopting, implementing and using EHR IS and HIE networks in order to improve healthcare delivery. We think that this study results will help decision makers in the health sector to better understand the outcomes of sharing data among health care institutions.

We noted that in most instances medical history is not viewed at all, probably due to the limited resources available to public medical facilities, combined with an especially emergent nature of the ED units. Therefore, in instances where medical history is viewed with care, medical staff may gain certain confidence, thus allowing medical staff to make more effective decisions with lower uncertainty-related biases.

Therefore, we suggest that additional engagement of doctors with patient medical history should produce better decision making, and in parallel eliminate unnecessary admission costs for the HMO, and therefore for its patients.

Contribution

In the field of healthcare, physicians need information to help them provide medical services. One of the major issues in this context is how information on patients, supplied by EHR IS, under the serious time constraints and overcrowding of an ED, can improve decision-making and its outcomes. This study attempted to inform researchers, policy makers, physicians and patients by providing further insights into the field of medical informatics.

First of all, the main conclusions of this study shed light on the importance of medical history available to physicians at the point of care. Physicians take advantage of medical history, and are aware of its importance. This study specifically selected types of diagnoses where information is more important in certain cases and less so in others. Guidelines thus can be readily implemented and updated.

In addition, we illustrated the specific value of external medical information versus local data. We found a reduction in the volume of short-term admissions and single-day admissions (as compared to [9-11]). This reduction was substantial for both local and external medical history, with the latter making a greater contribution. This finding confirms the potential benefits of using HIE interoperable systems and thus encourages decision makers to invest more effort in improving connectivity between various healthcare entities. Third, we extend previous research by integrating DD, interoperability and patient attributes in the variables. Finally, using a unique DB, this research has the advantage of covering a vast population.
Research Limitations and Future Research

This study has some limitations. First, in this analysis we were not able to differentiate justified from unjustified admissions. We believe that many of the single-day admissions and short-term readmissions could have been avoided and more sophisticated methods of segregating avoidable and unavoidable admissions would have been helpful.

Second, the actual medical conditions of the patient were not considered in this study. These data could have helped confirm or disconfirm our claim that viewing medical history improves medical care, which in turn may reduce future costs in terms of fewer readmissions. We partially controlled this by using the subsets of main DDs.

Third, future studies could focus on exploring the impact of using different historical medical information components on admission decisions for each DD. This is particularly relevant to analyzing external data. The results will help better understand interoperability between various points of care as well as providing greater insights into ways to display shared data.

Finally, different physicians maintain different philosophies regarding the use of the system. We suggest that future work should concentrate on adding the physicians’ attributes to the log file. Such identification was missing from this study log-file. In this context, network externalities and diffusion theory can be used to study the causes for system as well as specific information type usage. In addition, the assessment of the medical value of information could be expanded to other points of care and other departments as well. Data mining can be used to develop a situation-specific predictive model for decision-makers’ behaviour.

Abbreviations

EHR, Electronic Health Record; HIE, Health Information Exchange; HMO, Health Maintenance Organization IS, Information Systems; IT, Information Technology; ED, Emergency Department; DD, Differential Diagnosis.

Competing interests

The author(s) declare that they have no competing interests.

Authors’ contributions

All contributors co-participated in an equal manner.

Statement of ethical approval

The study was approved by the Ethics Committee of Tel Aviv University.
References

1. Brynjolfsson, E., and Hitt, L. Paradox lost? Firm-level evidence on the returns to information systems spending. *Management Science* 1996, **42**: 541-558.

2. Lawson, A.E., and Daniel, E.S. Inferences of clinical diagnostic reasoning and diagnostic error. *Journal of Biomedical Informatics* 2011, **44**:402-412.

3. Tripathi, M., Delano, D., Lund, B., Rudolph, L., Engaging Patients For Health Information Exchange, *Health Affairs* 2009, 28,2:435-443.

4. Esquivel, A., Sittig, D.F., Murphy, D.R. and Singh, H. Improving the Effectiveness of Electronic Health Record-Based Referral Processes. *BMC Medical Informatics and Decision Making* 2012, **12**:107.

5. Ramachandran, S., Erraguntla, M., Mayer, R., and Benjamin, P. Data mining in military health systems - clinical and administrative applications. In: *IEEE International Conference on Automation Science and Engineering 2007*, 158-163.

6. Schneider, E.B., Hyder, O., Brooke, B.S., Efron, J., Cameron, J.L., Edil, B.H., Schulick, R.D., Choti, M.A., Wolfgang, C.L., and Pawlik, T.M. Patient readmission and mortality after colorectal surgery for colon cancer: Impact of length of stay relative to other clinical factors. *Journal of the American College of Surgeons* 2012, **214**:390-398.

7. Cress, J.C. Helping reduce hospital readmissions using seven key elements. *Geriatric Care Management Journal* 2011, **21**:25–28.

8. Stone, J., and Hoffman, G.J. Research Report “Medicare Hospital Readmissions - Issues, Policy Options and Patient Protection and Affordable Care Act,” CRS Report for Congress PPACA; P.L. 111-148. 2010
9. Ben-Assuli, O., Leshno, M., and Shabtai, I. Using electronic medical record systems for admission decisions in emergency departments: Examining the crowdedness effect. *Journal of Medical Systems* 2012.

10. Shabtai, I., Leshno, M., Blondheimc, O. and Kornbluth, J. The value of information for decision-making in the healthcare environment. *Medical and Care Compunetics* 2007, 4:91-97.

11. Cooke, M.W., Higgins, J. and Kidd, P. Use of emergency observation and assessment wards: a systematic literature review. *British Medical Journal* 2003, 20: 138.

12. Denman, J.M., Bingham, P. and George, S. A confidential enquiry into emergency hospital admissions on the Isle of Wight, UK. *British Medical Journal* 1997, 51:386-390.

13. Arendts, G., Fitzhardinge, S., Pronk, K., Donaldson, M., Hutton, M. and Nagree, Y. The impact of early emergency department allied health intervention on admission rates in older people - a nonrandomized clinical study. *BMC Geriatrics* 2012, 12.

14. Sox, H.C., Blatt, M.A. and Higgins, M.C.: *Medical decision making*. American College of Physicians, Philadelphia 2007

15. Walker, J., Pan, E., Johnston, D., Adler-Milstein, J., Bates, D.W. and Middleton, B. The value of health care information exchange and interoperability. *Health Affairs* 2005, 24:10-18.

16. Ather, S., Chung, K.D., Gregory, P., and Demissie, K. (2004). The association between hospital readmission and insurance provider among adults with asthma. *Journal of Asthma* 2004, 41:709–713.
17. Olola, H.O.C., Narus, S., Mebeker, J., Poynton, M., Hales, J., Rowan, B., LeSier, H., Zumberren, C., Edwards, A.A., Crawford, R., Amundsen, S., Kabir, Y., Atkin, J., Newberry, C., Young, J., Hanifi, T., Risenmay, B., Sorensen, T., and Evans, S. The perception of medical professionals and medical students on the usefulness of an emergency medical card and a continuity of care report in enhancing continuity of care. *International Journal of Medical Informatics* 2011, **80**:412-420.

18. Vest, J.R., Zhao, H., Jaspersen, J., Gamm, L.D., Ohsfeldt, R.L. Factors motivating and affecting health information exchange usage. *Journal of the American Medical Informatics Association* 2011, **18**:143-149.

19. Yen, P. and Bakken, S. Review of health information technology usability study methodologies. *JAMIA* 2012, **19**:413-322.

20. Nahab, F., Takesaka, J., Mailyan, E., Judd, L., Culler, S., Webb, A., Frankel, M., Choi, D., and Helmers, S. Avoidable 30-day readmission among patients with stroke and other Cerebrovascular. The Neurohospitalist 2012, **2**:7-11.

21. Yam, C.H., Wong, E.L., Chan, F.W., Wong, F.Y., Leung, M.C., Yeoh, E.K.. Measuring and preventing potentially avoidable hospital readmissions: a review of the literature. *Hong Kong Medical Journal* 2010.

22. Welch, H.G., Larson, E.H., Hart, L.G., Rosenblatt, R.A. Readmission after surgery in Washington state rural hospitals. *Am J Public Health* 1992, **82**:407-411.

23. Vest, J.R. Health information exchange and healthcare utilization. *J Med Syst* 2009, **33**:223-231.
Figures

Figure 1 – Number of admissions and discharges by HMO

![](chart1.png)

Figure 2 – Number of referrals in all DDs distributed by type of information accessed

![](chart2.png)
## Tables

**Table 1 – Types of patient medical histories available to physicians via the EHR**

| Type of medical history | Specifics |
|-------------------------|-----------|
| Encounters              | Previous encounters and hospitalizations |
| Diagnoses               | Information regarding the patient's previous diagnoses |
| Medications             | A list of the permanent medications taken by the patient |
| Labs                    | Previous lab tests including blood tests, pathology history |
| Allergy Problems        | A list of the patient's known allergies |
| Community Clinics       | The patient's medical record, generated by family physicians |
| Demography Details      | Information regarding the demography of the patient |
| Surgical History        | A list of previous surgeries |

Note. * Data are fully available for HMO patients, while for non-HMO patients the information was limited to the specific hospital where they were seen last.
Table 2 - Patient characteristics: Comparison of HMO insured patients vs. other HMO insured patients

| Characteristics                              | Total Study Sample | The main HMO | Other HMOs  |
|----------------------------------------------|--------------------|--------------|-------------|
|                                              | n = 281,750 (100%) | n = 210,568 (74.74%) | n = 71,182 (25.26%) |
| Age (years)                                  | 46.25±24.98        | 48.64±25.32  | 39.17±22.49 |
| Male (%)                                     | 135,634 (48.14%)   | 99,951 (47.47%) | 35,683 (50.13%) |
| EHR IS Was Viewed (%) [Divided by Interoperability] | 87,842 (31.18%) | 68,851 (32.7%) | 18,991 (26.68%) |
|                                              | Local: 75,665 (26.86%) | Local: 58,468 (27.8%) | Local: 17,197 (24.16%) |
|                                              | External: 12,177 (4.32%) | External: 10,383 (4.9%) | External: 1,794 (2.52%) |
| Admissions (%)                               | 115,719 (41.07%)   | 89,473 (42.49%) | 26,246 (36.87%) |
| Readmission within seven Days (% of Admissions) | 3,741 (3.23%)     | 2,830 (3.2%) | 911 (3.47%) |
| Readmission within 30 Days (% of Admissions) | 8,625 (7.45%)     | 6,802 (7.6%) | 1,823 (6.95%) |
| Single-Day Admissions (% of Admissions)      | 25,308 (21.87%)    | 18,449 (20.6%) | 6,859 (26.13%) |
| Admission Period (days)                      | 4.26±5.54          | 4.4±5.81     | 3.79±4.46   |

Data are mean (±SD) or number of subjects (proportion); all univariate comparisons were significant at 0.001.
Table 3 - The impact of viewing medical history on various DDs (readmissions within seven days)

| Differential Diagnosis | Percentage of Readmissions when Medical History Was Not Viewed | Percentage of Readmissions when Medical History Was Viewed | Decrease in Readmissions within seven days |
|------------------------|---------------------------------------------------------------|------------------------------------------------------------|-------------------------------------------|
| All Diagnoses          | 4.1% (2,956)                                                 | 1.8% (785)                                                 | **56.10%***                               |
| GE                     | 6.4% (338)                                                   | 1.3% (25)                                                  | **79.69%***                               |
| AP                     | 10% (1,412)                                                  | 2.4% (181)                                                 | **77.69%***                               |
| CP                     | 2.1% (865)                                                   | 2.0% (508)                                                 | n/a                                       |
| PO                     | 2.6% (200)                                                   | 1.1% (50)                                                  | **57.69%***                               |
| UTI                    | 3.5% (141)                                                   | 0.7% (21)                                                   | **80%***                                  |

1 *** p<0.001, ** p<0.01, *p<0.05, + p<0.1; n/a not applicable (all similar tables below use the same conventions)

Table 4 - The impact of viewing medical history on various DDs (single-day admissions)

| Differential Diagnosis | Percentage of Single-Day Admissions when Medical History Was Not Viewed | Percentage of Single-Day Admissions when Medical History Was Viewed | Decrease in Single-Day Admissions |
|------------------------|------------------------------------------------------------------------|------------------------------------------------------------------|-----------------------------------|
| All Diagnoses          | 24.5% (17,812)                                                          | 17.4% (7,496)                                                   | **28.98%***                      |
| GE                     | 36.7% (1,931)                                                           | 22.5% (428)                                                     | **38.69%***                      |
| AP                     | 35.5% (4,991)                                                           | 21.3% (1,601)                                                   | **40.00%***                      |
| CP                     | 23.2% (9,646)                                                           | 18.9% (4,917)                                                   | **18.53%***                      |
| PO                     | 10.2% (785)                                                              | 7.4% (346)                                                      | **27.45%***                      |
| UTI                    | 11.4% (459)                                                              | 7% (204)                                                        | **38.60%**                       |
Table 5 - Logistic regression on Readmission within seven days for all DDs when viewing external medical history (Hypothesis 1a)

| Theory Variables in the Equation | All DDs (N=115,719) | GE (N=7,165) | AP (N=21,579) | UTI (N=6,950) | CP (N=67,650) | PO (N=12,375) |
|---------------------------------|----------------------|--------------|---------------|--------------|---------------|---------------|
|                                 | B (S.E.) | OR (S.E.) | B (S.E.) | OR (S.E.) | B (S.E.) | OR (S.E.) | B (S.E.) | OR (S.E.) | B (S.E.) | OR (S.E.) | B (S.E.) | OR (S.E.) |
| External history viewed         | -.653 (.119) | .520 (.001) | -1.146 (.586) | .318 (.051) | -1.362 (.240) | .256 (.001) | -1.177 (.510) | .308 (.021) | -.214 (.158) | .807 (.176) | -.143 (.390) | .867 (.714) |
| Age                             | -.024 (.001) | -.976 (.002) | -.012 (.001) | .998 (.001) | -.019 (.001) | .981 (.001) | -.019 (.003) | .982 (.001) | -.019 (.002) | .981 (.002) | -.030 (.002) | .971 (.001) |
| Gender                          | -.233 (.034) | -.792 (.001) | .097 (.110) | 1.102 (.376) | -.449 (.056) | .638 (.001) | -.219 (.180) | .803 (.222) | .234 (.060) | <.001 (.132) | <.001 (.132) | 1.138 (.132) |
| HMO                             | .085 (.039) | .109 (.031) | -.351 (.119) | .704 (.003) | .148 (.059) | .160 (.012) | .179 (.197) | .196 (.363) | .243 (.069) | <.001 (.158) | .243 (.380) |
| Constant                        | -2.094 (.045) | -.123 (.124) | -.239 (.065) | .091 (.001) | -1.709 (.211) | .181 (.001) | -2.717 (.033) | .066 (.001) | -3.052 (.132) | .047 (.001) | -2.769 (.172) | .063 (.001) |

Note. The table reports a series of multiple regression analyses. Block 2 (control for type of department) and Block 3 (control for type of hospital) are not shown here, but were also included in the regression. CP = chest pain; AP = abdominal pain; GE = gastroenteritis; UTI = urinary tract infection; PO = pneumonia organism; OR = Odd Ratio; a Coded 0 = female, 1= male. b Coded 0 = other HMO, 1 = main HMO. (all similar tables below use the same abbreviations)

Table 6 - Logistic regression on Single-day admissions for all DDs for external medical history (Hypothesis 2a)

| Theory Variables in the Equation | All DDs (N=115,719) | GE (N=7,165) | AP (N=21,579) | UTI (N=6,950) | CP (N=67,650) | PO (N=12,375) |
|---------------------------------|----------------------|--------------|---------------|--------------|---------------|---------------|
|                                 | B (S.E.) | OR (S.E.) | B (S.E.) | OR (S.E.) | B (S.E.) | OR (S.E.) | B (S.E.) | OR (S.E.) | B (S.E.) | OR (S.E.) | B (S.E.) | OR (S.E.) |
| External history viewed         | -.274 (.040) | -.760 (.001) | -.434 (.176) | -.648 (.014) | -.432 (.084) | -.649 (.001) | -.087 (.161) | .917 (.590) | -.169 (.053) | .844 (.001) | -.132 (.173) | .876 (.445) |
| Age                             | -.021 (.000) | .979 (.001) | -.018 (.001) | .982 (.001) | -.023 (.001) | .977 (.001) | -.015 (.002) | .985 (.001) | -.033 (.001) | .968 (.001) | -.019 (.001) | .982 (.001) |
| Gender                          | -.041 (.015) | .960 (.005) | -.004 (.053) | 1.000 (.933) | -.033 (.031) | .967 (.285) | -.100 (.090) | .904 (.263) | -.196 (.020) | .822 (.001) | .046 (.064) | 1.047 (.478) |
| HMO                             | -.152 (.017) | .859 (.001) | -.241 (.061) | .786 (.001) | -.066 (.034) | .936 (.052) | -.146 (.097) | .864 (.132) | -.116 (.022) | .891 (.001) | -.039 (.077) | .962 (.609) |
| Constant                        | .288 (.022) | 1.029 (.189) | -.014 (.064) | .986 (.822) | .202 (.038) | 1.224 (.001) | -.1210 (.110) | .298 (.001) | .935 (.047) | 2.547 (.001) | -.1349 (.086) | .260 (.001) |
Table 7 - Logistic regression on Readmission within seven days for all DDs when viewing local medical history (Hypothesis 1b)

| Theory Variables in the Equation | All DDs (N=115,719) | GE (N=7,165) | AP (N=21,579) | UTI (N=6,950) | CP (N=67,650) | PO (N=12,375) |
|---------------------------------|---------------------|--------------|---------------|---------------|--------------|---------------|
| B (S.E.) OR (Sig.)              | B (S.E.) OR (Sig.)  | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) |
| Local history viewed            | -.574 (.043) .563 (<.001) | -.139 (.225) .249 (<.001) | -.128 (.085) .276 (<.001) | -.140 (.258) .246 (<.001) | .015 (.058) 1.016 (.789) | -.567 (.172) .567 (.001) |
| Age                             | -.023 (.001) .977 (<.001) | -.009 (.002) .991 (<.001) | -.017 (.001) .983 (<.001) | -.017 (.003) .983 (<.001) | -.019 (.002) .981 (<.001) | -.028 (.002) .972 (<.001) |
| Gender                          | -.230 (.034) .795 (.110) | .108 (.325) 1.114 (.057) | -.443 (.211) .642 (.180) | -.226 (.211) .798 (.180) | .235 (.06) 1.265 (.132) | .139 (.292) 1.149 (.292) |
| HMO                             | .078 (.039) 1.081 (.120) | -.361 (.003) .697 (.06) | .137 (.021) 1.147 (.197) | .159 (.421) 1.172 (.069) | .239 (.001) 1.270 (.158) | .144 (.364) 1.155 (.364) |
| Constant                        | -.202 (.045) .132 (.125) | -.230 (.001) .10 (.085) | -.128 (.001) .276 (.212) | -.254 (.001) .079 (.133) | -.038 (.001) .047 (.173) | -.269 (.001) .067 (<.001) |

Table 8 - Logistic regression on single-day admissions for all DDs explained when local medical history (Hypothesis 2b)

| Theory Variables in the Equation | All DDs (N=115,719) | GE (N=7,165) | AP (N=21,579) | UTI (N=6,950) | CP (N=67,650) | PO (N=12,375) |
|---------------------------------|---------------------|--------------|---------------|---------------|--------------|---------------|
| B (S.E.) OR (Sig.)              | B (S.E.) OR (Sig.)  | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) |
| Local history viewed            | -.242 (.016) .785 (<.001) | -.253 (.069) .776 (<.001) | -.483 (.036) .617 (<.001) | -.457 (.096) .633 (<.001) | -.167 (.021) .846 (<.001) | -.120 (.072) .887 (.094) |
| Age                             | -.021 (.000) .979 (<.001) | -.018 (.001) .983 (<.001) | -.022 (.001) .978 (<.001) | -.015 (.002) .985 (<.001) | -.032 (.001) .968 (<.001) | -.018 (.001) .982 (<.001) |
| Gender                          | -.040 (.015) .961 (.031) | .008 (.855) 1.008 (.364) | -.028 (.090) .972 (.256) | -.102 (.020) .903 (.026) | -.197 (.001) .821 (.064) | .048 (.451) 1.050 (.451) |
| HMO                             | -.156 (.017) .855 (<.001) | -.246 (.061) .782 (<.001) | -.073 (.034) .929 (<.001) | -.145 (.133) .865 (<.001) | -.118 (.022) .888 (.076) | -.039 (.111) .962 (.111) |
| Constant                        | .066 (.022) 1.069 (.064) | .014 (.824) 1.014 (.039) | .283 (.111) 1.327 (<.001) | -.112 (.047) .326 (<.001) | .965 (.047) 2.625 (<.001) | -.131 (.087) .264 (<.001) |
### Table 9 - Logistic Regression on Readmission within seven days for all DDs comparing local and external medical history (Hypothesis 3)

| Theory Variables in the Equation | All DDs (N=43,030) | GE (N=1,900) | AP (N=7,511) | UTI (N=2,909) | CP (N=26,026) | PO (N=4,684) |
|----------------------------------|---------------------|--------------|--------------|--------------|---------------|--------------|
|                                  | B (S.E.) OR (Sig.)  | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) |
| Local history viewed *           | .241 (.127) 1.272 (.050) | .138 (.197) 1.149 (.482) | .331 (.260) 1.393 (.203) | .079 (.588) 1.082 (.894) | .263 (.167) 1.301 (.114) | .270 (.426) .763 (.526) |
| Age                              | -.012 (.002) (.003) | -.014 (.003) (.004) | -.009 (.004) (.026) | .003 (.012) .991 (.783) | -.012 (.003) .988 (.003) | -.021 (.008) .980 (.009) |
| Gender                           | .361 (.076) (.116) | .110 (.343) 1.117 (.158) | .088 (.576) 1.092 (.464) | .129 (.777) 1.137 (.542) | .462 (.101) 1.587 (.101) | .019 (.291) 1.019 (.947) |
| HMO                              | .228 (.095) (.139) | -.333 (.195) .716 (.195) | .383 (.571) 1.466 (.877) | -.089 (.120) .915 (.736) | .363 (.120) 1.438 (.120) | -.072 (.365) .931 (.884) |
| Constant                         | -.20.913 (n/a) (.998) | -.20.939 (n/a) (.1000) | -.20.854 (n/a) (.998) | -.20.620 (n/a) (.999) | -.21.151 (n/a) (.999) | -.19.675 (n/a) (.999) |

* Coded 0 = external history viewed, 1= local history viewed. (all similar tables below use the same abbreviations)

### Table 10 - Logistic Regression on single-day admissions for all DDs comparing local and external medical history (Hypothesis 3)

| Theory Variables in the Equation | All DDs (N=43,030) | GE (N=1,900) | AP (N=7,511) | UTI (N=2,909) | CP (N=26,026) | PO (N=4,684) |
|----------------------------------|---------------------|--------------|--------------|--------------|---------------|--------------|
|                                  | B (S.E.) OR (Sig.)  | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) | B (S.E.) OR (Sig.) |
| Local history viewed             | .123 (.043) 1.130 (.005) | .138 (.197) 1.149 (.482) | .023 (.093) 1.024 (.802) | -.125 (.188) .883 (.507) | .103 (.057) 1.109 (.069) | .028 (.184) 1.028 (.879) |
| Age                              | -.022 (.001) (.003) | -.014 (.003) (.004) | -.022 (.002) (.001) | -.011 (.004) .989 (.002) | -.029 (.001) .971 (.001) | -.003 (.003) .997 (.423) |
| Gender                           | .049 (.027) (.066) | .110 (.116) 1.117 (.343) | .068 (.061) 1.070 (.266) | -.155 (.156) .856 (.318) | -.083 (.034) .921 (.016) | .168 (.116) 1.183 (.147) |
| HMO                              | -.107 (.031) (.139) | -.333 (.067) .716 (.067) | -.182 (.197) .833 (.416) | .099 (.176) 1.104 (.616) | -.053 (.039) .948 (.177) | -.029 (.150) .971 (.846) |
| Constant                         | -.149 (.486) (.301) | -.20.939 (n/a) (.1000) | -.405 (.571) .667 (.478) | -.21.288 (n/a) (.999) | -.573 (1.259) .564 (.649) | -.21.451 (n/a) (.999) |