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To cite this article: Kun Wang, Christine Zwart, Clinton Wellnitz, Teresa Wu & Jing Li (2017) Integration of multiple health information systems for quality improvement of radiologic care, IISE Transactions on Healthcare Systems Engineering, 7:3, 169-180, DOI: 10.1080/24725579.2017.1329241

To link to this article: http://dx.doi.org/10.1080/24725579.2017.1329241

Accepted author version posted online: 16 May 2017.
Published online: 16 May 2017.

Article views: 12

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HEALTH INFORMATICS ON PROCESS IMPROVEMENT

Integration of multiple health information systems for quality improvement of radiologic care

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ABSTRACT
In radiology, several Health Information Systems (HISs) are commonly used: Electronic Health Records (EHR), Radiology Information System (RIS), and Picture Archive and Communication System (PACS). Each HIS records partial and complementary information about the radiologic care process. Depending on the institution, the HISs that touch radiologic care can be distinct, disparate, and with different formats and meta information. We note no reported research on integrating multiple HISs to allow for an end-to-end tracking of the care patients receive. Therefore, current Quality of Care (QoC) research is limited as it can only utilize data for partial workflow analysis. To develop a novel technology called Department Data Depot (DDD) that integrates multiple HISs in radiology. We propose nine metrics defined upon DDD data measuring various dimensions of care quality. To demonstrate the clinical utility of DDD, we developed and deployed the Radiology Quality Dashboard (RQD) at Mayo Clinic in Arizona. Four use cases illustrate how RQD is used to assist the clinical practice. A case study on how DDD enabled an effective intervention for reducing lengthy radiologist turnaround times (TATs) is presented.

1. Introduction

Health care spending in the US has been estimated to account for 17% of gross domestic product, nearly twice as much as that in other developed countries (Hartman et al., 2015). In spite of this enormous expenditure, the US ranked last in health care quality among developed countries according to a 2008 Commonwealth Fund report (Roehr, 2008). Quality of Care (QoC), according to a 2001 report by the Institute of Medicine (2001), includes six dimensions: timeliness, efficiency, effectiveness, patient safety, patient/family centeredness, and equity of care.

QoC improvement initiatives generally prioritize areas that incur the most expenditure. One such area is radiologic care, as it involves the use and maintenance of expensive imaging equipment. There is ample evidence showing that Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) have contributed significantly to the rising cost of health care (Hu et al., 2011). As a result, the Centers for Medicare and Medicaid Services (2010) have proposed that imaging devices costing greater than one million dollars should be amortized for replacement based on a 90% service utilization, in the hope of lowering per-patient reimbursement cost.

To improve the QoC in radiology, an important first step is to define metrics to measure the QoC. Metrics are numerical indicators used to measure the performance in areas considered important for an organization’s mission (Abujudeh et al., 2010). Metrics for the QoC in radiology have been discussed in a number of articles. Typical examples include report turnaround time (Abujudeh et al., 2010), patient access and wait times (Sarwar et al., 2015), equipment utilization rates and downtimes (Sarwar et al., 2015), exam volumes (Ondategui-Parra et al., 2005), and staff workload Ondategui-Parra et al., 2005).

With the rapid development and adoption of information technology in health care, electronic Health Information Systems (HISs) have been widely used in health institutions. This has provided an unprecedented opportunity for acquiring quantitative data on the care process, from which metrics for QoC can be extracted efficiently and automatically. In radiology, several HISs are commonly used, including the Electronic Health Records (EHR), Radiology Information System (RIS), and Picture Archive and Communication System (PACS). Each of these HISs records partial and complementary information about the entire radiologic care process. Specifically, the EHR contains patient information and detailed medical history. Other than patient information that overlaps with the EHR, the RIS includes radiology-specific measures, such as technologist imaging verification time. The PACS focuses on storing the digital images from the exams and related metadata information using the Digital Communications in Medicine (DICOM) standard (DICOM Standards, n.d.). To the best of our knowledge, no research has been done to integrate the multiple HISs together to allow end-to-end tracking of the care each patient receives in the Radiology Department; i.e., from check-in to check-out.
finalization of the radiologic report. As a result, the current QoC research is limited, as it is not capable of capturing the entire radiologic care workflow, given only segmented data available from a single HIS. A comprehensive assessment of radiology QoC requires that the multiple HISs be integrated such that various key QoC metrics can be extracted from the resulting “super-HIS.”

At Mayo Clinic, we have a home-grown radiology quality assurance system called Dose Index Tracker (DIT®) (Wang et al., 2011). The DIT system collects information directly from the DICOM headers of scanned images. Such information includes, but is not limited to, scanner information (ID, vendor, etc.), exam-related information (procedure, timestamps of each scanned image, radiation dose, etc.), and basic patient information. The DIT was designed to track patient-specific radiation dose across all radiology exams performed at Mayo Clinic, and to provide intelligent data analysis, reporting, and alerting in a clinical quality assurance context.

In this article, we present our development of a technology called Department Data Depot (DDD), which integrates four HISs, including an EHR, a RIS, a PACS, and the home-grown DIT system. In the development of DDD, we adopt the concept of loose-coupling techniques in database integration and propose a three-layer integration framework, including a data mashup lower-layer, an aggregation service middle-layer, and a result presentation upper-layer. The loose-coupling architecture is a mature and well-known technique which is designed to reduce the risk that a change made within one or more databases will create unanticipated changes within other related databases. Limiting interconnections can help isolate problems when things go wrong and simplify testing, maintenance, and troubleshooting procedures. As a tradeoff, such integration may slightly increase the response time of the system and necessitate extra maintenance of the mid-layer due to the nature of design. In the data mashup layer, a module is introduced to maintain the relations and constraints among the integrated HIS databases. When any of the source databases or the relations and constraints themselves change, we can easily alter the mid-layer of our integration to leave the upper levels untouched. In addition to the design and implementation of this framework, a significant amount of effort has been spent on addressing specific issues from incompatibility of the multiple HISs, such as inconsistent data fields, data measurement errors, missing values, and human errors. These issues could substantially affect the usability of the integrated system and therefore have been deliberately addressed in our research. Furthermore, we propose nine QoC metrics defined upon the integrated system: (1) exam duration; (2) technologist post-processing time; (3) technologist turnaround time (TAT); (4) radiologist TAT and (5) total TAT, which reflect the timeliness and efficiency of radiologic care; (6) patient waiting time and (7) patient TAT, which reflect the efficiency and patient satisfaction; (8) patient volume and (9) exam volume, which reflect the workload distribution. All of these metrics measure QoC from different and complementary perspectives. Finally, we present the deployment of DDD in the Radiology Department of Mayo Clinic in Arizona (MCA) through two case studies. DDD is deployed in MCA through a web portal, called the Radiology Quality Dashboard (RQD). In the first case study, we demonstrate, through four examples, how users can use RQD information in the clinical practice. In the second case study, we show how DDD enabled identification of the root cause of lengthy radiologist TAT for observation patient (ObP)—a specific patient subtype—and further enabled the development of an effective intervention for radiologic quality improvement.

Different from data integration and quality control applications in other fields, such systems in health care have restricted access policies to protect patient information according to HIPPA (Health Insurance Portability and Accountability Act). Indeed, our research team had to go through HIPPA training before we implemented the project, and the end users of the project are from Mayo Clinic in Arizona and have the right to access the information. When our DDD system acquires raw data records for other HISs, those outer source systems give us the privilege to query and store patient information. When we use our database to calculate quality metrics and generate reports, however, an anonymization procedure is applied in the mashup layer by removing all patient-related information except the patient type, such as “inpatient,” “outpatient” and “ED patient.” Also, the metrics of interest in this research are aggregated measures; i.e., they are not specific to an individual patient. As a result, the patients’ demographics and disease information are not used in the analysis.

The contributions of this article are multifold:

- Our work is the first of its kind and provides a technology for multi-HIS integration for radiology practice. By integrating these HISs together, DDD enables end-to-end tracking of the radiologic care each patient receives, with detailed time stamps and contents of each care activity as well as rich information on patients, providers, and equipment. While this article focuses on quality improvement, the data and information in DDD can support a variety of other goals including, but not limited to, scheduling, load balancing, and process optimization. In this sense, we envision that DDD has a potential for profoundly impacting radiology practice.

- Based on intensive interaction and dialogue with radiologists, technologists, and administrators in the Radiology Department cross-referenced with the available data in DDD, we propose nine QoC metrics that are important for monitoring, tracking, and evaluating the quality of radiologic care. These metrics have not previously been available.

- DDD was deployed in MCA in September 2015. Since then, it has been used extensively by clinicians, administrators, and researchers to monitor QoC, identify problem areas, and perform interventions to improve the quality of radiologic care. In this sense, the research in this article sets an example that close collaboration between industrial engineers and clinicians has great potential for transforming health care practices.

The rest of the article is organized as follows: Section 2 provides a literature review. Section 3 presents the development of DDD and definitions of the proposed QoC metrics based on the DDD. Section 4 presents two case studies on the deployment of DDD in the Radiology Department of MCA for quality improvement of radiologic care. Section 5 is the conclusion.
2. Literature review

The recent, widespread adoption of HISs in health institutions has made it possible to collect detailed, quantitative data on the care process. Availability of the data further enables QoC to be measured and improved. In this section, we will review major types of HISs, focusing on how they have been used in relation to QoC, especially in radiology.

The terms of EHR or Electronic Medical Records (EMR) are often used interchangeably with the HIS. In some care settings, the EHR is the only HIS in play. In this article, we use EHR to refer to the enterprise-level HIS of patient medical history. The EHR includes all key administrative clinical data relevant to a patient’s care pulled from multiple encounters and facilities, such as demographics, progress notes, medications, immunizations, vital signs, laboratory, and radiologic reports. The EHR was one of the earliest HISs and was in use when health care practices began transitioning from the paper era to the digital era. Early research on the EHR in relation to quality focused on design and implementation issues of the EHR to make it a proper information enabler. For example, Walker et al. (2008) proposed a coordinated set of steps for safe design, implementation, and improvement of the EHR. Middleton et al. (2013) made 10 recommendations on the EHR with respect to improving the safety and quality of care. Wang et al. (2003) performed a cost-benefit analysis of the EHR in ambulatory primary care settings and concluded that the EHR investment had a positive financial return. Miller et al. (2005) conducted similar case studies on 14 solo or small-group primary care facilities and suggested that the EHR would be “financially attractive” for some facilities and “financially acceptable” for most others. More recently, as the EHR has become a mature and widely adopted system, research has focused on how the data and information recorded by the EHR can be used for quality and performance improvement of health care (Amoah et al., 2014). For example, Poissant et al. (2005) studied the documentation time of physicians and nurses, and concluded that, with the help of the EHR, nurses save about 24% of the overall time spent on documenting during a shift. McVeigh et al. (2008) proposed several metrics to be extracted from the EHR that measure the timeliness, an important dimension of QoC, of several sub-processes of optometry practices, such as check-in, pretesting, doctor examination, and optical sub-processes. Despite the wealth of existing studies, little research has been conducted on quality improvement of radiologic care using the EHR. This is because the EHR is an enterprise-level system such that the data it collects lack sufficient granularity to help extract radiology-specific QoC metrics such as pre-radiologic-exam patient waiting time, exam duration, and radiologic report turnaround time.

The RIS and PACS are two specialized HISs for radiology. Radiology departments use a RIS to track patients, exams, result distribution, and procedure billing. A PACS provides economical storage and convenient access to images from multiple modalities. Wang et al. (2011) developed a DIT© to extract, store, and monitor critical radiation dose indicators stored in DICOM file headers found in PACS. Hu et al. (2011) developed five metrics for efficiency benchmarking, including exam duration, inter-series time, inter-patient time, appointment interval time, and table utilization using DICOM information stored in PACS. A radiology department’s RIS and PACS are generally designed to interface and can often be easily linked to provide more comprehensive information than using a single system alone. Research has been done to use RIS and PACS together for improving the quality and safety of radiologic care. For example, Nitrosi et al. (2013) developed a procedure to use Health Level 7 (HL7) standard messaging in RIS and PACS to reduce clinical risks due to patient reconciliation errors. In several independent studies, researchers developed various tracking systems with data from RIS and PACS to monitor the overall performance and exam status within the radiology department in order to improve patient satisfaction and outcome assessment (Nagy et al., 2009). Seltzer et al. (2000) integrated RIS, hospital information systems, and manually input data to extract several management metrics such as report turnaround time, access to appointments, and productivity.

As seen, most existing research was based on a single- or department-level HIS. However, radiologic care is a complex process, such that data describing the entire care process reside in multiple HISs. For example, patient check-in time, type, and demographics are available in EHR. Service time stamps, such as the times when imaging was started and finished, and when the image was verified by the technologist, are stored in RIS. The time when the radiologic report is finalized by the radiologist is recorded in PACS. Image files, together with meta data such as modality, body part, and with/without contrast, are also stored in PACS. As a result, although a few QoC metrics may be extracted from a single HIS alone, these metrics only provide partial, limited information about the QoC. A comprehensive assessment of the QoC in radiology requires that the multiple HISs be integrated into a “super-HIS” from which various key QoC metrics can be extracted. Without the integration, many important QoC metrics that require linked records from multiple HISs would be missed. For example, an important QoC metric is patient pre-exam waiting time; i.e., the time duration between check-in and imaging start. The two time stamps needed to compute the waiting time reside in EHR and RIS, respectively. Another important QoC metric, patient turnaround time, is measured by the difference between two time stamps; i.e., imaging start and radiologist completion of reading the image and finalizing the report, which are in RIS and PACS, respectively. Furthermore, to measure the distribution of the aforementioned time metrics as well as other QoC metrics, such as patient volume and exam volume with respect to different patient types, imaging modalities, facilities/sites, scanners, and body parts/sub-specialties, information needs to be pulled from EHR or PACS to group-partition these metrics.

3. Development of multi-HIS DDD and radiologic QoC metrics

In this section, we present our development of DDD that integrates multiple HISs. We also define and describe how we extract a collection of key QoC metrics from the DDD. We will present our research development in the context of the Radiology Department at MCA, but the developed technologies are generalizable to other health institutions.
### 3.1. Mapping out radiologic care process and interrogation of the multi-HIS

Before developing the DDD and extracting the key QoC metrics, we needed to identify the major steps involved in the care process performed within the Radiology Department for patients. Through observations and intensive dialogue with the radiologists, technologists, and administrators in the Radiology Department of MCA, we mapped out the radiologic care process, as depicted in the left-hand side of Fig. 1. Furthermore, we dove into each HIS used in radiology to identify what information about the mapped care process was stored in the HIS. There are three important observations: (1) no single HIS provides end-to-end measurement for the entire care process; (2) each of the four HISs in the right-hand side of Fig. 1 contains useful and unique information required to describe the entire care process (please see Fig. 4 for details), which suggests that all four HISs must be included in developing the DDD; (3) there is a common data field across all four HISs—i.e., the accession number—which is a unique identifier for each exam of each patient (one patient can have multiple exams). The accession number can be used as a key to link the four HISs together to track the entire care process on a per-patient per-exam basis. These findings lay the groundwork for the development of DDD.

### 3.2. DDD architecture

DDD integrates four major HISs deployed at MCA: an EHR—Cerner®; a RIS—Radiology Data Warehouse (RDW); a PACS monitoring system—PACSHealth that extracts exam status changes in GE Centricity PACS; and a custom-built radiation dose tracking system—DIT®. Database integration is an important technique that helps the data users interrogate heterogeneous records, information and relationships among multiple data sources and provides a unified data view. One traditional technique is called data warehousing (Immon, 1992), which extracts data from multiple sources, transforms the data into a proper and unified format, and then loads the data into another standalone target for further query and analysis. A major limitation of this technique is the tight relationship to the original data sources, which makes it difficult to adopt any upstream structural changes and increases maintenance/update costs (Moseley, 2009; Wu et al., 2007). More recently, loose-coupling techniques have been proposed for database integration, which provide a unified real-time data query interface over a target data source (Kaye, 2003). Such techniques are developed and used as an important part of Service Oriented Architecture (SOA) (Erl, 2008). Loose-coupling techniques rely on mappings between the data structures of the original data sources and the target data source. If required, transformation techniques are used to wrap the interfaces of original sources for a higher-level query. Depending on the mapping schemas, the techniques can be categorized into two basic types: Global As View (GAV), which maps records in the target data source to original data sources; Local As View (LAV), which maps records in the original data sources to the target data source. Our development of DDD adopts the concepts of loose-coupling techniques by creating higher-level data schema with LAV mapping. The original data records are unchanged and connected dynamically to construct a local record for data analysis. A significant challenge we encountered was how to resolve semantic conflicts among the different data sources, as heterogeneous definitions and/or meanings always exist when multiple data sources are to be linked together. To tackle this challenge, semantic and ontology-based integrations are developed by involving expert knowledge that explicitly defines schema terms.

Specifically, we propose a three-layer integration framework for DDD, including a data mashup layer, an aggregation service layer, and a result presentation layer, as shown in Fig. 2. Next, we introduce each layer with more details.

#### 3.2.1. Data mashup layer

The data mashup layer couples the data fields in each individual HIS into the DDD on the fly. The coupling uses “accession number” as a unique identifier for each exam of each patient and a common field shared by all the individual HISs. Each record in DDD corresponds to one exam. Each exam is associated with a
Table 1. Relevant data fields in each HIS to QoC metric calculation and included in DDD.

<table>
<thead>
<tr>
<th>Field Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AccessionNumber</td>
<td>Primary key to link individual HIS; e.g., &quot;81071204-1&quot;</td>
</tr>
<tr>
<td>Code</td>
<td>Procedure code; e.g., &quot;70030K&quot;, &quot;74364&quot;</td>
</tr>
<tr>
<td>Encntr</td>
<td>Encounter type: an indicator of patient type; e.g., outpatient, inpatient</td>
</tr>
<tr>
<td>Facility</td>
<td>Facility/site where the exam is taken; e.g., &quot;hospital&quot;, &quot;clinic&quot;</td>
</tr>
<tr>
<td>Modality</td>
<td>Imaging modality; e.g., &quot;MRI&quot;, &quot;CT&quot;</td>
</tr>
<tr>
<td>ServiceTime</td>
<td>Timestamp when the image scanning finishes; e.g., &quot;2016-07-18 10:12:32.000&quot;</td>
</tr>
</tbody>
</table>

PACS (GE-Centricity)

<table>
<thead>
<tr>
<th>Field Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AccessionNumber</td>
<td>Primary key to link individual HIS; e.g., &quot;81071204-1&quot;</td>
</tr>
<tr>
<td>FiftyTransition</td>
<td>Timestamp when the technologist finishes scanning; e.g., &quot;2016-07-18 10:12:32.000&quot;</td>
</tr>
<tr>
<td>MedicalRecordNumber</td>
<td>Medical record number: a patient ID; e.g., &quot;12345678&quot;</td>
</tr>
<tr>
<td>NinetyTransition</td>
<td>Timestamp when the radiologist finishes dictating the exam; e.g., &quot;2016-07-18 10:12:32.000&quot;</td>
</tr>
<tr>
<td>ProcedureCode</td>
<td>Procedure code; e.g., &quot;70030K&quot;, &quot;74364&quot;</td>
</tr>
<tr>
<td>TwentyTransition</td>
<td>Timestamp when the exam is ordered; e.g., &quot;2016-07-18 10:12:32.000&quot;</td>
</tr>
</tbody>
</table>

DIT (Mayo)

<table>
<thead>
<tr>
<th>Field Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AccessionNumber</td>
<td>Primary key to link individual HIS; e.g., &quot;81071204-1&quot;</td>
</tr>
<tr>
<td>FINISH_TIME</td>
<td>Timestamp when the last image of an exam arrives at PACS; e.g., &quot;2016-07-04 18:23:00.000&quot;</td>
</tr>
<tr>
<td>PROTOCOL_NAME</td>
<td>Exam protocol name; e.g., &quot;8a_Renal_Donor&quot;</td>
</tr>
<tr>
<td>START_TIME</td>
<td>Timestamp when the first image of an exam arrives at PACS; e.g., &quot;2016-07-18 10:12:32.000&quot;</td>
</tr>
<tr>
<td>STATION_ID</td>
<td>Unique scanner ID; e.g., &quot;JA_CT0PRA81818B&quot;</td>
</tr>
</tbody>
</table>

In reviewing Table 1, we note that these HIS databases have heterogeneous data fields, which may be inconsistent and even conflict with each other. Taking facility or site as an example, the collection of attributes to describe it, which correspond to the joint data fields from the four individual HISs. Here, only relevant ones associated with QoC metrics are coupled in DDD (see Table 1).

"Facility" data field from RDW is an indicator for the two sites of MCA (hospital vs. clinic); the "STATION_ID" from DIT can also help identify the site of each exam, as it is the unique ID of each scanner. Although representing the same concept, the data fields are named differently across different HISs. A second issue is that several data fields are input by staff manually, which may introduce human errors. To deal with such inconsistencies and errors in data mashup, we developed three heuristic rules based on intensive dialogues with the radiology staff.

**Heuristic Rule I:** technologist finish time \( t_{technologist\_finish} \) is the timestamp when a technologist finishes the exam procedure on a patient. At this time, all scanned images are ready to be sent to the radiologist to dictate and the patient will be transferred to the recovery room. \( t_{technologist\_finish} \) is needed for deriving an important QoC metric, technologist TAT. \( t_{technologist\_finish} \) does not exist in any of the four HISs, but is indirectly measured by two data fields: "ServiceTime" in RDW and "FiftyTransition" in PACS. The former is the time when the technologist manually indicates that scanning has finished. In contrast, the "FiftyTransition" marks the time when the images are marked as "Verified" in PACS, indicating that all image processing is complete. Typically, "ServiceTime" is earlier than "FiftyTransition" because it does not include the time the technologist spends on post-processing the scanned images. However, since the "ServiceTime" is manually entered into the system, depending on each technologist's working habit, this time stamp may be earlier or later than the exact \( t_{technologist\_finish} \). To eliminate the bias of the input and obtain a more accurate \( t_{technologist\_finish} \), we use the following rule:

\[
t_{technologist\_finish} = \text{later} \left( \text{"FiftyTransition"}, \text{"ServiceTime"} \right). \tag{1}
\]

The rationale behind this is that if "FiftyTransition" is later than "ServiceTime", it means that the technologist inputs the "ServiceTime" right after the scanning is finished but does not consider the post-processing time. Therefore, in such a situation, "FiftyTransition" is a better measure for \( t_{technologist\_finish} \). On the other hand, if "FiftyTransition" is earlier than "ServiceTime", there are likely extenuating circumstances or additional patient interactions that increase the hands-on component of the exam. In this case, "ServiceTime" is a more appropriate time stamp for \( t_{technologist\_finish} \).

**Heuristic Rule II:** check-in time \( t_{check-in} \) for patients in Emergency Department (ED): \( t_{check-in} \) is needed for deriving an important QoC metric, patient waiting time. It is measured by "CHECKIN_DT_TM" in Cerner. However, the "CHECKIN_DT_TM" is missing for patients in ED due to the unique care process of ED. A patient's radiology "check-in" (or alert of arrival) from the ED happens when an imaging exam is ordered by the physician, which is stored in the field of "TwentyTransition" in PACS. Therefore, we use "TwentyTransition" as \( t_{check-in} \) for ED patients, which produces the following rule:

\[
t_{check-in} = \begin{cases} 
\text{"TwentyTransition"}, & \text{if the patient is in ED} \\
\text{"CHECKIN_DT_TM"}, & \text{otherwise} 
\end{cases} \tag{2}
\]

**Heuristic Rule III:** patient type classification: It is important to be able to compute a QoC metric for different patient types, such as inpatient, outpatient, and ED patients. This would help reveal QoC problems in serving each type of patient and properly allocate resources to overcome the problems. Patient
type is stored in "ENCNTR_TYPE_DISPLAY" in Cerner and "Encntr" in PACS. Unfortunately, we can see that the two data fields have a large number of missing values (i.e., NULL values). To mitigate the problem, we use "ENCNTR_TYPE_DISPLAY" as the primary source to obtain the patient type, because its missing data problem is less severe than "Encntr." When the "ENCNTR_TYPE_DISPLAY" is missing for a patient, we check "Encntr." If "Encntr" is also missing, we label the patient as "NA."

\[
\text{Patient type} = \begin{cases} 
\text{ED patient}, & \text{if } "\text{ENCNTR\_TYPE\_DISPLAY}" = \text{‘Emergency’ OR ‘ENCNTR\_TYPE\_DISPLAY’ = NULL but } "\text{Encntr’ = ‘EM’} \\
\text{inpatient}, & \text{if } "\text{ENCNTR\_TYPE\_DISPLAY” = ‘Inpatient’ or ‘Observation’ OR ‘ENCNTR\_TYPE\_DISPLAY’ = NULL but } "\text{Encntr” = ‘IP’} \\
\text{outpatient}, & \text{if } "\text{ENCNTR\_TYPE\_DISPLAY” = ‘MCA Hospital C’, ‘MCA Patient’, ‘OP in a bed’, ‘Pre−Admit Outpatient’, ‘Recurring AIC’, ‘Recurring PM&R’, or ‘Recurring Rad Onc’ OR ‘ENCNTR\_TYPE\_DISPLAY’ = NULL but”Encntr” = ‘OP’ or ‘P’} \\
\text{NA,} & \text{otherwise}
\end{cases}
\]

### 3.2.2. Aggregation service layer

This layer hosts the algorithms to derive the nine QoC metrics (please see Section 3.3 for details). Execution of an algorithm is triggered by the user’s service request on the corresponding QoC metric, together with a time interval and strata that the user wants to utilize in the computation of the QoC. The QoC metric can be stratified by patient type, facility site, and scanner. Once an algorithm is triggered, it will query DDD, perform filtering and arithmetic operations, and return the user-requested QoC measurement that is presented on the result presentation layer (see the following).

### 3.2.3. Result presentation layer

We built RQD, a web portal, as the result presentation layer. RQD adopts HTML 5 techniques and provides users with easy access to the aggregation service layer from desktop computers, laptops, smartphones, and tablets. A snapshot of RQD is shown in Fig. 3. In particular, on the left side of RQD, a user can select the QoC metric of interest, start and end dates, and strata for which the QoC is to be computed. This information is sent to the aggregation service layer and results are presented on the right side of the RQD as graphs and/or tables.

### 3.3. Definition of radiologic QoC metrics

Based on the radiologic care process mapped out in Section 3.1, we define nine QoC metrics. Specifically, we propose five metrics measuring the timeliness and efficiency of radiologic care: exam duration, technologist post-processing time, technologist TAT, radiologist TAT, and total TAT. We propose two metrics on efficiency and patient satisfaction: patient waiting time and patient TAT. In addition, we propose two metrics on measuring...
Table 2. Definitions and formula of the proposed QoC metrics.

<table>
<thead>
<tr>
<th>QoC metrics</th>
<th>Definition</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exam duration</td>
<td>Time duration of the scanning process.</td>
<td>“FINISH_TIME” in DIT – “START_TIME” in DIT</td>
</tr>
<tr>
<td>Technologist TAT</td>
<td>Time duration for a technologist to perform the exam.</td>
<td>( t_{tech, finish} ) in (1) – “START_TIME” in DIT</td>
</tr>
<tr>
<td>Technologist post-processing time</td>
<td>Time duration for a technologist to verify the images, write exam notes, and clean up the exam room after the scanning process ends. This is a portion of technologist TAT.</td>
<td>( t_{tech, finish} ) in (1) – “FINISH_TIME” in DIT</td>
</tr>
<tr>
<td>Radiologist TAT</td>
<td>Time duration for a radiologist to read the images and complete the diagnostic report, after receiving the images from the technologist. This is the total time spent for the radiologic care of a patient.</td>
<td>“NinetyTransition” in PACS – ( t_{check, in} ) in (2)</td>
</tr>
<tr>
<td>Total TAT</td>
<td>Time duration between the patient check-in time and report completion by the radiologist. This is the total time spent for the radiologic care of a patient.</td>
<td>“NinetyTransition” in PACS – ( t_{check, in} ) in (2)</td>
</tr>
<tr>
<td>Patient TAT</td>
<td>Time duration between the patient check-in and check-out times. This is the total time for a patient’s physical stay in the Radiology Department.</td>
<td>“START_TIME” in DIT – ( t_{check, in} ) in (2)</td>
</tr>
<tr>
<td>Patient waiting time</td>
<td>Time duration between patient check-in time and the start of the scanning process. This is the inactive portion of a patient’s physical stay in the Radiology Department.</td>
<td></td>
</tr>
<tr>
<td>Patient volume</td>
<td>Number of patients.</td>
<td>Unique Count(MRN)</td>
</tr>
<tr>
<td>Exam volume</td>
<td>Number of exams (one patient may have multiple exams).</td>
<td>Unique Count(UniqueNumber)</td>
</tr>
</tbody>
</table>

Table 2 provides the definition and formula of each QoC metric. Figure 4 further shows the relative positions of the time stamps used in the formula (last column of Table 2) and from which HISs each time stamp can be obtained.

4. Application of DDD and QoC metrics in quality improvement of radiologic care

In this section, we present the applications of DDD technology in the Radiology Department of MCA. The first application demonstrates how RQD enabled by DDD was used to retrieve important information in order to help identify areas of improvement for radiologic care quality. The second application demonstrates how DDD enabled the identification of the root cause of lengthy radiologist TAT for a specific patient subtype, observation patients (ObP), and further enabled the development of an effective intervention for radiologic quality improvement.

4.1. RQD and its clinical use cases

With the DDD technology and nine QoC metrics, a number of radiologic-care-quality-related questions can be answered. Here, we present four examples of how RQD could potentially help improve care. At the time of preparing this article, we chose to select five full weeks of data (August 1, 2016 to September 4, 2016) and used CT as the example for illustration purposes. The same applies to other modalities, such as MR.

4.1.1. Example I

This study was motivated by a concern raised by the ED that the turnaround time of CT after regular radiologist working hours was longer than expected. As shown in Table 2, the turnaround
time is defined as the duration between check-in time and radiologist finish time. CT is an imaging modality extensively used by the ED. CT exams are typically interpreted by attending radiologists during regularly working hours (radiology hours) and by residents and fellows during extended working hours (non-radiology hours). In response to a request from the ED, we used DDD together with RQD to investigate this perceived problem.

As shown in Fig. 5, several observations can be obtained. First, the weekly average total TAT for both radiology and non-radiology hours ranges from 01:15—01:45 (hours:minutes), which is reasonable (Wang et al., 2015). Second, the total TAT during radiology hours is, in general, slightly longer than non-radiology hours, suggesting the perception of afterhours delays was unwarranted. Given the data, we performed hypothesis testing to see if the observed difference between the radiology and non-radiology hours is statistically significant. The p-values for the five weeks shown in Fig. 5 are 0.0135, 0.01229, 0.04456, 0.9193, and 0.2905, respectively. For the first three weeks in the selected range, the hypothesis tests support our observation that the total TAT during radiology hours is greater than that during non-radiology hours. However, the p-values of the last two weeks are not significant. This may be interpreted as a result of residents and fellows joining the medical program in late July. Staff radiologists may provide greater assistance during the initial startup weeks as trainees become familiar with the radiology practice. And the increment of TAT should have other reasons; for instance, fewer radiologists in the last two weeks. Through this investigation, we concluded that the ED’s concern regarding excessive TAT during non-radiology hours may not be valid overall. However, the Radiology Department may need to pay special attention to the period when new residents and fellows are first taking responsibility for overnight calls.

4.1.2. Example II

This study was motivated by the need for assessing the workload distributions among different scanners in order to better allocate resources and optimize scheduling. There are six CT scanners in MCA, with three located in the hospital and the others located in the clinic. The patient volume and exam volume (see Table 2 for details) are both reasonable indicators of scanner load.

Several observations can be obtained from Fig. 6. First, it is clear that the three scanners in the hospital have unbalanced loads, with the second scanner being heavily used while the first scanner is used substantially less. An ANOVA test was conducted to check if the patient volumes from three hospital scanners are all the same. The test results confirmed that there is statistical significance in the load imbalance across the three
scanners at the hospital ($p$-value < 0.001). Second, the three scanners in the clinic also have unbalanced loads to some extent, although the issue is not as severe as at the hospital. To confirm this, another ANOVA test was performed, which yielded $p$-value < 0.001, indicating that the three scanners in the clinic also have statistically significant load imbalances. Third, the overall load of scanners in the hospital is heavier than that in the clinic. A one-sided two-sample t-test was conducted with the null hypothesis $H_0$: $\mu_{\text{hospital}} = \mu_{\text{clinic}}$ and the alternative hypothesis $H_1$: $\mu_{\text{hospital}} > \mu_{\text{clinic}}$ where $\mu_{\text{hospital}}$ and $\mu_{\text{clinic}}$ denote the average weekly patient volume in the hospital and the clinic, respectively. The t-test yielded a $p$-value = 0.03526, which indicated that we should reject the null hypothesis and that the patient volume at the hospital is statistically higher. This is likely due to the longer hours of operation in the hospital versus the clinic. However, some of the other imbalances, such as the difference between Hospital Scanner 02 and 03, are more difficult to explain. It is our intention to explore this further with our clinical partners.

### 4.1.3. Example III

In patient care, patient waiting time reflects process efficiency and is also an important factor that affects patient satisfaction. This study is to assess the patient waiting time related to the radiology exams. To measure the patient waiting time, as defined in Table 2, requires the algorithm to know the patient check-in time (heuristically derived from EHR and PACS records with rule II, as shown in Fig. 4) and exam start time (DIT records, shown in Fig. 4).

Figure 7 shows the histogram of patient waiting time. The average waiting time is about one hour; 90% of the exams have patient waiting time less than two hours; five patients waited for more than three hours (the reasons for these extreme cases are yet to be explored). Patient waiting time is a complex issue. It was observed that patients often check in earlier than their scheduled times, which leads to long waiting time. Also, waiting time is related to nursing assessment and/or oral contrast (for some CT exams) administration. This is an area that deserves more attention from radiology administration and more in-depth explorations.

#### 4.1.4. Example IV

The last two steps in radiologic care are related to the activities from technologists and radiologists—two major service providers. Their TATs are important quality indicators. This study is to assess the technologist TAT and radiologist TAT. Both metrics share a time stamp, $t_{\text{tech\_finish}}$, and multiple data sources are involved (as shown in Fig. 4 and Table 2).

Figure 8 shows a common trend shared by the technologists and radiologists; i.e., their TATs for outpatients are the longest, followed by inpatients and then ED patients. This trend is consistent with the urgency and typical complexity of care for these three types of patients. The average technologist TATs for outpatients, inpatients, and ED patients are 21, 16, and 9 minutes, respectively. The average radiologist TATs for outpatients, inpatients, and ED patients are 32, 26, and 10 minutes, respectively. While these numbers fall into a reasonable range, clinicians and administrators may still seek for ways to further reduce the TAT and improve the quality of radiologic care.

#### 4.2. DDD-enabled intervention for improving radiologist TAT of observation patients (ObP)

ObP is a subtype of patients who have a condition for which the cause of symptoms is not immediately clear, so they are kept in the hospital for 23 hours to be monitored and/or to run more
tests. From a workflow perspective, ObP is considered an inpatient because the patient’s exam needs to be interpreted with priority. However, from a billing perspective, ObP is considered an outpatient.

In the fall of 2015 (before DDD was in place), the Radiology Department received complaints from ordering physicians that the exams of ObP were not being interpreted in a timely fashion; i.e., these exams tended to have overly long radiologist TATs that did not match with the urgency level of ObP. The Radiology Department conducted an investigation but the root cause of this problem was not clear. In the second quarter of 2016 after DDD was deployed, the investigation was resumed. The root cause of the lengthy radiologist TAT for ObP was found to be that, prior to DDD, patient type classification was based on a single HIS, RDW, in which ObP were classified as outpatients. As a result, the exams of ObP did not appear on the radiologists’ worklist for priority review. This caused delays in interpreting ObP exams by the radiologists. By integrating multiple HISs, DDD enabled patient type classification with more granularity, which led to ObP being separated out from outpatients as a standalone patient subtype. Leveraging this capability provided by DDD, the Radiology Department started an intervention in the second quarter of 2016. A computer program was modified to automatically identify ObP exams from DDD and push those exams to the front of radiologists’ worklists to be interpreted with priority.

To measure the effectiveness of the intervention, we collected data before and after the intervention. We focused on digital X-rays (Computed Radiology (CR) exams) of ObP interpreted by residents on Saturdays, since ordering physicians had previously complained about the lengthy TAT for these exams. The Radiology Department also wanted to exclude the possibility that the problem was related to the residents themselves. We queried DDD and obtained data from the first quarter of 2016; i.e., before the intervention took place. This included 101 CR ObP exams interpreted by residents on Saturdays. We also queried DDD to obtain data between 06/16 and 08/10/2016; i.e., after the intervention, which included 58 exams. We computed radiologist TAT as defined in Table 2 on each exam. Figure 9 shows the probability density plots on radiologist TAT for pre- and post-intervention exams. It is observed that the

5. Discussion and conclusion

In this article, we developed a novel technology that integrated four HISs commonly used in the Radiology Department into a super-HIS called DDD. We adopted loose-coupling techniques in database integration and proposed a three-layer integration framework, including a data mashup layer, an aggregation service layer, and a result presentation layer. DDD enabled end-to-end tracking of the care each patient receives in the Radiology Department, with detailed time stamps and contents of each care activity as well as rich information on patients, providers, and equipment. Furthermore, we proposed nine QoC metrics defined upon DDD: exam duration, technologist post-processing time, technologist TAT, radiologist TAT, and total TAT, which reflect the timeliness and efficiency of radiologic care; patient waiting time and patient TAT, which reflect efficiency and patient satisfaction; patient volume and exam volume, which reflect the workload distribution. All of these metrics measure QoC in radiology from different but complementary perspectives. DDD was deployed through a web portal, RQD, in MCA in the second quarter of 2016. Since then, it has been used extensively by clinicians, administrators, and researchers to monitor QoC, identify problem areas, and perform interventions to improve the quality of radiologic care. Specifically, we demonstrated, through four examples, how users can use RQD information to understand the care workflow and performance. RQD may provide answers to some clinical-practice-related questions and concerns, and help identify opportunities for quality improvement. In addition, we showed a case study on a DDD-enabled intervention that effectively reduced the radiologist TAT for ObP. Specifically, our comparison between the pre- and post-intervention radiologist TAT showed that the intervention significantly eliminated ObP exams that take the residents longer than one hour to complete and cut the average TAT by more than half.
Several heuristic rules were adopted to handle the human errors that are inevitable in databases which require manual information entry. Over the course of the project, we have observed some issues related to discrepancies and inconsistencies of the data from human errors. The experienced radiologists and imaging informatics scientists from Mayo Clinic helped us understand the details of the radiology exam procedures and provided several examples that contain obvious input errors, such as wrong exam dates in “ServiceTime” and improper check-in time (e.g., two days before the exam date). Together, we developed heuristic rules to solve potential problems automatically for the HIS databases deployed in Mayo Clinic. Since the rules are applied to the time stamps collected from three commercial off-the-shelf HISs, the heuristic rules should be generalizable and applicable to other hospital systems. This has not yet been validated, as the staff from other health care organizations may have different working conditions. We want to emphasize that, even if the rules cannot be directly applied to other organizations, these rules could provide some guidelines for other practitioners looking to mitigate human errors as we did at Mayo Clinic.

The integration of the DIT database may limit the usage of the DDD and RQD systems, since DIT is not a commercial system that is available for all facilities. DIT provides several types of accurate time stamps and exam information for calculation and analysis. We believe that DIT can be replicated in other health care organizations with some (not substantial) effort, as most such information can be acquired directly from the DICOM header in scanned images. For those hospital, clinic, and health care facilities where DIT or a similar system has not yet been deployed, the practitioners could consider implementing a program to parse the necessary information from images. We have also received multiple inquiries about the DIT system since 2011, and currently more than 20 members of the European Community of Medical Physicists have joined a fully collaborative effort to facilitate broader use of DIT for addressing quality assurance issues.

As with other domain-specific integrations, the domain experts, radiologists and imaging informatics scientists at Mayo Clinic played an important role in the research and helped us in several ways: they helped us understand the radiology exam procedures and illustrate the timelines in all HIS as shown in Fig. 4; they pointed out the potential errors and verified our heuristic rules; and they provided feedback to the defined metrics in terms of what they expect and how they want to compare metrics among different modalities, patient types and sites.

There are several future research directions we would like to pursue. First, we are continuously enriching our collection of QoC metrics. Second, advanced analytics can be performed on the rich datasets generated by DDD for QoC monitoring, abnormality detection, automatic alarming, and root cause identification, and to support other decision making in radiology.

Acknowledgment

We would like to thank our collaborators for their help and advice.

Funding

The authors thank the Radiology Department of MCA for providing funding for this research.

References


