JMIR Medical Informatics

Impact Factor (2023): 3.1
Volume 1 (2013), Issue 1   ISSN 2291-9694   Editor in Chief: Christian Lovis, MD, MPH, FACMI

Contents

Original Papers

Original Paper

A Web-Based Data-Querying Tool Based on Ontology-Driven Methodology and Flowchart-Based Model

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Abstract

Background: Because of the increased adoption rate of electronic medical record (EMR) systems, more health care records have been increasingly accumulating in clinical data repositories. Therefore, querying the data stored in these repositories is crucial for retrieving the knowledge from such large volumes of clinical data.

Objective: The aim of this study is to develop a Web-based approach for enriching the capabilities of the data-querying system along the three following considerations: (1) the interface design used for query formulation, (2) the representation of query results, and (3) the models used for formulating query criteria.

Methods: The Guideline Interchange Format version 3.5 (GLIF3.5), an ontology-driven clinical guideline representation language, was used for formulating the query tasks based on the GLIF3.5 flowchart in the Protégé environment. The flowchart-based data-querying model (FBDQM) query execution engine was developed and implemented for executing queries and presenting the results through a visual and graphical interface. To examine a broad variety of patient data, the clinical data generator was implemented to automatically generate the clinical data in the repository, and the generated data, thereby, were employed to evaluate the system. The accuracy and time performance of the system for three medical query tasks relevant to liver cancer were evaluated based on the clinical data generator in the experiments with varying numbers of patients.

Results: In this study, a prototype system was developed to test the feasibility of applying a methodology for building a query execution engine using FBDQMs by formulating query tasks using the existing GLIF. The FBDQM-based query execution engine was used to successfully retrieve the clinical data based on the query tasks formatted using the GLIF3.5 in the experiments with varying numbers of patients. The accuracy of the three queries (ie, “degree of liver damage,” “degree of liver damage when applying a mutually exclusive setting,” and “treatments for liver cancer”) was 100% for all four experiments (10 patients, 100 patients, 1000 patients, and 10,000 patients). Among the three measured query phases, (1) structured query language operations, (2) criteria verification, and (3) other, the first two had the longest execution time.

Conclusions: The ontology-driven FBDQM-based approach enriched the capabilities of the data-querying system. The adoption of the GLIF3.5 increased the potential for interoperability, shareability, and reusability of the query tasks.

(JMIR Med Inform 2013;1(1):e2) doi:10.2196/medinform.2519

KEYWORDS

electronic medical records; query languages; information retrieval query processing; ontology engineering; clinical practice guideline

Introduction

A substantial number of health care records are routinely accumulated in clinical data repositories because of the increasing use of electronic medical record (EMR) systems. Previous studies have shown that these large volumes of clinical data offer great potential for discovering new knowledge and improving the quality of health care [1,2].

Experts from various domains can apply a query approach to elucidate the distributions of complex data by formulating and executing queries used for identifying the desired data that are stored in large clinical data repositories. Previous studies have proposed several query approaches based on specific query tasks that assist domain experts in retrieving clinical data for further analyses [3-5].

Extant literature on data querying from clinical data repositories are based on the following three considerations: (1) the interface design used for query formulation, (2) the representation of query results, and (3) the models used for formulating query criteria.

Regarding the design of a user interface for formulating queries, users can formulate queries by employing low-level query languages, such as Structured Query Language (SQL), or by using query-building tools that allow them to create query tasks easily using the features available with these tools.

The application of low-level query languages, such as SQL, presents several potential difficulties. First, experience in database querying is required. The users who employ SQL commands to query a database directly must possess a detailed understanding of the information in that database, including the table definitions, the table column types, and the relationships among the tables. Second, the SQL command syntax for complex queries could be difficult to write. When data querying involves a query algorithm, the SQL command syntax is complex, which can make it difficult to analyze the query results of these intermediate processes.

To minimize the complexity of formulating queries by using SQL commands, researchers have proposed and developed specific query-building tools to assist users in building and executing database queries. For example, RetroGuide was proposed to assist users who had limited database experience in formulating database queries [5]. The query task is formulated based on a flowchart by using the workflow editor, and the query criteria are specified in the nodes of the flowchart.

Regarding the representation of query results, various formats can be employed to present the queried data, including free text, structured tables, and visual charts. Rich data representation methodologies can assist in improving the users' understanding of the database query results.

RetroGuide provides a table-based three-level hierarchical report of query results, including a summary report, detailed report, and information view of each patient [6]. Mabotuwana and Warren introduced a prescription timeline visualization function that allows clinicians to monitor the prescription situations of their patients by using graphical timeline charts [3].

Regarding the models used for formulating the database query criteria, the adoption of interoperable formulation information models has improved the opportunity for users to consistently query various clinical data repositories. Moreover, information models that allow powerful expression for query criteria formulation can enhance the capabilities of database queries.

Austin et al developed an information model for designing generic interfaces for EMR systems [4]. They collected a diverse set of examples of clinical questions that could be applied to represent database queries. Based on the queries, they identified several general patterns and designed an information model that represented clinical research queries.

Ontology-based approaches have been widely employed in various medical domains [7-10]. Mabotuwana and Warren proposed an ontology-driven [11] approach to formulate specific query criteria for enhancing the query capabilities of general practice medicine to improve the management of patients with hypertension.

In this study, we developed a Web-based approach for enriching the data query based on the three considerations discussed above. A prototype system was developed to test feasibility of applying a methodology for building a query execution engine using flowchart-based data-querying models (FBDQMs) by formulating query tasks using the existing Guideline Interchange Format (GLIF). The FBDQM was introduced, developed, and implemented in formulating query tasks by employing the flowchart and objects defined in the GLIF3.5 [12]. A graphical user interface that allows users to select entire or partial query criteria from a predefined query task, execute the formulated query, and present the query results was developed. The method proposed in this study could assist users with limited database experience in querying medical data. In addition to assisting users in formulating query tasks by using the flowchart-based models, the proposed approach involves employing a visual graphical interface for presenting the query results. The GLIF3.5 enhances the capability of queries, thereby increasing the potential for interoperability through the relevant standardized medical schemes involved in the GLIF3.5 (see Multimedia Appendices 1 and 2).

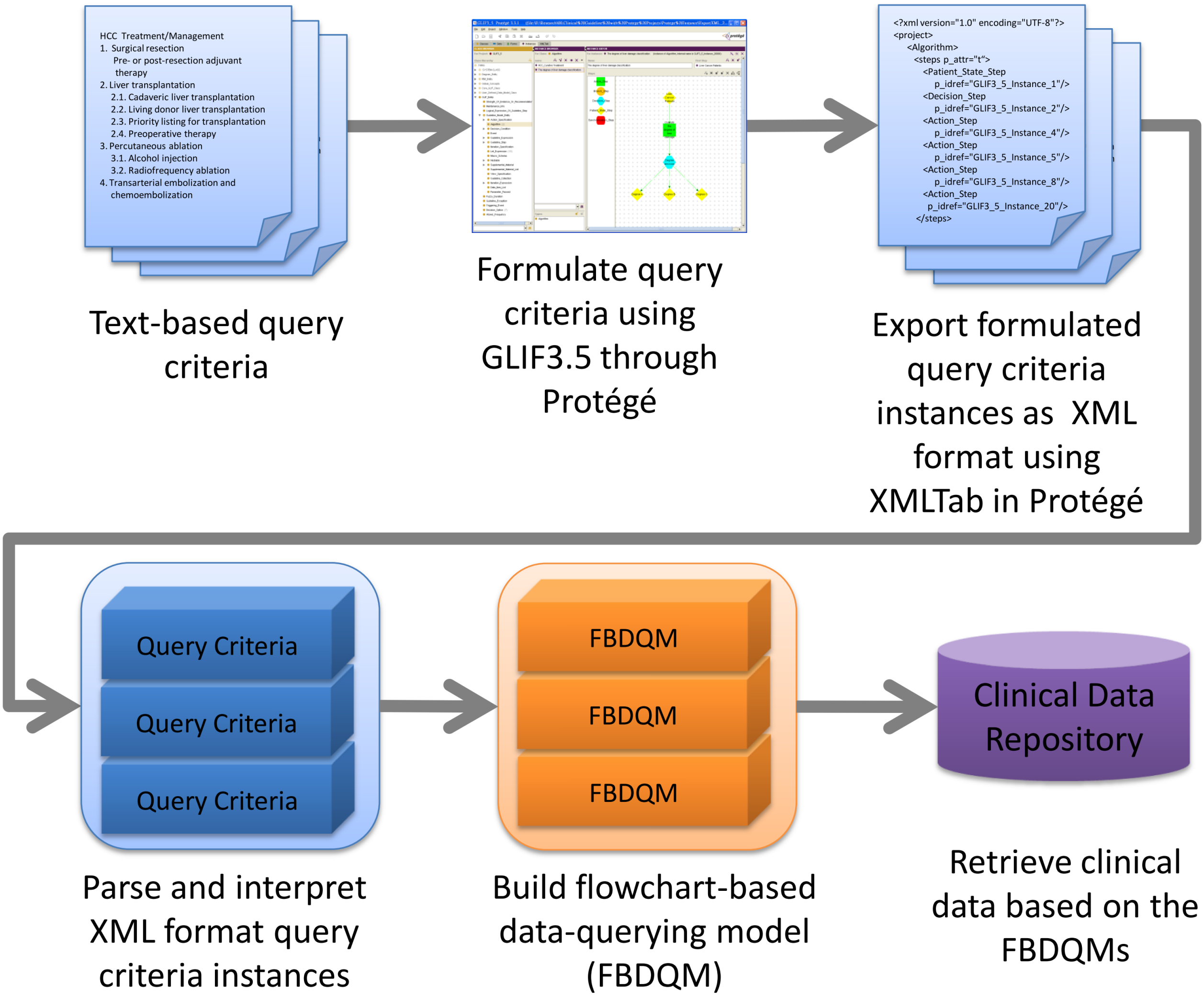
Methods

Overview of Methods

Figure 1 presents an overview of the methods proposed in this study. The text-based query tasks were formulated using the GLIF3.5 through the Protégé editing environment [13-15]. A native Protégé plug-in tool was used to export the formulated query tasks as Extensible Markup Language (XML) files. Subsequently, the XML files were imported into the proposed

FBDQM-based query execution engine. The proposed engine interpreted the XML-formatted query tasks, executed the query operations, retrieved the clinical data, and displayed a representation of the query results.

Figure 1. The overview of the methodology used in the data-querying tool based on ontology-driven methodology and flowchart-based model.



HCC Treatment/Management
1. Surgical resection
   Pre- or post-resection adjuvant therapy
2. Liver transplantation
   2.1. Cadaveric liver transplantation
   2.2. Living donor liver transplantation
   2.3. Priority listing for transplantation
   2.4. Preoperative therapy
3. Percutaneous ablation
   3.1. Alcohol injection
   3.2. Radiofrequency ablation
4. Transarterial embolization and chemoembolization

```
<?xml version="1.0" encoding="UTF-8"?>
<project>
    <Algorithm>
      <steps p_attr="t“>
        <Patient_State_Step
            p_idref="GLIF3_5_Instance_1"/>
        <Decision_Step
            p_idref="GLIF3_5_Instance_2"/>
        <Action_Step
            p_idref="GLIF3_5_Instance_4"/>
        <Action_Step
            p_idref="GLIF3_5_Instance_5"/>
        <Action_Step
            p_idref="GLIF3_5_Instance_8"/>
        <Action_Step
          p_idref="GLIF3_5_Instance_20"/>
      </steps>
```

Clinical Practice Guideline Representation Languages

Clinical guideline representation languages were developed for formulating paper-based clinical guidelines in a computer-interpretable format. Currently, several medical-related institutions are developing numerous clinical practice guideline representation languages and models, including Asbru, EON, GLIF, GUIDE, PRODIGY, and PROforma [16,17]. The clinical guideline representation languages could be suitable for representing medical information in various computer-interpretable formats, including logic, criteria, and data items. Therefore, an existing clinical guideline representation language was employed to formulate the query criteria and query task items. The GLIF3.5 was selected to formulate the query tasks because a GLIF framework includes a set of steps that link together to form a flowchart [18]. The format of a flowchart can be employed to formulate the workflow of the query tasks, and complex query task workflows can be divided into several multistep subquery tasks. The GLIF model is object oriented, and XML-based syntax is used to present the class and instances of the class [18]. After formulating a GLIF-based query task, the query task can be translated into XML format for further interpretation. GLIF provides various abstraction levels. At the conceptual level, the rules and logic are represented as a flowchart, which allows users to formulate an overview of a query task before specifying all necessary detailed information. The rules and logic can be further specified at the computable level.

Query Task Formulation

To formulate the query tasks using GLIF3.5, the concepts and criteria of the text-based query tasks should be categorized as the corresponding classes of the GLIF3.5 ontology. The *algorithm* class in GLIF3.5 is a flowchart that is used for describing the clinical guideline workflow. In this study, the flowchart was used for presenting the query task workflow.

To formulate the query tasks, users must employ Protégé, a knowledge-based editing software that provides a graphical user interface for the formulation of query tasks based on the GLIF3.5 flowchart. The query tasks are formulated by building the flowchart and specifying the criteria and data items in each node of the flowchart through the Protégé environment (see Multimedia Appendix 3).

The entire query task can be separated into numerous subtasks, and each subtask can be represented using a node in the flowchart. The following five predefined GLIF3.5 classes were used: (1) action, (2) decision, (3) branch, (4) synchronization, and (5) patient state. The detailed components of each node were further specified through Protégé based on the predefined GLIF3.5 ontology.

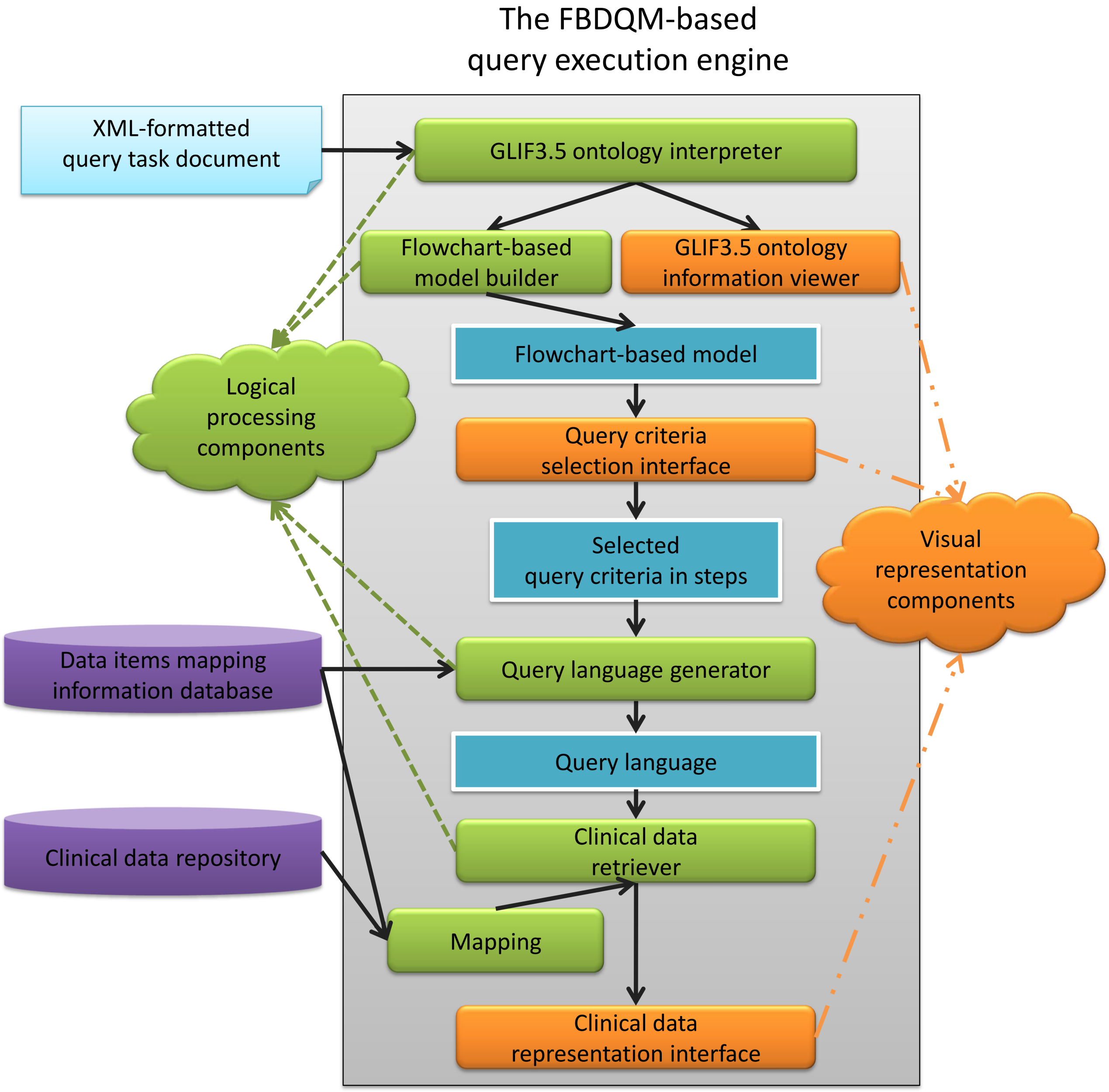
After using the GLIF3.5 ontology to formulate the query tasks, the nodes were exported from Protégé in the XML format and subsequently imported into the query execution engine for data query and retrieval of the clinical data repository (see Multimedia Appendix 4).

System Architecture

A Web-based data-querying tool was implemented and the clinical data were queried using the FBDQM-based query execution engine. The architecture of the query execution engine comprises eight major components (Figure 2). These eight major components can be further separated into the following two sets: (1) logical processing components and (2) visual representation components.

The set of logical processing components includes the GLIF3.5 ontology interpreter, flowchart-based model builder, query language generator, clinical data retriever, and mapping component. The set of visual representation components contains the GLIF3.5 ontology information viewer, query criteria selection interface, and clinical data representation interface.

Figure 2. The architecture of the FBDQM (flowchart-based data-querying model)-based query execution engine.



GLIF3.5 Ontology Interpreter

A query task is formulated using the predefined GLIF classes. A GLIF3.5 ontology interpreter is necessary for parsing the GLIF-based query tasks and translating them into data query components for data retrieval. For example, following the interpretation process, a flowchart-based model builder was employed to create a flowchart-based model. A flowchart was displayed in the query criteria selection interface to provide an overview of the query task, and additional relevant information (eg, the criteria and data items in each node of the flowchart) could be viewed in the GLIF3.5 ontology information viewer.

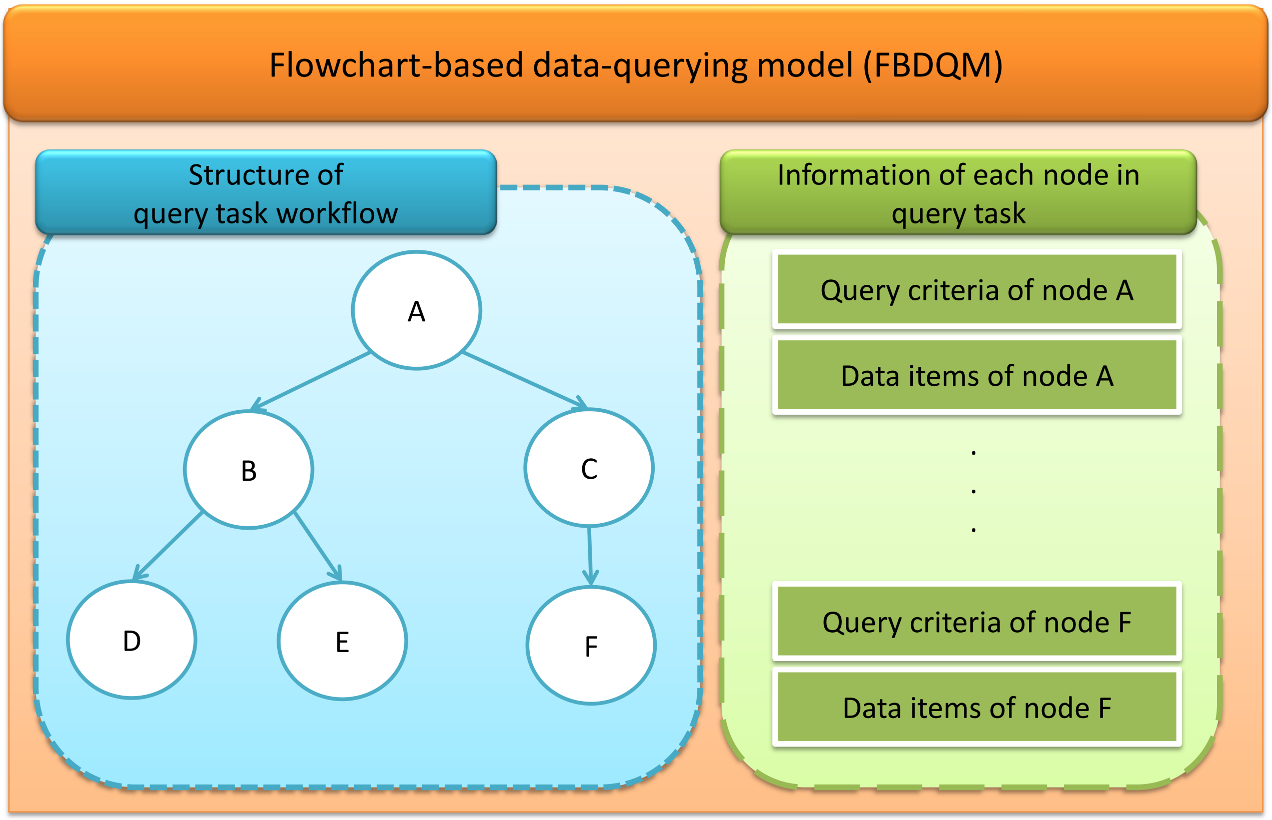
The formulated query tasks were exported as XML-formatted documents and subsequently imported into the GLIF3.5 ontology interpreter in the query execution engine. The GLIF3.5 ontology interpreter was employed to interpret the query criteria and data items in the following five classes: (1) action, (2) decision, (3) branch, (4) synchronization, and (5) patient state. The original meanings of these classes in GLIF3.5 and their usages in this study are detailed as follows [12]. An action class is used for indicating an action to be performed. For example, this class was employed to detail medically oriented actions, such as medical treatment strategies. When the concepts in the query operation are relevant to medically oriented actions, these concepts are detailed based on the attributes of the action class. A decision class is used for specifying the criteria of various choices in a decision point. The decision option has a condition value attribute used to describe the detailed criteria of an option. When a query task contains the decision point and requires various criteria to determine the corresponding query operations, the decision class is used. The branch and synchronization classes work together. These two classes are used to express multiple concurrent paths in a flowchart. The concurrent paths are separated from the branch class and combined in the synchronization class. These two classes are used for representing multiple concurrent paths in a query task. The patient state class comprises the two functions. It is used to detail the clinical state of a patient and as a flowchart entry point. When the concept and the rule included in the query operation are relevant to the patient's status, the patient state class is used for detailing the status. This class can also be used for detailing the start status of the query task.

Flowchart-Based Model Builder

The flowchart-based model builder generates the flowchart-based model based on the interpreted results from the GLIF3.5 ontology interpreter. An interpreted query task is used to generate a corresponding FBDQM. The generated FBDQM contains the information relevant to the formulated query tasks, including the structure of the flowchart describing the overall query task and the detailed information of each query subtask, such as the query criteria and the related data items in each node (Figure 3). The FBDQM query tasks were derived primarily from instances of the algorithm class and objects related to the algorithm class.

A graphical flowchart of the FBDQM is used to present the workflow of a query task through the query criteria selection interface. Logical query criteria and relevant FBDQM data items are the inputs used by the query language generator to generate the corresponding query languages.

Figure 3. The flowchart-based data-querying model (FBDQM) containing the structure of query task workflow and the information of each node in the query task.



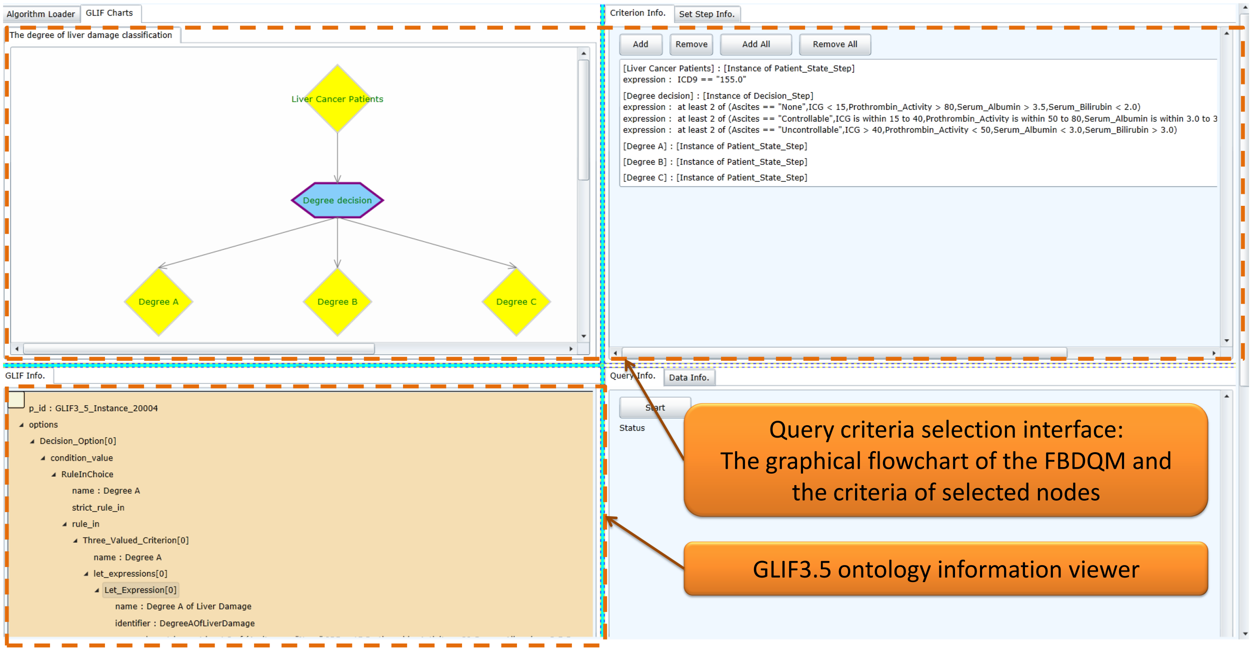
Query Criteria Selection Interface

The query criteria selection interface in Figure 4 shows the graphical flowchart of the generated FBDQM. The query criteria selection interface provides flexibility in dynamically selecting all or certain flowchart nodes included in the execution of a query operation. All possible query elements were defined using GLIF through Protégé, and the user could subsequently select either specific or all of the criteria using the criteria selection interface. The query execution engine executes as many queries as the selected nodes in the flowchart that each node is essentially a separate query. For example, when a user queries all male patients with osteoporosis and a hip fracture [19], the criteria could be specified using a GLIF model containing various numbers of nodes (eg, patient state) to suit the needs of the user. A user could formulate a GLIF model with three nodes, where the first node contains a criterion for identifying gender, such as “gender=male,” the second node contains a criterion for identifying patients with osteoporosis, such as “ICD=733.00,” and the third node contains a criterion for identifying the patients with a hip fracture, such as “ICD=820.0.” A user could also formulate a GLIF model with only one node containing three criteria, such as “gender=male and ICD=733.00 and ICD=820.0.”

The left side of Figure 5 shows that all nodes in the flowchart were selected for the query operation, and the right side of the figure shows that certain nodes in the flowchart were selected for the query operation. Figure 6 shows the query criteria of selected nodes that were displayed on the interface.

Furthermore, the query criteria selection interface provides the functionality of a mutually exclusive setting. For example, the degree decision node shown in Figure 5 comprises three child nodes (Degree A, Degree B, and Degree C). When a patient can only be classified into one of these three degrees, the degree decision node is set as a mutually exclusive node, and the priorities of its child nodes are set accordingly. Once the patient meets all the criteria of these three nodes, the patient is assigned to the node with the highest propriety.

Figure 4. The query criteria selection interface and the GLIF3.5 ontology information viewer.



```
[Liver Cancer Patients] : [Instance of Patient_State_Step]
expression :  ICD9 == "155.0"
[Degree decision] : [Instance of Decision_Step]
expression :  at least 2 of (Ascites == "None",ICG < 15,Prothrombin_Activity > 80,Serum_Albumin > 3.5,Serum_Bilirubin < 2.0)
expression :  at least 2 of (Ascites == "Controllable",ICG is within 15 to 40,Prothrombin_Activity is within 50 to 80,Serum_Albumin is within 3.0 to 3
expression :  at least 2 of (Ascites == "Uncontrollable",ICG > 40,Prothrombin_Activity < 50,Serum_Albumin < 3.0,Serum_Bilirubin > 3.0)
[Degree A] : [Instance of Patient_State_Step]
[Degree B] : [Instance of Patient_State_Step]
[Degree C] : [Instance of Patient_State_Step]
```

```
p_id : GLIF3_5_Instance_20004
◢ options
  ◢ Decision_Option[0]
    ◢ condition_value
      ◢ RuleInChoice
          name : Degree A
          strict_rule_in
        ◢ rule_in
          ◢ Three_Valued_Criterion[0]
              name : Degree A
            ◢ let_expressions[0]
              ◢ Let_Expression[0]
                  name : Degree A of Liver Damage
                  identifier : DegreeAOfLiverDamage
```

Query criteria selection interface:
The graphical flowchart of the FBDQM and
the criteria of selected nodes

GLIF3.5 ontology information viewer

Figure 5. The flexibility in selecting all or partial nodes of the flowchart for participating in the execution of query operation.

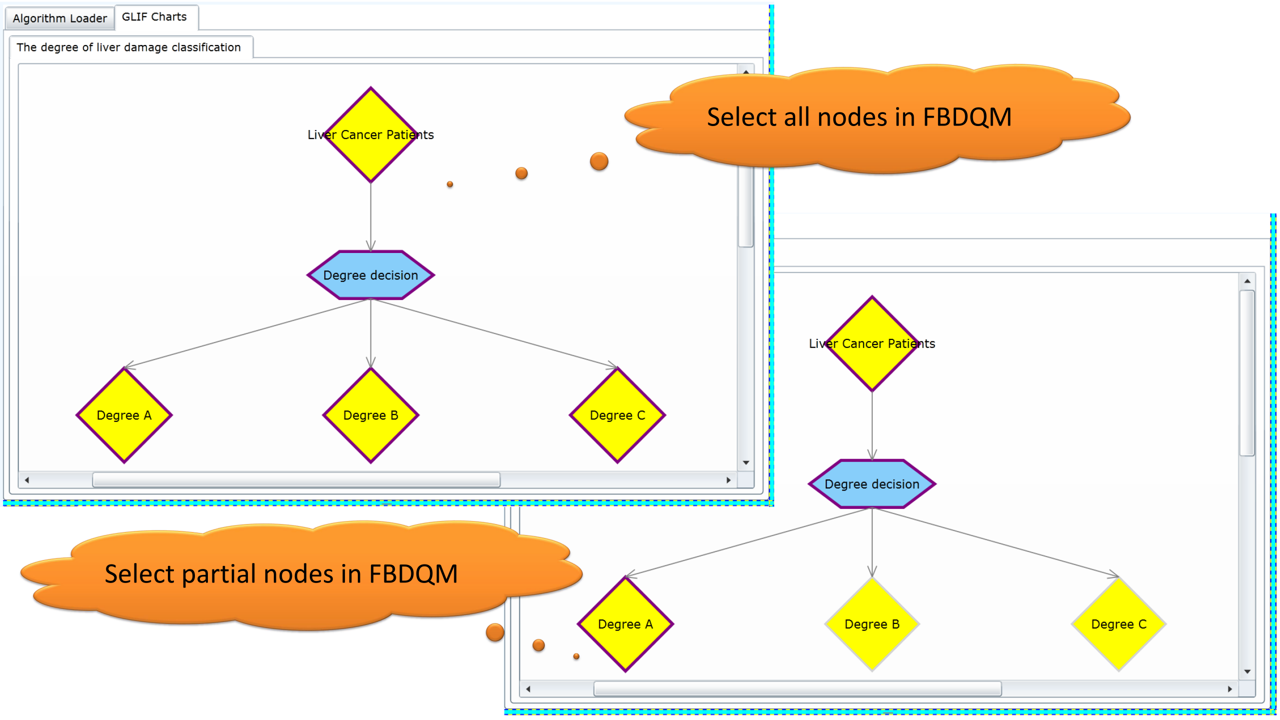
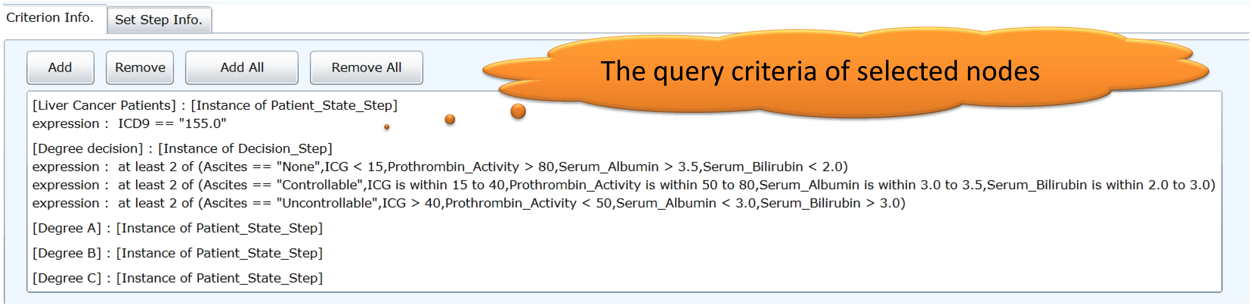


Figure 6. The query criteria of the selected nodes can be displayed in the query criteria selection interface.



```
[Liver Cancer Patients] : [Instance of Patient_State_Step]
expression :  ICD9 == "155.0"
[Degree decision] : [Instance of Decision_Step]
expression :  at least 2 of (Ascites == "None",ICG < 15,Prothrombin_Activity > 80,Serum_Albumin > 3.5,Serum_Bilirubin < 2.0)
expression :  at least 2 of (Ascites == "Controllable",ICG is within 15 to 40,Prothrombin_Activity is within 50 to 80,Serum_Albumin is within 3.0 to 3.5,Serum_Bilirubin is within 2.0 to 3.0)
expression :  at least 2 of (Ascites == "Uncontrollable",ICG > 40,Prothrombin_Activity < 50,Serum_Albumin < 3.0,Serum_Bilirubin > 3.0)
[Degree A] : [Instance of Patient_State_Step]
[Degree B] : [Instance of Patient_State_Step]
[Degree C] : [Instance of Patient_State_Step]
```

GLIF3.5 Ontology Information Viewer

Various interfaces were designed to provide multiple layers of views for the query tasks. An overview of the query tasks can be displayed in a flowchart in the query criteria selection interface. When a query task is highly complex, an overview of this query task can be viewed in a simplified flowchart. Each node of the flowchart contains a set of query criteria, and the detailed information (eg, the data items included in query criteria) can be viewed in the GLIF3.5 ontology information viewer by selecting the flowchart node.

Figure 7 shows information relevant to the GLIF3.5 ontology in each node of the FBDQM presented in the GLIF3.5 ontology information viewer. When a specific node of the flowchart is selected, the detailed information of the GLIF3.5 ontology, including the name of the node, the query criterion expressions specified in the node, and the data items in the query criterion expressions, is displayed in the ontology information viewer.

Mapping Component

The specific standards for medical terminologies and information models, such as vMR [20,21], are not assumed for using the GLIF to formulate query tasks. However, the GLIF provides the attributes for the encoders that specify further information such as the name, ID, and source of a concept (eg, name: cough, ID: C0010201, and source: UMLS). Therefore, to query the local clinical data repository, the mapping process is necessary for translating the concept specified in GLIF into the corresponding data in the local clinical data repository.

For example, as shown in Table 1, an ICD concept in the query task was mapped to the ICD9_Code from the diagnosis data table in the database. Laboratory items such as *Ascites* and *Prothrombin_Activity* were mapped to the corresponding data items with specific item names (ie, *Ascites* and *Prothrombin activity*) from the laboratory data table. Through the mapping process, a query language generator generates the corresponding SQL-based query languages to retrieve the corresponding data from the database.

To map the data items in a GLIF-formatted query task and those in a local clinical data repository, two mapping concepts proposed in the knowledge-data ontological mapper (KDOM) were employed [22]. The KDOM bridges the gap between the computer-interpretable guidelines encoded in the GLIF and the specific EMRs, and comprises the following four types of mapping between the guidelines and the medical records: (1) direct one-to-one field mapping, (2) temporal abstraction mapping, (3) classification hierarchy mapping, and (4) binary logical mapping. The concepts employed in this study were direct one-to-one field mapping and binary logical mapping. Direct one-to-one field mapping was implemented by predefining a mapping table, in which each record identified a single source data item encoded in the GLIF-formatted query tasks and a single destination data item in the local data repository. Binary logical mapping was implemented to manage complex query criteria, such as "at least condition."

Query Language Generator

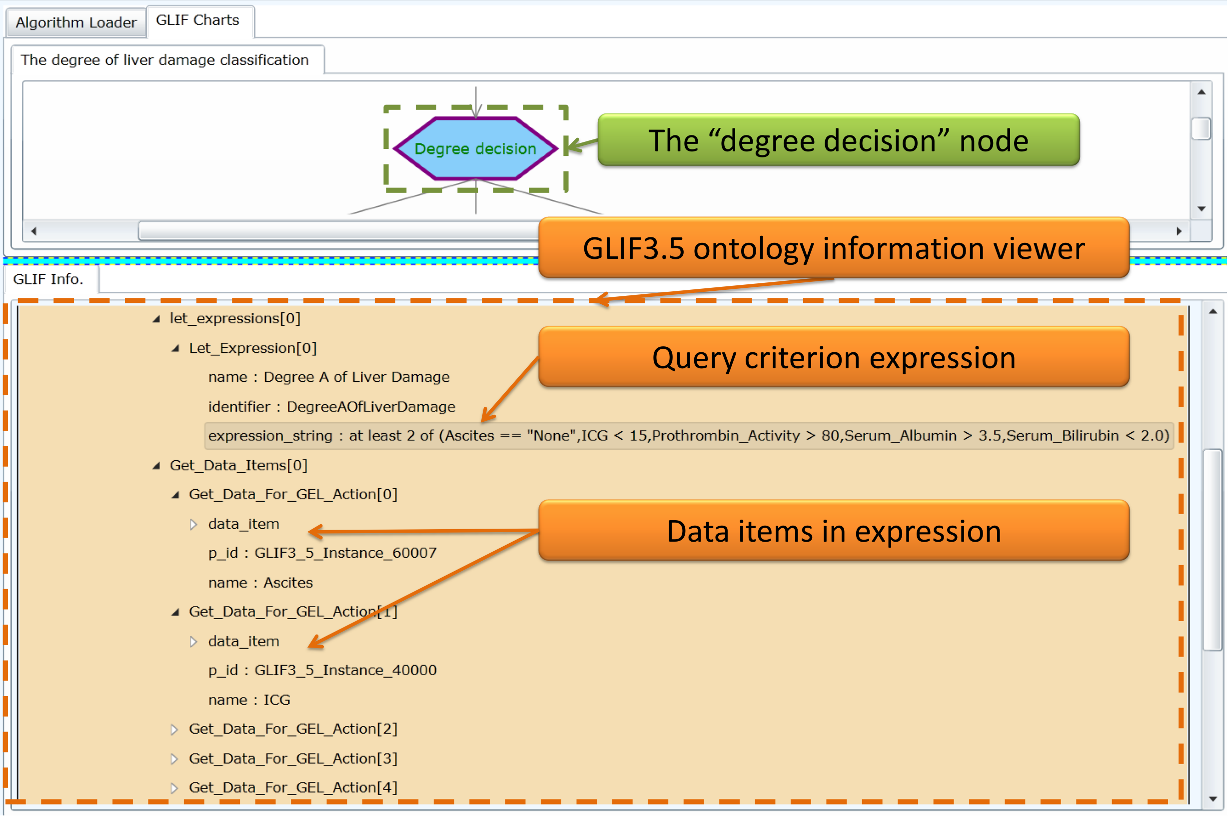
The query criteria in the selected nodes from the FBDQM were transferred to the query language generator to generate the query language.

During the query language-generation process, the data items included in the query criteria of the selected nodes could be mapped onto the corresponding data items in the clinical data repository. In the query language generator, predefined mapping information is applied to map the data items. Mapping involves both the direct and indirect mapping. In direct mapping, the data items are mapped directly to the values of a specific column of a database table (eg, "select Personal_ID from Diagnosis where ICD9_Code='155.0'"; the data item was mapped directly to the value of the "ICD9_Code" column). In indirect mapping, the data items are mapped indirectly though multiple column values of a database table (eg, "select Personal_ID from Laboratory where Result_String='Controllable' and Item_Name='Ascites'"; the data item was mapped indirectly though multiple column values, ie, the "Result_String" column and the "Item_Name" column).

After the data item mapping process is complete, the query language generator creates the corresponding SQL-based data query. The query language generator reads the query criterion in GLIF3.5 format and translates it into one or several simplified SQL criteria. Some examples of the query criteria in GLIF3.5 and the corresponding translated SQL queries are presented in Table 1. For example, the query criterion in GLIF3.5, "ICD9=155.0," was translated into one SQL criterion, "select Personal_ID from Diagnosis where ICD9_Code= '155.0'." The query criterion in GLIF3.5, "at least 2 of (Ascites=='Controllable', ICG is within 15 to 40, Prothrombin_Activity is within 50 to 80, Serum_Albumin is within 3.0 to 3.5, Serum_Bilirubin is within 2.0 to 3.0)," was translated and divided into five SQL criteria (Table 1).

To implement specific advanced queries to retrieve data from the repository, both SQL and high-level languages (ie, C#) were employed. For example, to implement the problem of "at least 2 of (Subcriterion 1, Subcriterion 2, Subcriterion 3, Subcriterion 4, and Subcriterion 5)" shown in Table 1, five subcriteria were implemented using SQL, and "at least 2" was further verified by implementing querying function in C#.

Figure 7. The GLIF3.5 ontology information viewer. The selected node, "degree decision," and its corresponding information in GLIF3.5 format.



The "degree decision" node

GLIF3.5 ontology information viewer

Query criterion expression

Data items in expression

```
◢ let_expressions[0]
  ◢ Let_Expression[0]
      name : Degree A of Liver Damage
      identifier : DegreeAOfLiverDamage
      expression_string : at least 2 of (Ascites == "None",ICG < 15,Prothrombin_Activity > 80,Serum_Albumin > 3.5,Serum_Bilirubin < 2.0)
◢ Get_Data_Items[0]
  ◢ Get_Data_For_GEL_Action[0]
    ▷ data_item
      p_id : GLIF3_5_Instance_60007
      name : Ascites
  ◢ Get_Data_For_GEL_Action[1]
    ▷ data_item
      p_id : GLIF3_5_Instance_40000
      name : ICG
  ▷ Get_Data_For_GEL_Action[2]
  ▷ Get_Data_For_GEL_Action[3]
  ▷ Get_Data_For_GEL_Action[4]
```

Table 1. The examples of the query criteria in GLIF3.5 and the corresponding translated SQL queries.

Query criteria format	Query criteria
GLIF3.5	1. ICD9=155.0
Translated SQL queries	1. select Personal_ID from Diagnosis where ICD9_Code="155.0"
GLIF3.5	2. at least 2 of (Ascites=="Controllable," ICG is within 15 to 40, Prothrombin_Activity is within 50 to 80, Serum_Albumin is within 3.0 to 3.5, Serum_Bilirubin is within 2.0 to 3.0)
Translated SQL queries	2.1. select Personal_ID from Laboratory where Result_String="Controllable" and Item_Name="Ascites" 2.2. select Personal_ID from Laboratory where Result_Nubmer between 15 and 40 and Item_Name="ICG" 2.3. select Personal_ID from Laboratory where Result_Nubmer between 50 and 80 and Item_Name="Prothrombin activity" 2.4. select Personal_ID from Laboratory where Result_Nubmer between 3.0 and 3.5 and Item_Name="Serum albumin" 2.5. select Personal_ID from Laboratory where Result_Nubmer between 2.0 and 3.0 and Item_Name="Serum bilirubin"

Clinical Data Retriever

The clinical data retriever executes the query operation based on the query criteria in the selected nodes from the FBDQM. The query execution process commences from the nodes in the top layer of the flowchart and proceeds to those in the bottom layers. During query operation process in each node, the patients' data are retrieved based on the translated SQL criteria, and the patients are reserved when they meet the query criteria specified in the node. The four types of notations that are used to represent the workflow and operations of the query execution in the FBDQM-based query execution engine are as follows: (1) QC(node), (2) PL(node), (3) PLS(node), and (4) PN(node).

QC(node) represents the query criteria included in the node. PL(node) constitutes the patient list, which contains the patients satisfying the query criteria included in the node. PLS(node) represents the size of the patient list, PL(node), indicating the number of patients who satisfy the query criteria included in the node. Finally, PN(node) is the list of the parent nodes of the node.

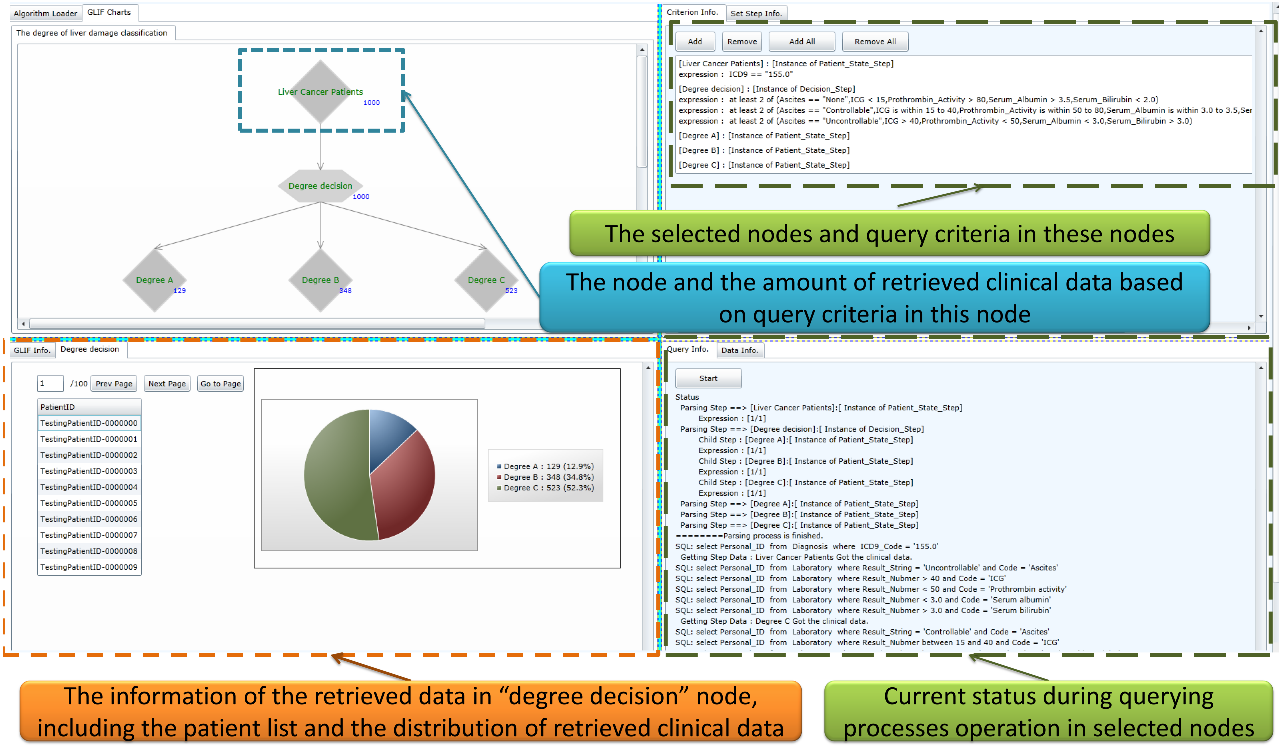
The left side of Figure 3 shows a flowchart comprising six nodes (nodes A, B, C, D, E, and F). Node A has two child nodes (nodes B and C), node B also has two child nodes (nodes D and E), and node C has one child node (node F). In the example, five nodes were selected for the query execution process (nodes A, B, C, D, and E). When the query operation was executed on one node, the patients in PL(PN(node)) were regarded as the query target set, and the query criteria contained in QC(node) were applied to PL(PN(node)). The query operation of the node was executed for patients who satisfied the query criteria of the parent nodes [ie, PL(PN(node))] with the query criteria of the node, QC(node). When a single node had no parent node, all patients in the clinical data repository were regarded as the query target set. For example, the first query operation, shown in Figure 3, was executed on node A, which had no parent node. The query execution of node A was based on QC(A), and QC(A) was applied to all patients in the repository. Following the first operation, the query result PL(A) was retrieved from the clinical data repository. The second query operation was executed using node B. The query execution on node B operated based on the patients in PL(A). The query criteria in QC(B) were applied to PL(A). For each patient in PL(A), when the patient satisfied all the query criteria in QC(B), that patient was retrieved and included in PL(B). Similarly, the query execution of node D was based on the patients in PL(B). The query criteria in QC(D) were applied to PL(B). Furthermore, the patient retrieved in the query operation of the lower layer node satisfied more query criteria (ie, that which satisfied the criteria in this layer node and its parent node) than the patient retrieved in the higher layer node (ie, that which satisfied the criteria in this higher layer node, but not the criteria in the lower layer node). Therefore, if the patient was included in PL(D), the patient must be included in both PL(B) and PL(A). PLS(D) was smaller than or equal to PLS(B), and PLS(B) was smaller than or equal to PLS(A). Similarly, PLS(C) was smaller than or equal to PLS(A). PLS(F) was zero because node F was not selected for the data query execution, and no patients were retrieved for this node.

Clinical Data Representation Interface

The query results retrieved by using the FBDQM-based query execution engine in Figure 8 are represented using the following three formats: (1) the number of retrieved patients shown beside the nodes of the graphical flowchart, (2) the table-based patient list, and (3) the distribution information shown in the graphical pie chart.

Following the query execution of one node, the number of patients retrieved by the query operation is displayed dynamically beside the node in the flowchart. For example, in Figure 9, the number 1000 beside the degree decision node and the number 129 beside the Degree A node indicate the number of patients who satisfied the query criteria described in these nodes. The detailed query result of each node can be viewed upon the completion of the overall query executions of all nodes. The users can then select one node in the flowchart, and the detailed query result of that node, such as the table-based retrieved patient list of that node, is displayed. When a selected node has several branch child nodes, the distribution of the query results in each child node is presented using a graphical pie chart (Figures 9 and 10). For example, the distribution of the query results in the degree decision node is shown in the graphical pie chart in Figure 9 [ie, Degree A=129/1000 (12.90%), Degree B=348/1000 (34.80%), and Degree C=523/1000 (52.30%)].

Figure 8. The clinical data representation interface.



```
[Liver Cancer Patients] : [Instance of Patient_State_Step]
expression :  ICD9 == "155.0"
[Degree decision] : [Instance of Decision_Step]
expression :  at least 2 of (Ascites == "None",ICG < 15,Prothrombin_Activity > 80,Serum_Albumin > 3.5,Serum_Bilirubin < 2.0)
expression :  at least 2 of (Ascites == "Controllable",ICG is within 15 to 40,Prothrombin_Activity is within 50 to 80,Serum_Albumin is within 3.0 to 3.5,Ser
expression :  at least 2 of (Ascites == "Uncontrollable",ICG > 40,Prothrombin_Activity < 50,Serum_Albumin < 3.0,Serum_Bilirubin > 3.0)
[Degree A] : [Instance of Patient_State_Step]
[Degree B] : [Instance of Patient_State_Step]
[Degree C] : [Instance of Patient_State_Step]
```

The selected nodes and query criteria in these nodes

The node and the amount of retrieved clinical data based on query criteria in this node

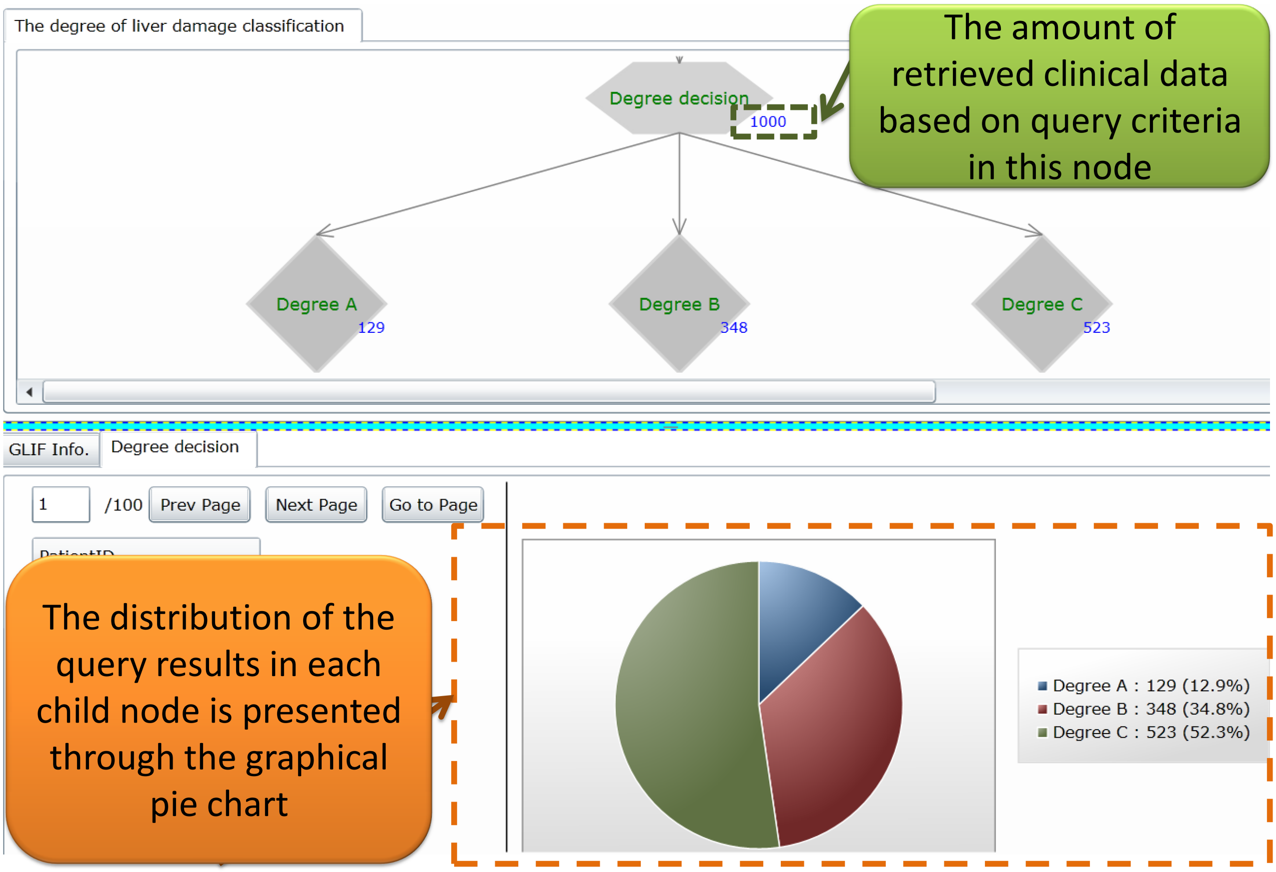
PatientID
TestingPatientID-0000000
TestingPatientID-0000001
TestingPatientID-0000002
TestingPatientID-0000003
TestingPatientID-0000004
TestingPatientID-0000005
TestingPatientID-0000006
TestingPatientID-0000007
TestingPatientID-0000008
TestingPatientID-0000009

```
Status
  Parsing Step ==> [Liver Cancer Patients]:[ Instance of Patient_State_Step]
        Expression : [1/1]
  Parsing Step ==> [Degree decision]:[ Instance of Decision_Step]
        Child Step : [Degree A]:[ Instance of Patient_State_Step]
        Expression : [1/1]
        Child Step : [Degree B]:[ Instance of Patient_State_Step]
        Expression : [1/1]
        Child Step : [Degree C]:[ Instance of Patient_State_Step]
        Expression : [1/1]
  Parsing Step ==> [Degree A]:[ Instance of Patient_State_Step]
  Parsing Step ==> [Degree B]:[ Instance of Patient_State_Step]
  Parsing Step ==> [Degree C]:[ Instance of Patient_State_Step]
========Parsing process is finished.
SQL: select Personal_ID  from  Diagnosis  where  ICD9_Code = '155.0'
  Getting Step Data : Liver Cancer Patients Got the clinical data.
SQL: select Personal_ID  from  Laboratory  where Result_String = 'Uncontrollable' and Code = 'Ascites'
SQL: select Personal_ID  from  Laboratory  where Result_Nubmer > 40 and Code = 'ICG'
SQL: select Personal_ID  from  Laboratory  where Result_Nubmer < 50 and Code = 'Prothrombin activity'
SQL: select Personal_ID  from  Laboratory  where Result_Nubmer < 3.0 and Code = 'Serum albumin'
SQL: select Personal_ID  from  Laboratory  where Result_Nubmer > 3.0 and Code = 'Serum bilirubin'
  Getting Step Data : Degree C Got the clinical data.
SQL: select Personal_ID  from  Laboratory  where Result_String = 'Controllable' and Code = 'Ascites'
SQL: select Personal_ID  from  Laboratory  where Result_Nubmer between 15 and 40 and Code = 'ICG'
```

The information of the retrieved data in "degree decision" node, including the patient list and the distribution of retrieved clinical data

Current status during querying processes operation in selected nodes

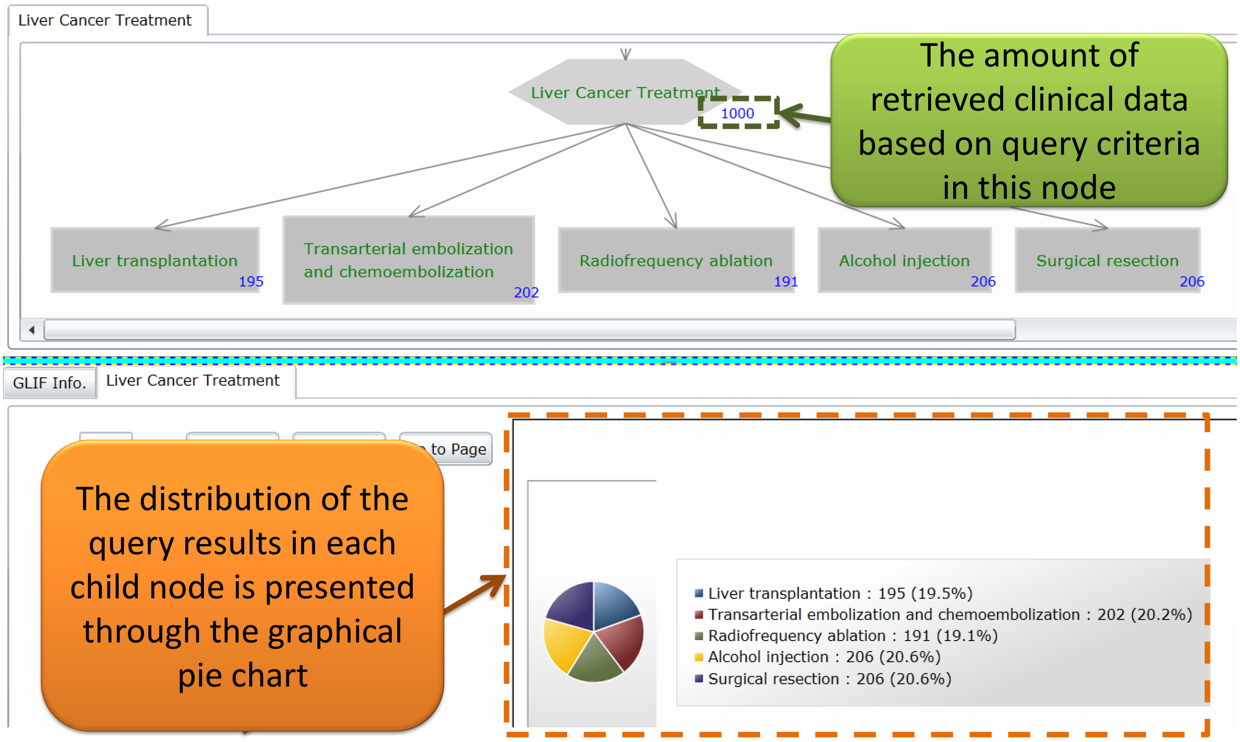
Figure 9. The clinical data representation interface showing the retrieved results of "degree of liver damage when applying a mutually exclusive setting" query task.



The amount of retrieved clinical data based on query criteria in this node

The distribution of the query results in each child node is presented through the graphical pie chart

Figure 10. The clinical data representation interface showing the retrieved results of "treatments of liver cancer" query task.



The amount of retrieved clinical data based on query criteria in this node

The distribution of the query results in each child node is presented through the graphical pie chart

Evaluation of Functionality and Performance

The liver domain was selected because the clinicians who collaborated in this study are liver experts, and the related research topics are relevant to the treatment of liver cancer. The degree of liver damage is a critical factor in the selection of appropriate treatment strategies. Therefore, query tasks related to the treatment strategies of liver cancer and classifying the degree of liver damage were selected to evaluate the functionality and performance of the proposed system.

The accuracy and the time performance of the system were evaluated using three medical query tasks relevant to liver cancer based on the clinical data generator in the experiments with various numbers of patients (ie, 10 patients, 100 patients, 1000 patients, and 10,000 patients). Among the three query tasks, one was selected from the treatment strategy of liver cancer, and the remaining two were selected from the classification of the degree of liver damage [23-27].

To examine a broad variety of patient data, the clinical data generator is implemented to automatically generate the clinical data in the repository, and the generated data are employed to evaluate the system. The clinical data generator automatically creates the data items by randomly setting the values and subsequently storing data items, such as information regarding laboratory test results and treatment procedures, in the clinical repository. For example, the laboratory test results for Prothrombin_Activity were randomly selected from a predetermined range. The clinical data generator created the patients' clinical data, including the diagnosis information, laboratory test results, and treatment procedures. Table 2 lists the distribution of the number of patients exhibiting various degrees of liver damage (ie, Degrees A, B, and C), both with and without applying the mutually exclusive setting. The distribution of the number of patients who received various treatments for liver cancer, including liver transplantation, transarterial embolization and chemoembolization, radiofrequency ablation, alcohol injection, and surgical resection, are also listed. The difference between the query tasks with and without applying the mutually exclusive setting is whether the system permits a patient to belong to more than one criterion among the set of criteria. When the mutually exclusive setting is applied in a query task for the degree of liver damage, a patient could only belong to one criterion among a set of criteria (ie, only Degree A, B, or C). When the mutually exclusive setting is applied, a summation of the number of patients belonging to three degrees is exactly equal to the total number of patients. For example, in a query task for the degree of liver damage in which the mutually exclusive setting was applied to a dataset of 100 patients, the total number of patients among the three degrees was exactly 100 (ie, the total number of patients in this dataset).

Three query tasks (degree of liver damage, degree of liver damage when applying a mutually exclusive setting, and treatments for liver cancer) were involved in the experiments. Both the degree of liver damage query task and the degree of liver damage when applying a mutually exclusive setting query task contained a total of 4 GLIF3.5-formatted query criteria, and a total of 16 translated SQL-formatted query criteria, whereas the treatments for liver cancer query task comprised a total of 6 GLIF3.5-formatted query criteria and 6 translated SQL-formatted query criteria.

Table 2. The distribution numbers of patients in four datasets that are randomly generated by the clinical data generator.

Dataset[a]	Degree of liver damage	Degree of liver damage when applying a mutually exclusive setting	Treatments for liver cancer
#1	Degree A: 1/10	Degree A: 4/10	LT[b]: 5/10
	Degree B: 3/10	Degree B: 7/10	TACE[c]: 2/10
	Degree C: 6/10	Degree C: 6/10	RFA[d]: 0/10
			AI[e]: 3/10
			SR[f]: 0/10
#2	Degree A: 11/100	Degree A: 52/100	LT[b]: 22/100
	Degree B: 36/100	Degree B: 60/100	TACE[c]: 23/100
	Degree C: 53/100	Degree C: 53/100	RFA[d]: 21/100
			AI[e]: 19/100
			SR[f]:15/100
#3	Degree A: 129/1000	Degree A: 555/1000	LT[b]: 195/1000
	Degree B: 348/1000	Degree B: 549/1000	TACE[c]: 202/1000
	Degree C: 523/1000	Degree C: 523/1000	RFA[d]: 191/1000
			AI[e]: 206/1000
			SR[f]: 206/1000
#4	Degree A: 1258/10,000	Degree A: 5298/10,000	LT[b]: 1984/10,000
	Degree B: 3409/10,000	Degree B: 5477/10,000	TACE[c]: 1970/10,000
	Degree C: 5333/10,000	Degree C: 5333/10,000	RFA[d]: 2079/10,000
			AI[e]: 1980/10,000
			SR[f]: 1987/10,000

[a] The datasets #1, #2, #3, and #4 are regarded as the datasets with different numbers of patients, including 10, 100, 1000, and 10,000 patients.

[b] LT: Liver transplantation.

[c] TACE: Transarterial embolization and chemoembolization.

[d] RFA: Radiofrequency ablation.

[e] AI: Alcohol injection.

[f] SR: Surgical resection.

Results

Experimental Results

In the experiments, the clinical data generator automatically generated various numbers of patients' clinical data. Four datasets (ie, 10 patients, 100 patients, 1000 patients, and 10,000 patients) were generated randomly, and contained clinical data such as diagnosis data, laboratory test results, and treatment procedure data. The three query results of the three query tasks based on these four datasets were collected manually as the benchmark (ie, gold standard), against which the query results of the proposed system were compared to evaluate the accuracy of the proposed system. The accuracy of the three query tasks (ie, degree of liver damage, degree of liver damage when applying a mutually exclusive setting, and treatments for liver cancer) was 100% for all four experiments based on the four patient groups. This shows that the proposed system could perform all of the query operations accurately for the experiments.

Table 3 lists the time performance of the proposed system for the four experiments based on the three query tasks. The table shows the percentage of time taken to execute the entire query task. The total query execution time was divided into the following three phases: (1) "SQL operations", (2) "criteria verification", and (3) "other." The SQL operations phase was the time taken to retrieve the data from the clinical data repository based on the translated SQL queries included in the entire query task. Criteria verification phase was the time taken to verify whether the retrieved patients' data (which were retrieved using the translated SQL queries) met the query criteria defined in the nodes for the entire query task. For example, the five subcriteria of a query criterion, "at least 2 of (Subcriterion

1, Subcriterion 2, Subcriterion 3, Subcriterion 4, and Subcriterion 5)" shown in Table 1 were implemented using SQL, and "at least 2" was further verified by using the implemented querying function in C#. The "other" execution time was the time taken to parse the query criteria that were defined in the entire query task, translate the GLIF3.5 formatted query criteria into SQL queries, and set the query results in the representation interface. The total value was the total time taken to perform the entire query task. The total query operation time was divided into three phases (ie, SQL operations, criteria verification, and other) to evaluate the variance in time taken on these phases when the proposed system was applied to various datasets (ie, 10-10,000 patients). Table 3 shows the percentages for the distribution of the three phases and the execution time results (in seconds). Moreover, the figure shows the variances of time taken among the four experiments. For example, in the experiment in which the degree of liver damage of 10,000 patients was queried, 8.124 of the total execution time 36.666 seconds (22.16%) was spent executing SQL operations, 28.455/36.666 seconds (77.60%) was spent verifying the criteria, and 0.087/36.666 seconds (0.24%) was spent on other tasks.

Figure 11 shows the performance of the proposed system based on the three query tasks in the four experiments involving various numbers of patients. The times taken for the SQL operations, criteria verification, and other tasks are represented by the three lines in Figure 11, and the execution time results (in seconds) are listed in Table 3.

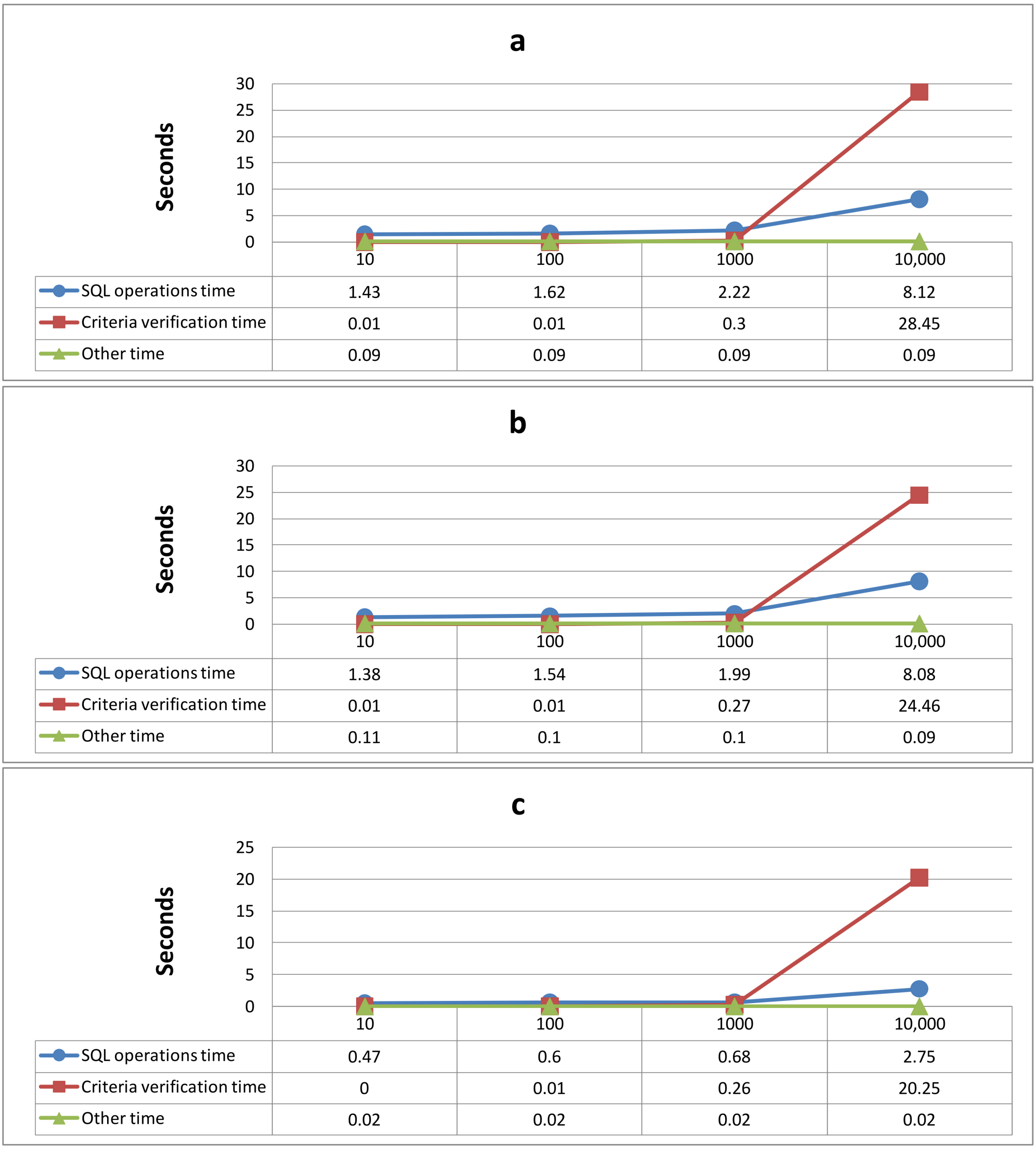
Software

The proposed system is an experimental version designed to test a novel methodology for building a query execution engine using FBDQMs by formulating query tasks using the existing GLIF. The proposed system was implemented based on Visual C# .NET, and Microsoft Silverlight technology was used to display the updated information dynamically during the data retrieval process. The system developed for this study is based on a Web-based architecture and is not provided as an open source. A new client-side user must install the Silverlight framework in the client-side computer to access the proposed system through a browser (eg, Internet Explorer or Google Chrome). For the server-side system, the database functions were provided by Microsoft SQL Server 2008. When the database was migrated (eg, from Microsoft SQL Server 2008 to Oracle), the programs relevant to data retrieval (eg, a program to retrieve data from a database based on specific SQL comments) must also be recoded.

Table 3. The performance in time of the system in experiment with three query tasks.

Item (patient number)	Degree of liver damage (seconds)	Degree of liver damage when applying a mutually exclusive setting (seconds)	Treatments for liver cancer (seconds)
SQL operations	93.82% (1.427)	92.60% (1.377)	95.76% (0.474)
Criteria verification	0.46% (0.007)	0.34% (0.005)	0.61% (0.003)
Other tasks	5.72% (0.087)	7.06% (0.105)	3.64% (0.018)
Total (10)	100% (1.521)	100% (1.487)	100% (0.495)
SQL operations	93.82% (1.623)	93.45% (1.542)	95.99% (0.598)
Criteria verification	0.75% (0.013)	0.55% (0.009)	0.96% (0.006)
Other tasks	5.43% (0.094)	6.00% (0.099)	3.05% (0.019)
Total (100)	100% (1.730)	100% (1.650)	100% (0.623)
SQL operations	85.13% (2.221)	84.22% (1.985)	70.90% (0.675)
Criteria verification	11.46% (0.299)	11.50% (0.271)	26.79% (0.255)
Other tasks	3.41% (0.089)	4.29% (0.101)	2.31% (0.022)
Total (1000)	100% (2.609)	100% (2.357)	100% (0.952)
SQL operations	22.16% (8.124)	24.75% (8.076)	11.95% (2.750)
Criteria verification	77.60%(28.455)	74.97% (24.461)	87.96%(20.248)
Other tasks	0.24% (0.087)	0.28% (0.092)	0.10% (0.022)
Total (10,000)	100% (36.666)	100% (32.630)	100% (23.020)

Figure 11. The performances of the system based on the three query tasks in four experiments with different number of patients, including a) degree of liver damage, b) degree of liver damage when applying a mutually exclusive setting, and c) treatments for liver cancer.



Discussion

Results of the Query Tasks

The results of the three query tasks show that when more query target patients are in the database, more total execution time is spent on the query operation. The phases that required the greatest length of execution time were the SQL operations and the criteria verification phases (Table 3).

The proposed system simplified complex GLIF3.5-formatted query criteria into one or more SQL-based units. The complicated query criteria was verified during the criteria verification process after the patient sets were retrieved based on the simplified SQL queries during the SQL query process. Therefore, the increase in the execution time for the criteria verification process was greater than that for the SQL query process when the total number of patients increased. Table 3 shows that more than 90% of the total execution time was spent performing the SQL query process in two experiments (ie, 10 patients and 100 patients). Compared with these two experiments, the percentage of the total execution time for the SQL query processes decreased, and the percentage of the execution time for the criteria verification process increased during the experiments involving 1000 patients and 10,000 patients. Figure 11 shows a greater increase in the time taken for the criteria verification process (the red lines with the square points in the three query tasks) than for the SQL query process (the blue lines with the circle points in the three query tasks) when the patient set is larger, especially in the experiment with 10,000 patients.

For the query tasks when applying the mutually exclusive setting, once the patients had been verified and had met the criteria for the one-child nodes, the patients did not require further verification for the other child nodes. In this situation, less time was required to perform the criteria verification process. Therefore, the query task with the mutually exclusive setting required less time than those without applying the mutually exclusive setting (Table 3).

Advantages of the Approach

The approach proposed in this study provides several beneficial features. First, the adoption of GLIF3.5 increases the potential for interoperability and shareability of database queries. This study was inspired by the work of GLIF3.5 and employed GLIF3.5 classes such as "algorithm" to formulate the query tasks. Thus, the benefits provided by GLIF3.5 can be inherited. GLIF3.5 is a clinical guideline representation language that was originally developed for formulating and sharing computer-interpretable clinical practice guidelines. The concepts, patient data items, and query criteria in the query tasks can be represented using standard vocabularies, medical data models, and medical logical expression languages of criteria (eg, the Unified Medical Language System, UMLS; HL-7's Reference Information Model version 1.0, RIM; and Guideline Expression Language, GEL [12,22,28]).

Second, GLIF3.5 contains flowchart-based models. The GLIF3.5 algorithm class is used to formulate the algorithm included in the clinical guidelines [12,22,28]. In the discussed RetroGuide, the flowchart-based query methodology is used to assist users with limited database experience in formulating the query tasks. In this study, the flowchart-based instances provided by GLIF3.5 were adopted to assist users in formulating the overall workflow of the query tasks. Each node in the flowchart was considered a subprocess of the overall query process. Third, this system provides a visual representation of the query results. The query results including the amount of patient data retrieved (shown beside the nodes of the graphical flowchart), the table-based patient list, and the distribution information (shown in the graphical pie chart) are presented on the visual graphical interface. Fourth, the query criteria selection interface provides the flexibility for users to select all or certain nodes in the flowchart to execute the query operation process. Finally, the formulated query tasks can be stored as a Protégé project file, thereby facilitating the reusability of the query tasks.

Related Work

Austin et al in 2008 proposed a method for consistently querying one or more EMR systems based on many years of European research and standardization of the interoperable communication of EMRs [4]. Their work contributed to and highlighted the feasibility of standardizing query interfaces. However, this study did not focus on defining information models, but an existing model, GLIF, was employed for formulating the query tasks.

A year later, Mabotuwana and Warren proposed a tool for displaying the prescription information of patients by employing visual timeline graphical charts and applying an ontology-driven approach for formulating query criteria [3]. An ontology-driven approach was used for formulating the query criteria, and the query results were presented using graphical charts. However, unlike the visual timeline graphical charts of Mabotuwana and Warren, the query results in this study were not presented using temporal information. Their visualization of the timeline provided clear and rich information that was relevant to the prescription of a selected patient. In this study, the GLIF was applied to formulate the flowchart-based query tasks. A user can select the nodes in the flowchart for executing the query operation, and the flowchart showed the query results (eg, the number of patients).

In RetroGuide, a query task was formulated based on the flowchart using the workflow editor. Instead of employing medical-specific knowledge representation standards such as Asbru, EON, GLIF, and PROForma [29], the authors of RetroGuide employed a standard workflow definition language, XML Process Definition Language (XPDL), which was a cross-industry workflow technology, and they presented the possibility of applying various workflow engines or editors at different institutions. RetroGuide provided table-based three-level hierarchical reports of query results (ie, summary report, detailed report, and the information view of a patient). Previous research showed that numerous medical-specific knowledge representation standards have a considerable capability for modeling workflow and providing highly sophisticated medicine-specific modeling constructs [19].

Although the query language generator and the clinical data retriever employed in this study can retrieve the clinical data by interpreting GLIF-formatted query tasks using the GLIF3.5 ontology interpreter, the components in this study do not function as a regular guideline execution engine. The components developed in this study provide functions for querying the clinical data based on specific criteria, although they do not function as a guideline execution engine for updating the medical decisions determined by clinicians. There is a prior published report on GLIF execution engine called GLEE [30]. There are several differences between the components in this study (ie, in the FBDQM) and those in the GLEE. Primarily, the GLEE applies a specific guideline to a selected patient, presents optional steps for clinicians on the client side of the system, and waits for the clinicians to make their selections. Subsequently, the GLEE schedules the following steps and updates the relevant records. The primary purpose of the FBDQM is to query the patients' data based on the user-specified query criteria.

Cohort identification is an essential process of clinical research. Previously, cohort identification approaches such as the informatics for integrating biology and the bedside (i2b2) hive [31] from the i2b2 group were proposed. The i2b2 hive is an open-source software platform that enables managing medical records and genomic data to facilitate research. The i2b2 hive comprises a set of modules that communicate based on Web services. The i2b2 hive is suitable for estimating cohort sizes and generating research cohorts through simple inclusion-exclusion criteria [32], and the query results can be represented using a timeline view. In our study, a flowchart-based method was proposed for formulating the workflow of query tasks. A complex query task was divided into several subquery tasks by applying various flowchart nodes, and the query results of these subquery tasks were shown in separate nodes. Therefore, a flowchart-based method provides a hierarchical view for displaying the query results through various hierarchical layers, implying that the patient data retrieved in the query operation of the lower layer node satisfied more query criteria (ie, satisfying the criteria in this layer node and its parent node) than the patient data retrieved in the higher layer node (ie, satisfying the criteria in the higher layer node, but not the criteria in the lower layer node). This flowchart-based method allowed the observation of variations among the query results in the different layers.

Limitations

Although this system enriches the capability of data querying using the ontology-driven and FBDQM-based approaches, it does present several limitations. First, the query criteria in nodes cannot be directly modified or created using the criteria selection interface. The query criteria must be formulated in advance using the GLIF3.5 format in Protégé. Subsequently, these criteria are exported in the XML format and are managed by the proposed system. If the query criteria in the node require modification, or if new criteria must be added in the node, the criteria should be modified or created using the Protégé environment.

Second, to perform the data mapping, the data item mapping table should be predefined in the database. The query language generator used the predefined mapping information to map the data items. During the mapping process, the data items in the query criteria are mapped to the data items in the database. When the mapping information is not predefined in the database, the mapping process might be performed incorrectly.

Third, *one-item-to-one-item* mapping was supported in the study. In one-item-to-one-item mapping, one item within the query criteria is mapped to an item in the database. Other mapping types, such as *one-item-to-many-items* mapping and *many-items-to-one-item* mapping are not supported in this study. For example, in the data repository, the ICD9 codes could appear with various data sources in the database (eg, ICD9 codes for inpatients and ICD9 codes for outpatients). During the data-mapping process, the data-mapping table should only specify one source (ie, ICD9 codes for inpatients or ICD9 codes for outpatients) for mapping the ICD9 code values. The framework does support the idea of a valueset by indicating values using the “or” operator. For example, the framework does not support the ability to enumerate a list of ICD9 codes for a node such as “ICD=155.0 OR 155.2 OR 156.3,” although it supports the managing of a list of ICD9 codes specified as “ICD=155.0 OR ICD=155.2 OR ICD =156.3.”

Fourth, although the proposed approach could assist users with limited database experience in formulating the query tasks, they must understand how to employ the GLIF3.5 components to formulate the query tasks.

The fifth limitation is related to the problem of common representation for patient parameters (eg, diagnoses, procedures, demographic data, and laboratory results). In this study, the data formulated using the GLIF are not mapped to the common representations, such as vMR [20,21]. A common representation for patient parameters facilitates the interoperability of queries across various databases. In this study, a mapping process was included to map the query task data items to data items in a local database.

Sixth, GELLO is an object-oriented query and expression language [33]. In this study, GELLO was not involved in mapping query tasks and data items in the local data repository. Conversely, the SQL queries employed for the querying data processes in this study are generated directly according to the query criteria in the GLIF-formatted query tasks through the mapping and query language generator mechanism in the study.

Seventh, this study has a limited set of examples related to the liver disease domain, and it is not been tested in numerous domains. When a mapping table (ie, the source data item is mapped to a destination data item in the local database) for other disease domains is defined, the system could be capable of managing query tasks for other diseases.

The eighth limitation is that this query platform is focused only on the cohort estimation counts (ie, patient counts). The query platform can be used for collecting patient IDs (ie, cohort) but not for cohort data (eg, cancer cohort with data on tumor size, survival, and laboratory values) in the dataset results. For example, it can solve problems involving the number of patients in the database with liver tumors measuring 2 cm or smaller and a range of value of a specific laboratory, but not a dataset on all liver cancer patients with the data on tumor size and this specific laboratory result.

GLIF as format is not being actively improved; GLIF3.5 is the current version. Furthermore, because the interpreter developed in this study was based on the GLIF schema, the method proposed in this study is useful only for interpreting query tasks formulated using the GLIF. Query tasks based on the GLIF are created using an interface provided by Protégé. This system is a laboratory experiment for presenting the feasibility of the methodology presented in this study. Users of the proposed system are both creators and key collaborators.

Future Work

This experiment was conducted to evaluate the feasibility of applying a methodology used for building a query execution engine by formulating query tasks using the existing GLIF. The framework can be used in clinical research when a researcher must identify patients based on specific criteria. The framework could be enhanced further by retrieving both cohort and patient data (eg, structured data and relevant clinical narrative reports). Furthermore, because the query tasks were formulated using clinical guideline representation language, the framework can also be used to verify the status of guideline compliance by querying the patient data using an encoded guideline.

Conclusion

The FBDQM-based query execution engine comprises eight major components, including logical processing components and visual representation components. The proposed FBDQM-based query execution engine was implemented to interpret the XML-formatted query tasks that were formulated using GLIF3.5, execute the query operations, retrieve clinical data, and represent the query results. In the experiments involving different numbers of patients, the FBDQM-based query execution engine performed successfully in retrieving the clinical data based on the query tasks formatted using GLIF3.5.

The ontology-driven and FBDQM-based approach enriched the data query capabilities along the three major considerations: using the query interface for query task formulation, representing query results, and employing models to formulate query criteria. The potential for interoperability, shareability, and reusability of the query tasks was increased by adopting GLIF3.5.

Acknowledgments

The authors acknowledge the members of the research team lead by F Lai of National Taiwan University for their contributions toward this study.

The authors would also like to thank Professor Mor Peleg for her generous support in providing the materials related to GLIF.

F Lai received grants from the National Science Council, Taiwan (NSC 101-2221-E-002-203-MY3). The funding organizations were not involved in designing or conducting the study, evaluation, analysis, nor the preparation of the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

The video file for demonstrating the proposed approach.

[MP4 File (MP4 Video), 6MB - medinform_v1i1e2_app1.mp4]

Multimedia Appendix 2

The link to YouTube video for the demonstration of the proposed study.

[PDF File (Adobe PDF File), 76KB - medinform_v1i1e2_app2.pdf]

Multimedia Appendix 3

More information related to the formulation of query tasks using GLIF3.5 through Protégé and the translation of query tasks into the XML format document.

[PDF File (Adobe PDF File), 79KB - medinform_v1i1e2_app3.pdf]

Multimedia Appendix 4

The XML file containing two examples of query tasks described in this paper. These query tasks are formulated using GLIF3.5 and translated into XML documents. These query tasks are only used for testing the performance of the proposed system and have not been validated medically by clinicians. They should only be seen as examples of query tasks encoded using GLIF3.5.

[XML File, 22KB - medinform_v1i1e2_app4.xml]

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Abbreviations

EMR: electronic medical record
FBDQM: flowchart-based data-querying model
GEL: Guideline Expression Language
GLEE: GLIF execution engine
GLIF3.5: Guideline Interchange Format version 3.5
KDOM: knowledge-data ontological mapper
RIM: Reference Information Model
SQL: Structured Query Language
UMLS: Unified Medical Language System
XML: Extensible Markup Language
XPDL: XML Process Definition Language

Edited by G Eysenbach; submitted 06.01.13; peer-reviewed by V Huser, T Mabotuwana; comments to author 12.05.13; revised version received 20.06.13; accepted 17.08.13; published 08.10.13.

Please cite as:
Ping XO, Chung Y, Tseng YJ, Liang JD, Yang PM, Huang GT, Lai F
A Web-Based Data-Querying Tool Based on Ontology-Driven Methodology and Flowchart-Based Model
JMIR Med Inform 2013;1(1):e2
URL: http://medinform.jmir.org/2013/1/e2/
doi:10.2196/medinform.2519
PMID:25600078

Original Paper

Factors Associated With Adoption of the Electronic Health Record System Among Primary Care Physicians

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Abstract

Background: A territory-wide Internet-based electronic patient record allows better patient care in different sectors. The engagement of private physicians is one of the major facilitators for implementation, but there is limited information about the current adoption level of electronic medical record (eMR) among private primary care physicians.

Objective: This survey measured the adoption level, enabling factors, and hindering factors of eMR, among private physicians in Hong Kong. It also evaluated the key functions and the popularity of electronic systems and vendors used by these private practitioners.

Methods: A central registry consisting of 4324 private practitioners was set up. Invitations for self-administered surveys and the completed questionnaires were sent and returned via fax, email, postal mail, and on-site clinic visits. Current users and non-users of eMR system were compared according to their demographic and practice characteristics. Student's *t* tests and chi-square tests were used for continuous and categorical variables, respectively.

Results: A total of 524 completed surveys (response rate 524/4405 11.90%) were collected. The proportion of using eMR in private clinics was 79.6% (417/524). When compared with non-users, the eMR users were younger (users: 48.4 years SD 10.6 years vs non-users: 61.7 years SD 10.2 years, $P<.001$); more were female physicians (users: 80/417, 19.2% vs non-users: 14/107, 13.1%, $P=.013$); possessed less clinical experience (with more than20 years of practice: users: 261/417, 62.6% vs non-user: 93/107, 86.9%, $P<.001$); fewer worked under a Health Maintenance Organization (users: 347/417, 83.2% vs non-users: 97/107, 90.7%, $P<.001$) and more worked with practice partners (users: 126/417, 30.2% vs non-users: 4/107, 3.7%, $P<.001$). Efficiency (379/417, 90.9%) and reduction of medical errors (229/417, 54.9%) were the major enabling factors, while patient-unfriendliness (58/107, 54.2%) and limited consultation time (54/107, 50.5%) were the most commonly reported hindering factors. The key functions of computer software among eMR users consisted of electronic patient registration system (376/417, 90.2%), drug dispensing system (328/417, 78.7%) and electronic drug labels (296/417, 71.0%). SoftLink Clinic Solution was the most popular vendor (160/417, 38.4%).

Conclusions: These findings identified several physician groups who should be targeted for more assistance on eMR installation and its adoption. Future studies should address the barriers of using Internet-based eMR to enhance its adoption.

(JMIR Med Inform 2013;1(1):e1) doi:10.2196/medinform.2766

KEYWORDS

electronic medical record; physicians; adoption; associated factors; medical informatics

Introduction

Background

The introduction of Internet-based information technology (IT) into the health care system is widely perceived as a significant step to improve the quality of services provided by health care institutions [1-5]. As a result, transition of paper medical records to electronic ones is becoming more common in health care systems around the globe [6-9]. These electronic patient records are established in a real-time system with various functions, including instantaneous sharing of patients' medical history by different health care providers [10]. The delivery of high quality medical services to patients could be much enhanced by reducing medical errors and facilitating more efficient communication among health care professionals by eMR use [9,11]. It becomes a global trend for such electronic systems to be implemented in health care institutions, of either a regional or national scale worldwide [12,13]. Apart from the United States and the United Kingdom, Asia-Pacific countries like Japan, Taiwan, and Singapore also followed this trend and have initiated the development of the computerized system [13]. Although the benefits brought by eMR are substantial, the adoption levels of eMR among these countries are relatively low. The major barriers include the high cost of the hardware and software systems, concerns over the required technological expertise, inertia among physicians, and also lack of government support to bring about changes [9,12].

Hong Kong is one of the most densely populated cities in the world. In order to meet the rising demand for high quality health care, the clinical management system (CMS) developed by the Hospital Authority (HA) was implemented in the public hospitals to allow clinicians timely access to electronic clinical information. It relied exclusively on the Internet as a significant conduit to medical data access. Since 1999, the electronic patient record (HA ePR) was developed to bring information from different modules of CMS into one standardized repository, offering a clinician-friendly interface to access a longitudinal, lifelong patient record [14]. In 2010, there have already been 8 million patient records, 1 million annual admissions, 13 million ambulatory visits, 2 tegabytes ePR data volume, 4 tegabytes ePR images, and 750 million ePR laboratory records in the HA database. The ePR represents one of the most important systems in HA as it consists of more than 12,000 users, 90,000 patients, 2 million transactions via the CMS, as well as 300,000 ePR transactions on a daily basis. The presence of Internet access and high clinician acceptance and utilization are crucial for the Internet-based HA ePR to act as an essential clinical and management tool in clinical practice. These are necessary conditions for transition of paper records to electronic ones [15]. In order to further enhance the benefits brought by HA ePR, the Hong Kong Special Administrative Region government has started the development of a territory-wide Internet-based computerized system—the electronic Health Record (eHR) Sharing System in Hong Kong, which allowed the physicians from both private and public sectors to share patient information. Since currently the private sector provides a significant portion of primary care in Hong Kong, the engagement of clinicians in the private sector becomes one of the key success factors for proper functioning of the system. There is an urgent need for evaluation of the adoption level of the eMR system among private physicians as this provides important information for health informaticians and policy makers to plan future strategies to revamp and enhance the Internet-based eHR sharing.

Objectives

The objectives of this study were (1) to measure the level of, and factors associated with, the adoption of the eMR system among physicians working in the private sector of Hong Kong, (2) to explore the enabling and hindering factors of the use of eMR, and (3) to evaluate the key functions of eMR and the popularity of electronic systems and vendors used by these private practitioners.

Methods

Survey Instruments

A questionnaire was designed and drafted by an academic family physician (MCS) with reference to literature tailor-made to the local context of primary health care in Hong Kong. These questions were face-validated by a panel of epidemiologists, family physicians, informaticians, and academic professors in public health. The questionnaires were then pilot-tested among 15 private practitioners randomly selected from the registry of private practitioners who were honorary tutors of the School of Public Health and Primary Care, Chinese University of Hong Kong (CUHK), and subsequent amendments made according to their recommendations. This study was approved by the Survey and Behavioral Research Ethics Committee of CUHK.

Target Population and Sampling Methodology

The target population consists of all registered practitioners in Hong Kong working in the private sector. We identified the following sources to trace the contact information of these private practitioners: (1) the Hong Kong Doctors' website of the Hong Kong Medical Association (HKMA) for the public (n=2464), (2) a list of clinical tutors working in the private sector, carrying an honorary teaching appointment in the School of Public Health and Primary Care of the Chinese University of Hong Kong (n=149), (3) a research database containing the contact details of previous collaborating private practitioners who consented to disclose their contact information for future research (n=247), (4) private doctors' list from a medical insurance company (Bupa) and members of the Association of Private Medical Specialist (APMS) (n=760), (5) Hong Kong Doctors' networks in different districts (n=86), and (6) site visits to clinics of various buildings with high concentration of doctors (n=618). We established a central practitioner registry consisting of all registered doctors currently practicing in the private sector from the above sources (N=4405).

We assumed a desired precision level of 5% and the proportion of private practitioners having computerized systems in their clinics being 86% according to a survey conducted by the HKMA in 2006 [11]. Using N=4p(1-p)/(precision)^2 (where p=proportion of private practitioners who used computers), the minimum sample size was estimated at 193. However, since the use of eMR by some physicians in their clinics might change with time, we used a hypothetical proportion of 50% which would yield the largest sample size, leading to an estimated N=400. Owing to the relatively low response rate of medical doctors to surveys sent (398/6772, 5.88%) in the aforementioned study by the HKMA [11], we decided to send invitations to all private practitioners in our central registry to secure larger sample size. In addition, to increase response rate, we conducted (1) clinic visits to various buildings with high concentration of doctors, (2) visits to sessions awarding Continuous Medical Education (CME) points to the attending physicians hosted by some doctors' networks with permissions from the seminar organizers, (3) invitations to the chairmen of the private doctors' Networks in the New Territories West Private Practitioner Network and the Taipo Doctors' Network, and (4) Invitations to doctors who are chairmen of larger-scale Health Maintenance Organizations (HMOs) to disseminate the surveys to their practice doctors.

Data Collection

Invitations were sent via faxlines, emails, post with return postage included, site visits, and visits to CME seminars. All surveys were self-administered. Survey invitations were conducted through all these contact channels for each registered doctor identified in our central registry. Hence there may exist multiple invitations to one single practitioner and we checked each returned survey for potential duplication. Up to three telephone or email reminders were sent to the participant physicians to encourage more responses. In addition, we conducted 618 clinic visits to buildings with high concentration of medical doctors and visited two CME seminars (on April 15th-16th, 2010).

For each survey returned, we checked for the presence of consent signature, full name of the doctor as appeared in the first page of the invitation letter, as well as the completeness of the questionnaires. To ensure confidentiality and anonymity, the first page with doctors' identity was detached from the survey and each questionnaire was assigned a survey number as a unique identifier by one researcher. Another researcher who collected and entered the data was therefore blinded to the identities of the participant physicians.

Statistical Analysis

The Statistical Package for Social Sciences version 16.0 (Chicago, Illinois) was used for all data entry and analyses. The major outcome variable was the proportion of private practitioners who used computers in their clinics. We performed descriptive analyses for all survey items. The eMR users and non-users were compared according to their demographic characteristics and practice information using chi-square tests of independence and student's *t* tests for categorical and continuous variables, respectively. To account for the potential sampling bias due to different invitation methodology (clinic site visits and invitations via practice or network chairmen vs usual faxline /email/ postal invitations), we compared the two groups of participants with regard to their demographic and practice characteristics to detect any heterogeneity. All *P* values less than or equal to .05 were regarded as statistically significant.

Results

Participant Characteristics

We received a total of 524 completed surveys via fax, email, postal returns, and on-site collections in clinics and CME seminar venues, giving a response rate of 11.90% (524/4405). The mean age of the study participants was 51.11 years (SD 11.8). Approximately 80.3% (421/524) were male physicians (Table 1). The majority had practice experience of more than 20 years (354/524, 68.9%), and was working under a HMO (444/524, 84.7%). Most were engaged in solo practice (379/524, 72.3%), and possessed specialist qualifications (318/524, 60.7%) recognized by the Hong Kong Academy of Medicine. The survey participants were mainly general practitioners or family physicians (218/524, 41.6%), followed by medical internists (68/524, 13.0%), and surgeons (67/524, 12.8%).

Profiles of eMR Users vs Non-Users

We analyzed the difference in the characteristics between eMR users (ie, those private practitioners who adopted any electronic computer system for medical consultations in their clinics) and the non-users. Among these private doctors, 417 (79.6%) used computerized systems in their clinics for consultations (Table 1). The adoption levels among family medicine specialists and general practitioners were 83.3% (61/73) and 76.5% (111/145), respectively. The proportions of specialists (who acquired a specialist fellowship recognized by the Hong Kong Academy of Medicine) and non-specialists using eMR were 81.0% and 79.1%, respectively (*P*=.690). They used computers in their clinics for an average of 7.2 years (SD 5.7 years). The eMR users were significantly younger (users: 48.4 years SD 10.6 years vs non-users: 61.7 years SD 10.2 years, *P*<.001) and consisted of a higher proportion of female physicians (users: 80/417, 19.2% vs non-users: 14/107, 13.1%, *P*=.013) as compared with the non-users. The users had less clinical experience (with more than 20 years of practice: users: 261/417, 62.6% vs non-user: 93/107, 86.9%, *P*<.001), and a lower proportion worked under a HMO (users: 347/417, 83.2% vs non-users: 97/107, 90.7%, *P*<.001). There were no statistically significant differences between the users and non-users with regard to their training status (*P*=.105) and clinical specialty (*P*=.617).

Table 1. Participant characteristics (N=524).[a]

	Overall (N=524) n (%)	eMR[b] users (n=417) n (%)	Non-users (n=107) n (%)	*P* value n (%)
Age in years, mean (SD)	51.11 (11.8)	48.44 (10.6)	61.72 (10.2)	<.001
Gender				
Male	421 (80.3)	333 (79.9)	88 (82.2)	.013
Female	94 (17.9)	80 (19.2)	14 (13.1)	
Practice experience in years				
Male, practice experience 0-20 yrs	125 (24.3)	119 (28.5)	6 (5.6)	<.001
Male, practice experience >20 yrs	294 (57.2)	213 (51.1)	81 (75.7)	
Female, practice experience 0-20 yrs	33 (6.4)	32 (7.7)	1 (0.1)	.024
Female, practice experience >20 yrs	60 (11.7)	48 (11.5)	12 (11.2)	
Practice Setting: Health Maintenance Organization	444 (84.7)	347 (83.2)	97 (90.7)	<.001
Type of practice				
Solo	379 (72.3)	283 (67.9)	96 (89.7)	<.001
With partners	130 (24.8)	126 (30.2)	4 (3.7)	
Training status				
None	150 (28.6)	111 (26.6)	39 (36.4)	.105
Current or completed Basic training	29 (5.5)	25 (6.0)	4 (3.7)	
Current or completed higher training	24 (4.6)	22 (5.3)	2 (1.9)	
Academy Fellow	318 (60.7)	257 (61.6)	61 (57.0)	
Specialty				
Emergency medicine	3 (0.6)	3 (0.7)	0 (0.0)	.617
Community Medicine	2 (0.4)	2 (0.5)	0 (0.0)	
Otorhinolaryngology	9 (1.7)	7 (1.7)	2 (1.9)	
Family Medicine (specialist)	73 (13.9)	61 (14.6)	12 (11.2)	
General Practice (non-specialist)	145 (27.7)	111 (26.6)	34 (31.8)	
Obstetrics and Gynaecology	37 (7.1)	28 (6.7)	9 (8.4)	
Anaesthesiology	4 (0.8)	2 (0.5)	2 (1.9)	
Ophthalmology	19 (3.6)	19 (4.6)	0 (0.0)	
General Medicine	68 (13.0)	53 (12.7)	15 (14.0)	
Orthopedics	31 (5.9)	23 (5.5)	8 (7.5)	
Pediatrics	39 (7.4)	34 (8.2)	5 (4.7)	
Psychiatry	9 (1.7)	7 (1.7)	2 (1.9)	
Radiology	8 (1.5)	8 (1.9)	0 (0.0)	
Surgery	67 (12.8)	55 (13.2)	12 (11.2)	

[a] Some figures did not add up to 100% due to missing values for some variables.

[b] eMR: electronic medical record

Reasons for Using or Not Using Computerized Systems Among Private Practitioners

Among the 417 eMR users, the majority perceived efficiency of computerized systems (379/417, 90.9%) as the reason of using computers in their clinics (Figure 1). The other major reasons for using computerized systems included “their ability to reduce medical errors” (229/417, 54.9%), “eliminate the need to store paper records” (159/417, 38.1%), and followed by “eliminate illegibility of practice partners” (122/417, 29.3%). A relatively low proportion of participant physicians used computers due to their “ability to share patient information in the public sector” (93/417, 22.3%).

Turning to the reasons of not using computers among the other 107 physicians, the most frequently chosen responses included “not patient-friendly during consultations” (58/107, 54.2%) and “computer use is more time-consuming” (54/107, 50.5%) (Figure 2). Significant proportions of respondents also perceived the lack of technical support (50/107, 46.7%), concerned about data migration from paper to system (48/107, 44.9%), and worried about inconvenience caused during computer down-time (44/107, 41.1%).

Key Functions Included by the Computerized System

Among the eMR users, electronic patient registration system (376/417, 90.2%) was the most common key functions of the computerized systems (Figure 3). The majority also adopted their computers for drug dispensing which includes the use of dispensing system (328/417, 78.7%) and electronic drug labels (296/417, 71.0%). This is followed by appointment booking system (265/417, 63.5%) and electronic clinical notes (242/417, 58.0%).

Types of Computer Systems in Current Use

SoftLink Clinic Solution (160/417, 38.4%) followed by HKMA Clinical Management System 3.0 (CMS 3.0) (46/417, 11.1%) were the most popular computer systems (Figure 4). Around 24.2% (101/417) of private physicians did not know the names of computer systems in use, or gave an invalid response. There was a wide variety of different computer systems adopted by the private physicians.

Vendors

SoftLink (121/417, 29.0%) represented the most frequently chosen vendors among the physicians (Figure 5). The other not uncommonly used vendors included HKMA/Mobigator (20/417, 4.8%), iSoft system development Co (14/417, 3.4%), and NetCaves (10/417, 2.4%). Around 5.8% (24/417) of physicians managed the computers by themselves.

The mean duration of vendor use was 53.9 months (SD 44.0 months) (Table 2). The top reasons for choosing these vendors were introduction by friends (172/417, 41.2%), cost concerns on setup and maintenance (125/417, 30.0%), and reputation of the vendors (125/417, 30.0%). A significant proportion adopted the vendors from the practice management (31/417, 7.4%), while a number of physicians treasured the free service and the continuing system support offered by the vendors (22/417, 5.3%).

Tests for Sampling Biases

Participants were divided into two groups based on the approach method, where group 1 used clinic site visits and invitations via practice or network chairmen and group 2 used faxline /email/ postal invitations. These groups were tested for heterogeneity with regard to the participants’ demographic and practice characteristics. When group 1 was compared with group 2, there were no differences in age (group 1: mean 55.21 years, SD 15.73 years vs group 2: mean 52.75 years, SD 14.74 years, *P*=.157) and gender (male proportion: group 1: 80.0% vs group 2: 80.6%, *P*=.942) respectively. In addition, we detected no statistically significant differences when years of clinical practice (*P*=.337) and the practice setting (HMO vs non-HMO) (*P*=.105) were tested between the two groups.

Figure 1. Reasons for using computerized systems in clinics. x-axis: 1=Offer more efficient service; 2=Ability to share patient information in public sector; 3=Reduce medical errors; 4=Eliminate need to store paper records; 5=Eliminate illegibility of my practice partners; 6=Others.

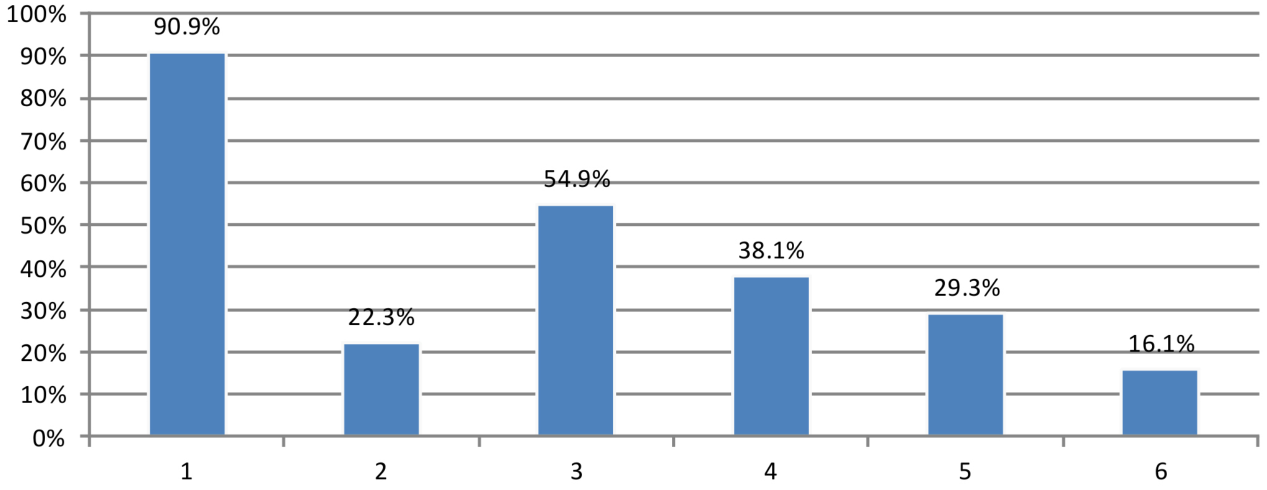

Figure 2. Reasons for not using computerized systems in clinics. x-axis: 1=Cost concerns (Setup/ maintenance); 2=Computer use is more time-consuming; 3=Not supported by the practice partners/ practice organization; 4=Concerns on data migration from paper to system; 5=Insufficient space for computer installation; 6=System not support Chinese language; 7=Not patient-friendly during consultations. 8. Inconvenience caused during down-time 9. Lack of technical support 10. Concerns on computer hackers 11. Others.

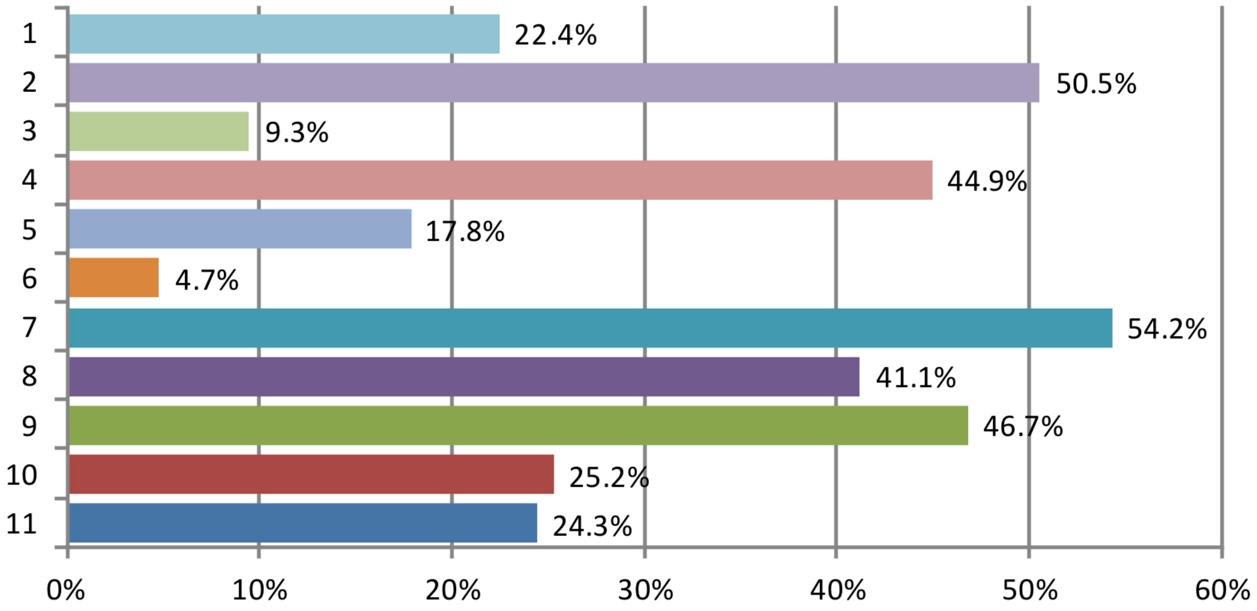

Figure 3. Key functions included by the computerized system. x-axis: 1=Electronic patient registration system; 2=Appointment booking system (e.g. arrangement of next patient visit); 3=Electronic clinical notes (eg, recording of patient history); 4=Dispensing system (eg, printing of prescriptions); 5=Order Entry functions (eg, laboratory, radiological exam order); 6=Picture Archiving and Communication System (PACS); 7=Electronic Health Care Voucher System (eHS); 8=Electronic Drug labels; 9=Public Private Interface-electronic Patient Record (PPI-ePR).

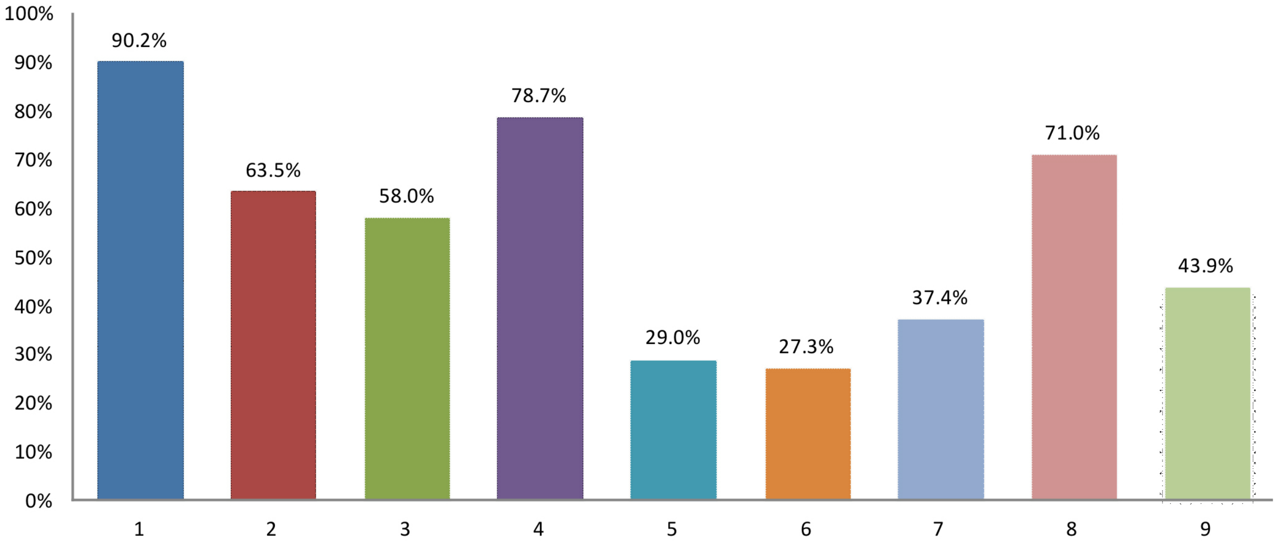

Figure 4. Names of computer system currently in use. Invalid response was defined as naming of computerized systems as Operation Systems (eg, Microsoft Vista) or computer hardware. HKMA: Hong Kong Medical Association.

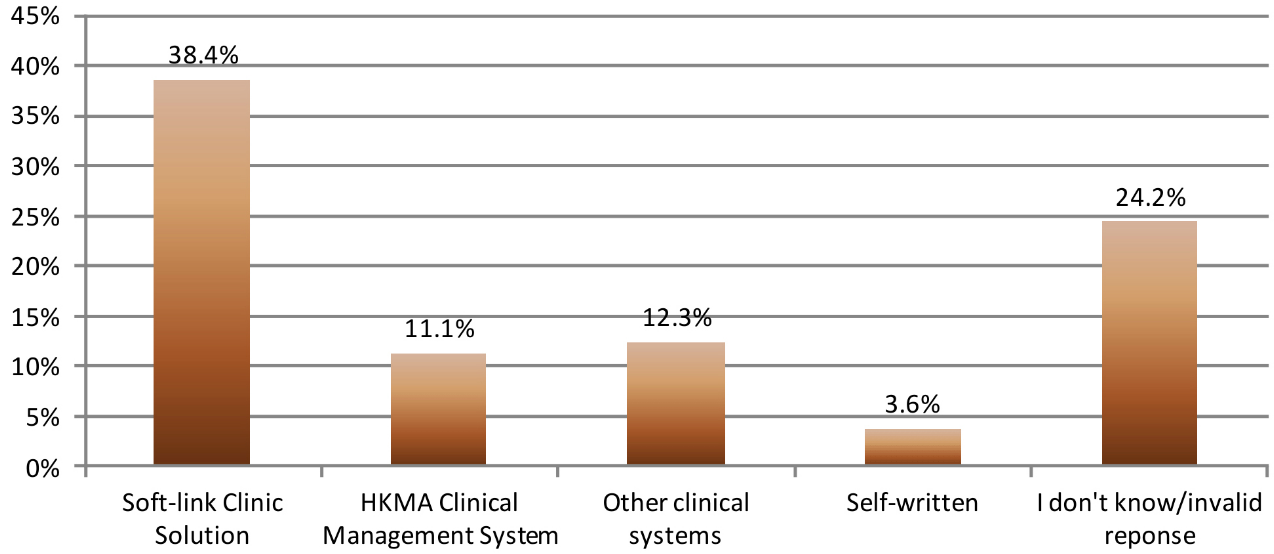

Figure 5. The proportion of participants adopting various vendors. HKMA: Hong Kong Medical Association.

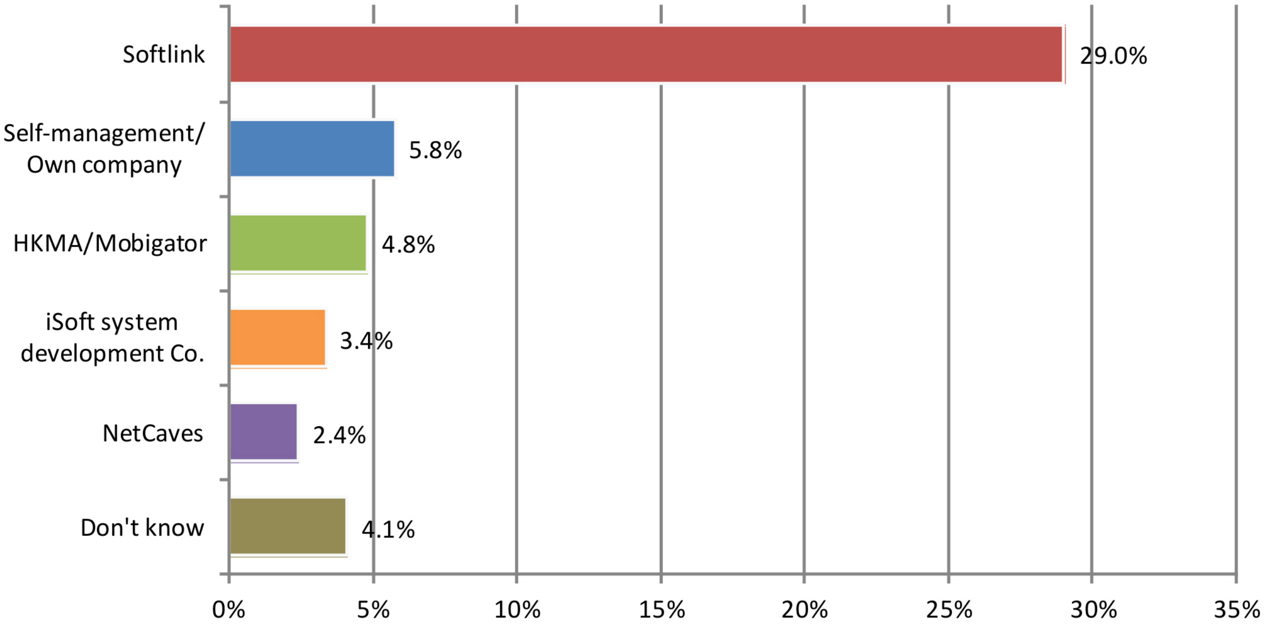

Table 2. Study participants' reasons for choosing the current vendors for eMR (N=524).[a]

Reasons for choosing the current vendor	n	%
Cost concerns (setup/maintenance)	125	30.0
Reputation	125	30.0
Introduction by friends	172	41.2
Chosen by practice management	31	7.4
At random	18	4.3
Others	85	20.4

[a] Duration of vendor services: mean 53.85, SD 44.00

Discussion

Principal Findings

This study found that among 524 private physicians, 79.6% (417/524) adopted computerized systems in their clinics. The computer users were significantly younger, more were female, possessed less clinical experience, and less worked under an HMO. The major reasons of using computers in their clinics included perceived computer efficiency, reduction of medical errors, elimination of need to store paper records as well as issues related to case note illegibility. The high and similar prevalence of using eMR in the clinical practice of both specialists and non-specialists indicated that a communication culture on sharing patient records through extensive computer network has been established between these 2 groups of physicians as this brings convenience of extracting updated information of patients through eMR during consultation. This was also reflected from their heavy use of electronic patient registration system, dispensing system, and electronic drug labels printing system, which are part of the eMR system. Among the users, the key functions of computerized systems included electronic patient registration and drug dispensing. Among the non-users, the use of computers was regarded by most as patient-unfriendly and time-consuming during clinical consultations and it was quite surprising that the impression of eMR system between eMR and non-eMR users was quite different. Therefore, there may probably be a misunderstanding on the eMR system and further efforts should be made, especially tackling the opinions from the non-users, in order to increase the overall prevalence of using eMR system. SoftLink Clinic Solution was the most frequently used computer system and also vendor. It is a comprehensive software system allowing physicians an easy documentation of electronic medical notes and access to clinical images and laboratory reports of patients. Drug label printout system is also integrated into the system. The preference of the computer system was found to be diversified and this might lead to more adoption of SoftLink Clinic solution over other current choices in the market. The choice of vendors was mostly influenced by friends, setup and maintenance costs, and their reputation.

There is a scarcity of local studies on the adoption levels of eMR in the private sector. To our knowledge, there was only one study conducted by Ho et al [16] who sent 6772 questionnaires to both HKMA members and non-members via the HKMA Circulars in 2006. The response rate was 5.88% (398/6772) and they found that 86% (342/398) used computers in workplace. When enquired about the use of clinic management package in the study by Ho et al, only 43% (171/398) gave a positive response. The higher proportion of physicians using computerized systems in the clinics as reported in this study (317/398, 79.6%) was however not directly comparable to their studies as we used a different methodology and a broader definition of computers was referred to (ie, we included any electronic health records in addition to computer management system).

The level of computer adoption in this study is high (417/524, 79.6%). When a sub-analysis of Ho's study [16] was conducted where only private physicians were included, the adoption level was 81.7% (192/235), a figure similar to the present study. However, as the private sector provides more than 70% of primary care in Hong Kong, and that we do not have data on the compatibility of the current use of computerized systems to share health records with the public sector, there seems to have a further room to enhance computer use among private practitioners. In this connection, the major reasons of computer use, namely their efficiency, ability of reducing medical errors and case note illegibility, as well as their capability to eliminate the needs for medical record storage, should be promulgated to the eMR non-users. On the other hand, the issues of patient-unfriendliness and the perceived time-consuming nature associated with computer use should be addressed [17,18]. Besides, there have been studies reporting that non-users might perceive threat to their professional autonomy by eMR, including loss of control over their clinical work and restrictions of their clinical freedom [19]. The eMR initiatives need to demonstrate the unique advantages of adopting computerized systems in the clinics by promoting the different attractive functions possessed by the current computer softwares. More technical assistance is warranted for installation, maintenance and support of computers for private practitioners as this was quoted by many as a hindering factor of computer use [20-23].

The low proportion of eMR users whose reason to use computers in their clinics was to share patient information with the public sector might reflect their low intention to do so. This is echoed by the relatively low proportion of computer users having Public Private Interface-electronic Patient Record (PPI-ePR) Sharing Pilot Project, which is a pilot programme allowing sharing patients' electronic records among the public and private sectors, as the key functions of their installed systems. Many of the motivators to use computers identified in this study were related to efficiency and convenience of clinical practice instead of information sharing between the public and private sector. The importance of sharing patients' records between the two sectors should be more emphasized among private practitioners. Extra personal incentives could also be provided to encourage the use of the eMR system [24].

The friends of the private physicians, many might well be medical colleagues, were found to be more influential on the choice of vendors than the set-up and maintenance cost required for the eMR system and the reputation of vendors. This reflected that the costs of the eMR system might not be a heavy burden for the physicians and recommendations from other physicians will be a good initiation for the use of eMR system in the clinical practice. Seminars could be organized where colleagues of the same specialty share their positive experience of using eMR in their clinics tailor-made to their clientele for the eMR non-users. In addition, as free services including computer setup and ongoing system support have been raised as an important consideration by a number of physicians who were currently using eMR, initiatives on provision of such services at low costs could be considered for the non-users to incentivize their adoption of computerized systems in their clinics.

Limitations

This study included more than 500 surveys and the precision achieved is higher than the traditionally used 5%. However, some of its limitations should be mentioned. First, the response rate was modest (524/4,405, 11.9%) although previous studies among physicians yielded even lower response rates at the levels of approximately 5% (398/6772). There existed non-response bias, and it is conceivable that those without computers might be less interested to participate in the survey. Second, we do not have the contact information of all private practitioners in Hong Kong. In addition, the sampling frame is a mix between the usual invitation group: by postal mailing, faxline, email, and the on-site visit group: clinic visits and survey invitations during CME seminar, thus introducing sampling bias. However, this sampling bias should be regarded as minimal as shown by our separate analysis where no differences in the demographic and practice characteristics between the two groups were detected. Last, the surveys received names of computers and vendors interpreted by the participant physicians differently. All programs or applications must run on an Operation System as a platform. For instance, Microsoft Vista is an Operation system. Clinic management system is a generic name for the software used for clinic management (including clinic solution, WinMed, HKMA CME 2.0 and HKMA CMS 3.0 etc) and the Clinic Solution is one of the Clinic management systems. The Clinic Solution is the CMS developed by the SoftLink, hence SoftLink is the name of the company but not a software. It is not expected that the participant physicians could provide details of computerized systems and vendors at these different levels in details, and hence a distinction could not be made here due to the lack of additional information.

Conclusions

In summary, this survey provided a cross-sectional description of the current adoption of eMR and their vendors in the private sector, and depicted the major reasons of their use and non-use. Based on the demographic characteristics of the non-users (more likely older, male physicians, more practice experience, work under HMO, and solo practice), knowledge of eMR installation and maintenance should be conveyed to these physician groups. The competitive advantages of eMR use in clinics, namely their efficiency and convenience favorable to the practice, should be shared with the non-users by the current users, preferably having similar clientele. The major reasons of not using eMR, among the non-users should be further addressed and tackled with. These include strategies to make computer use in clinics equally patient-friendly as compared to not using computers, as well as addressing the possible misperception that computer adoption is time-consuming. More technical supports, including lower cost computer setup and system support services, should be made readily available for the current non-users to remove barriers of eMR use. Future studies should be conducted to capture more data from practices not reachable due to absence of contact information. Site visits may lead to a high response rate and future research should consider further survey services by clinic visits.

Acknowledgments

We wish to express our sincere gratitude to Dr Ho Chung Ping, MH, the chairman of the IT committee of the HKMA for his expert advice on this project. He also conducted clinic visits together with the principal investigator for survey invitations and collection in the Champion building, for which the team members are very appreciative. We are grateful for the invaluable opinions and networking of private practitioners from Dr Chiu Sik Ho, the chairman of the Taipo doctors' network; Dr Eddie Chan Tat, the chairman of the New Territories West Private Practitioners' Network; Dr Aaron Lee Fok Kei, the founding President of the CUHK SPHPC Alumni Association; Dr Pang Lai Sheung, chairman of the Human Health Medical Group; and Dr Lau, the chairman of the New Town Medical Group. We thank all the participant physicians in this survey study. This study was funded by the Hospital Authority, Hong Kong.

Conflicts of Interest

None declared.

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Abbreviations

APMS: the Association of Private Medical Specialist
CME: Continuous Medical Education
CMS: clinical management system
CUHK: Chinese University of Hong Kong
eHR: electronic Health Record
eMR: electronic medical record
ePR: electronic patient record
HA: Hospital Authority
HKMA: Hong Kong Medical Association

HMO: Health Maintenance Organizations
IT: information technology

Edited by G Eysenbach; submitted 13.06.13; peer-reviewed by L Rusu, H Zhai; comments to author 16.07.13; revised version received 14.08.13; accepted 14.08.13; published 26.08.13.

Please cite as:
Cheung CSK, Tong ELH, Cheung NT, Chan WM, Wang HHX, Kwan MWM, Fan CKM, Liu KQL, Wong MCS
Factors Associated With Adoption of the Electronic Health Record System Among Primary Care Physicians
JMIR Med Inform 2013;1(1):e1
URL: http://medinform.jmir.org/2013/1/e1/
doi:10.2196/medinform.2766
PMID:25599989

Original Paper

Bridging Organizational Divides in Health Care: An Ecological View of Health Information Exchange

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Abstract

Background: The fragmented nature of health care delivery in the United States leads to fragmented health information and impedes patient care continuity and safety. Technologies to support interorganizational health information exchange (HIE) are becoming more available. Understanding how HIE technology changes health care delivery and affects people and organizations is crucial to long-term successful implementation.

Objective: Our study investigated the impacts of HIE technology on organizations, health care providers, and patients through a new, context-aware perspective, the Regional Health Information Ecology.

Methods: We conducted more than 180 hours of direct observation, informal interviews during observation, and 9 formal semi-structured interviews. Data collection focused on workflow and information flow among health care team members and patients and on health care provider use of HIE technology.

Results: We structured the data analysis around five primary information ecology components: system, locality, diversity, keystone species, and coevolution. Our study identified three main roles, or keystone species, involved in HIE: information consumers, information exchange facilitators, and information repositories. The HIE technology impacted patient care by allowing providers direct access to health information, reducing time to obtain health information, and increasing provider awareness of patient interactions with the health care system. Developing the infrastructure needed to support HIE technology also improved connections among information technology support groups at different health care organizations. Despite the potential of this type of technology to improve continuity of patient care, HIE technology adoption by health care providers was limited.

Conclusions: To successfully build a HIE network, organizations had to shift perspectives from an ownership view of health data to a continuity of care perspective. To successfully integrate external health information into clinical work practices, health care providers had to move toward understanding potential contributions of external health information. Our study provides a foundation for future context-aware development and implementation of HIE technology. Integrating concepts from the Regional Health Information Ecology into design and implementation may lead to wider diffusion and adoption of HIE technology into clinical work.

(JMIR Med Inform 2013;1(1):e3) doi:10.2196/medinform.2510

KEYWORDS

health information systems; qualitative research; ethnography; community networks; information sharing; organizational models; information ecology

Introduction

Background

Over 10 years ago, the Institute of Medicine identified the health care system of the United States to be “fragmented”, “distributed”, and “complex”. These attributes were viewed as challenging and potentially hazardous to the health care system [1,2]. Health care organizations have made significant progress in improving patient safety and moving toward patient-centered care over the last decade [3,4]. The current fragmented structure of health care delivery [5], however, directs patients to providers at multiple organizations for care [6,7], leading to dispersed and fragmented health information [8] and decreased continuity of care [9]. Care fragmentation impedes coordinated and cohesive health care delivery [1,2,9,10] and creates patient safety risks [3-5].

Health information technology solutions such as electronic health records can assist in reducing information fragmentation [5,11,12] within organizations, but solutions to share information across organizational boundaries are also needed [6,7,9,13]. Technology-supported [8,14-16] and federally funded [9,17] health information exchange (HIE) pilots are beginning to improve access to patient health information across organizational boundaries. Patients have also shown enthusiasm for this type of health information technology and accept that HIE can improve health care delivery [18]. Various approaches to interorganizational HIE have faced challenges due to disparate health information technology [19,20], organizational issues [21,22], and contextual factors related to workflow [23,24] and medical specialty [25]. Federal mandates requiring interoperability in health information technology design [26] have improved technological support for data exchange, but limited research has examined the direct impact of HIE on patients, health care providers, and the health care system as a whole.

We propose a new context-aware [27,28] perspective, the Regional Health Information Ecology, for examining the complex sociotechnical and organizational structures that emerge with successful implementation of HIE technology. Along with this perspective, our research question was how does the structure of a regional health care environment change when health information flows across organizational boundaries with technology support? Our goal in examining information exchange through this perspective was to investigate how technology and the health care system can coevolve to reduce information fragmentation and improve care coordination. While the setting for our study was a specific HIE technology implementation and a regional publicly funded HIE model, lessons learned relating to the Regional Health Information Ecology are widely applicable to different types of HIE technology at various design and implementation stages.

Analytical Framework

A central tenet driving our research is that new analytical approaches are needed to examine the complex relationships involved in and generated by HIE technology projects. During initial fieldwork focused on HIE-related workflow, we observed interorganizational interactions that were evocative of ecology studies. After completing an extensive open-ended grounded theory analysis [29] of our qualitative ethnographic data [23], we applied the Information Ecology Framework [30] to provide structure for additional data analyses.

The Information Ecology Framework takes a sociotechnical approach [31] toward understanding interrelationships among people and technology in specific local settings. Nardi and O’Day described the information ecology concept as [30]:

> *A system of people, practices, values, and technologies in a particular local environment. In information ecologies, the spotlight is not on technology, but on human activities that are served by technology.*

Five primary properties support application of the information ecology concept to a wide variety of environments (Table 1): system, locality, diversity, keystone species, and coevolution.

Researchers have applied the Information Ecology Framework to diverse contexts, including libraries [32,33], classrooms [34,35], computerized physician order entry [36], health care service delivery for homeless young people [37], surgical units in hospitals [38], virtual communities [39,40], and theme parks [41]. These scenarios share a common goal: to analyze data through the Information Ecology lens to better comprehend relationships among contextual elements.

Researchers working with large research datasets have proposed extending information ecology concepts to systematic levels and broader scales [42]. Rather than focusing only on interactions within a specific local ecology, this perspective extends the information ecology metaphor to interactions among ecologies [42]. Building on this idea, we examined HIE relationships by extending information ecology concepts and developing a new construct, the Regional Health Information Ecology. The Regional Health Information Ecology construct comprises multiple competing organizations with multiple clinical locations working together toward the common goal of information sharing, forming a dynamic exchange centered on health information.

Table 1. Information ecology components.

Component	Component characteristics
System	Interrelationships and dependencies among different parts of the ecology
Locality	Context in which technology is used including ownership of technology, networks around the technology, and connections related to the technology
Diversity	Niches for different roles and functions, different kinds of people and tools working together in a complementary fashion
Keystone species	Informal categories of people and tools necessary for the ecology to survive, based around informal rather than formal roles
Coevolution	Social and technical aspects of the ecology evolving together

Methods

Overview

The study design incorporated an iterative process of direct observation [43], semi-structured interviews [44], and data analysis to evaluate the impact of a Web-based HIE technology across widely varying clinical contexts, organizations, practice settings, and technology infrastructures. Our prior research into workflow, information flow, and technology use indicated that direct observation and semi-structured interviews were appropriate methods for the open-ended research questions motivating the study [45]. We previously discussed the setting, site selection, and data collection methods for the current study in great depth in a publication focused on workflow and HIE technology [23]. We provide a brief overview of data collection methods here and focus on the primary distinguishing characteristic of this portion of the larger study: applying a novel approach during data analysis using the Regional Health Information Ecology construct.

Study Setting and Sampling Plan

The study setting was the MidSouth eHealth Alliance, a regional health information organization in Memphis, Tennessee [14]. The organization, also referred to as “eHealth” by HIE technology users, comprised the majority of health care organizations in the region. The exchange design used a “pull” approach [14]. Users logged into the HIE website, separate from their internal electronic health record. Depending on site-specific factors, users retrieved patient information using links based on the site’s recent patients registry or by entering identifying information for the patient such as name and date of birth. Data were retrieved based on a matching algorithm [46] and presented to the users in a list of matching documents. Patient data were included in the exchange unless a patient opted out of participation.

The primary HIE technology users during the study were health care providers in emergency department (ED) settings and in two major safety net [47] ambulatory care groups [48]. We designed a purposive sampling plan [49,50] to cover regional geographic zones, HIE technology usage levels, and both ED and ambulatory contexts. The health information technology infrastructure and use of HIE technology varied substantially across participating organizations and research sites [23,48]. The study took place before mandates requiring interoperability of electronic health records were enacted [51]. The Vanderbilt University Institutional Review Board and appropriate regulatory groups at each research site approved all study procedures. All data relating to specific participating organizations were anonymized throughout this report, at the request of participating organizations.

Data Collection

Observation and Informal Interviews

One researcher (KMU) observed health care providers engaged in clinical work for over 180 hours, spread across 6 EDs and 8 ambulatory clinics spread through the Memphis region. Observation focused on interactions with the HIE technology and work practices to provide contextual details about HIE technology use. All primary observation subjects had HIE technology access, but actual technology use varied among subjects. The observer recorded detailed notes about technology use and work practices during observation. Throughout observation, the observer conducted informal interviews with observation subjects and other health care workers. The observer sought to be unobtrusive throughout data collection, avoiding disruption of routine work practices as much possible. The observer transcribed notes into an electronic notebook application [52] and later transferred these notes to NVivo 8 software [53] to organize qualitative data analysis.

Semi-Structured Interviews

A researcher (KMU) conducted nine semi-structured telephone interviews, after completing observation. When possible, we selected interview subjects who we also observed. To incorporate the widest range of perspectives on HIE, we also interviewed some subjects who were not observed (eg, health care providers with limited work schedules, medical directors, information technology managers). Interview questions explored information seeking behavior, information needs, impact of HIE technology use, and general feedback on HIE technology design and implementation. We designed the interview questions to provide member checking [54] of observation data analysis and to collect additional open-ended feedback about the HIE technology. We audiotaped the interviews, transcribed the interview recordings, and transferred the interview transcripts to NVivo 8 for data analysis. Interview subjects received a small gift card in appreciation of their time.

Data Analysis: Axial Coding

Our initial approach to data analysis involved an open-coding grounded approach [29]. After completing this initial grounded approach to data analysis, we moved into framework-focused data analysis and an axial coding approach [55,56]. Our approach to data analysis first developed theory emerging from the data itself and later applied existing theoretical frameworks to our understanding of the data. For example, during open coding, codes related to reasons health care providers used the HIE technology and the outcomes of technology use emerged repeatedly across observation data. These codes coalesced into the themes “prompts for HIE use” and “outcomes of HIE use.”

The Information Ecology Framework provided structure during axial coding. We assessed all observation and interview data for elements of the Regional Health Information Ecology construct, using five Information Ecology elements (Table 1) to guide coding. During axial coding guided by the Information Ecology Framework, we focused on understanding roles involved in information exchange and informal and formal interorganizational connections. For example, codes related to individuals involved in information exchange identified the “keystone species” for information exchange. Based on axial coding analysis, we manually developed graphical models about inter- and intraorganizational connections before and after HIE technology availability using diagramming software [57]. The graphical models provided visual maps of the Regional Health Information Ecology construct.

Confirmability

Our research employed a systematic and rigorous approach toward ensuring and evaluating credibility, transferability, and dependability [54]. We designed a multistage confirmability strategy with components during fieldwork, during data analysis, and after fieldwork.

We established credibility, analogous to internal validity [54], through three distinct processes: field research activities, peer debriefing, and member checking. Field research activities to establish credibility included prolonged engagement, persistent observation, and triangulation. We allotted lengthy periods of time in the project timeline to allow for prolonged engagement with and immersion in the environment [58]. We conducted data analysis concurrent with data collection, allowing emerging themes to provide depth and direction of data collection, meeting the purpose of persistent observation [59]. Triangulation strategies included using multiple sources of data and applying multiple methods [60]. Interaction with a peer debriefer and member checks were used throughout the research project as additional approaches to ensure credibility. A peer debriefer served as a “devil’s advocate” in discussing methodology, data analysis, and general fieldwork topics [54]. Member checking through informal and formal interviews consisted of discussing research findings with research subjects to collect additional layers of data, to gain feedback on the accuracy of the data, and to provide a different perspective on the findings [54].

Our emphasis for transferability, analogous to external validity [54], was on transferability of research findings to similar contexts. To facilitate this, we developed a rich description of findings and a thorough description of context to allow comparison of contextual similarities between different research sites. The project timeline allocated adequate time to investigate several distinct sites, providing evidence of transferability of the findings.

Dependability is analogous to reliability [54]. Throughout the project, the primary researcher engaged in activities to encourage reflexivity. Reflexivity involves being aware of the influence of the researcher’s perspective on the collection, interpretation, and analysis of the data [61]. Journaling allowed the researcher to record information such as personal reasons for selecting the research topic, perspectives on the research, reactions to fieldwork activities, and other information not appropriate in formal field or methodology notes. The process promoted awareness of potential sources of bias for the investigator and made the perspective of the researcher transparent to others. In addition, this process allowed the investigator to “bracket” sources of individual bias in an attempt to filter them from the research [62].

Results

Health Information Exchange

The core of HIE involves constantly shifting and evolving relationships among people, organizations, and technology. Prior to HIE technology availability, Memphis organizations and individuals exchanged health information manually through both formal and informal processes. Manual information exchange processes used approaches such as phone calls, faxing, and mail. Access to HIE technology automated portions of the formal level of data exchange. Information exchange processes remained fragmented, despite the HIE technology. Health care providers at all participating sites used manual information exchange processes in addition to technology-supported processes. Reasons that we observed for parallel manual and automated processes included amount and type of data available through the HIE technology, lack of HIE technology access, and limited technology use. Coexistence of manual and automated processes allowed us to examine HIE practices and the information ecology both with and without technology support for information exchange.

Mapping Information Ecology Concepts on the Regional Level

Key Components

Based on observation and interview data, we mapped the five main Information Ecology Framework components to the Regional Health Information Ecology (Table 2).

Table 2. Key components of the Regional Health Information Ecology.

Component	Component characteristics
System	Multiple competing health care organizations in the region
	Multiple clinical sites within each organization
	Need for data exchange within organizations and among competitors to support continuity of patient care
	Transfers in responsibility for patient care among inpatient and outpatient environments
	Information flow mediated by patient involvement
Locality	Overall local region
	Health care community within the region
	Organizations within the health care community
	Individual sites within organizations
	Specific departments at each site (ie, ED, specialty clinic)
Diversity	Many formal and informal roles involved in information exchange:
	Patients and caregivers: report visits to other hospitals/clinics
	Physicians: ask nurses and administrative staff to obtain external records
	Resident physicians: informal sources of patient health information
	Nurses: obtain formal consent for information exchange from patients
	Administrative staff: collect records from other organizations
	Records clerks: locate records and fax to other organizations
Keystone species	Information consumers: nurses, nurse practitioners, physicians, individuals who need information from other sites as part of the medical decision-making process
	Information exchange facilitators: people with knowledge of who to contact at other organizations and of procedures/requirements of other organizations
	Information reservoirs, informal: resident physicians contacted by resident physicians at other locations, patients discussing visits to other hospitals
	Information reservoirs, formal: patients bringing medical records from other sites, information repositories such as electronic health records and paper charts
Coevolution	Constantly shifting process for obtaining health information, related to:
	Organizational policies
	Information repositories at different institutions
	Changes in staffing
	Resource shifts
	Technology availability and accessibility

Ecology Component: System

The Regional Health Information Ecology *system* consisted of multiple health care organizations with long-standing competitive relationships. Each organization comprised multiple clinical sites, including hospitals and ambulatory clinics. Shared health information technology infrastructures facilitated the flow of health information within each separate organization and provided access to patient records at multiple clinical locations. Prior to the HIE technology, each organization was in effect an information silo and did not share data with other organizations. One administrator described views of information in her organization by saying, “We were used to our information being in our control.” Patients moved between inpatient and outpatient environments and between different organizations, resulting in incomplete patient health data within any single organizational information silo. The patient mediated information flow prior to HIE technology, with health care team members seeking external information in response to a patient mentioning visits to other organizations.

Ecology Component: Locality

To capture the full extent of *locality* during data collection, we observed at sites across the region seeking to broadly represent local clinical environments. The sites represented multiple organizations and both ED and ambulatory environments. Each site represented a distinct local context and used different types of information repositories to store health information, ranging from paper charts to electronic health records. Until HIE technology implementation, a single unifying form of technology did not exist across all participating sites. Physicians in ED settings repeatedly described the patient population in the region as “mobile”, with one physician noting that “With all these hospitals in close proximity, patients tend to go where they think wait time is lowest at that time.”

Ecology Component: Diversity

Individuals in a variety of roles participated in HIE activities, exhibiting role *diversity*. Patients and their caregivers played key roles in information exchange, by reporting visits to other clinical sites and prompting physicians to seek out external health information. Members of the clinical care team including nurses, nurse practitioners, and physicians participated in information exchange to different degrees. Administrative staff and records clerks facilitated information exchange, particularly in the manual information exchange processes, where administrative staff faxed requests to other organizations and records clerks retrieved data.

Ecology Component: Keystone Species

We identified three function-based *keystone species* that formed the basis of HIE regardless of HIE technology presence: information consumers, information reservoirs, and information exchange facilitators.

Information consumers needed and sought information from external sites for a variety of reasons. Providers in the ambulatory care environment required information from hospitals or referral sites their patients visited to ensure continuity of patient care and to provide data for use in medical decision making. Ambulatory, ED, and inpatient care providers sought external medical detail to learn about already-completed diagnostic procedures and other general medical history details.

Information reservoirs come from many different perspectives and roles and have both formal and informal roles in storing health information. Based on official health information privacy regulations, medical records clerks served as the main formal information reservoirs. After receipt of appropriate patient authorization forms, medical records clerks working at a specific site retrieved patient data from their site’s electronic or paper-based information repositories and sent data to the requesting site. Multiple informal reservoirs of external information participated in information exchange, including patients, family and friends of patients, residents, and other providers. Patients provided a layperson’s perspective on details of care episodes at other sites, results of recent diagnostic procedures, and information on diagnoses. While this level of information was helpful, clinicians often required additional detail for medical decision making. One ambulatory physician described information from patients by saying,

> *I have a lot of patients who just don't seem to understand what happened to them or what they tell me just doesn't make sense. So, I go to eHealth to clarify those sorts of questions. If they don’t seem to be able… they don’t seem to understand what happened to them. Or what they were told.*

The gap between a layperson’s description and the level of information needed for clinical decision making was also a problem in the ED, as a physician described,

> *Sometimes, the patients that we see in the emergency room don’t solely come to [my hospital] for their care, and they have been to other hospitals in the Memphis area and had tests done or lab work drawn, x-rays, EKGs, etc and they don’t know the full extent of the results of those tests. They can tell us that they had them done and if the doctor said that something was wrong... but they can’t give us the detail that we need with which to treat them on that particular day and so, that’s one way that eHealth helps us a lot because we’re able to pull up results from most of the other hospitals in the Memphis area and see exactly what they’re trying to explain to us in laymen’s terms and help us determine what studies to gear our workup for that particular day.*

During observation, we also identified another informal information reservoir: resident physicians. Residents affiliated with an academic medical program in the region formed an informal communications network as they rotated through different organizations in the region, providing them with access to different information repositories. This informal route often provided faster access to data than formal information exchange processes. Residents were both information reservoirs and information consumers in this instance.

Information exchange facilitators bridged the gap between information consumers and information reservoirs by assisting in intersite information transfer. Prior to HIE technology availability, a variety of groups filled this role: referral clerks, medical records clerks, registrars, other administrative staff, and also medical staff including nurses and physicians.

Ecology Component: Coevolution

The final information ecology concept that we mapped to the Regional Health Information Ecology was *coevolution*, the evolution of technology and individual work practices together over time. Both manual and technology-supported HIE processes were constantly shifting due to multiple factors. The individuals participating in information exchange constantly shifted due to changes in medical, administrative, and information technology staffing. Organizational policies toward HIE technology evolved over time, resulting in changes to what roles had technology access and who was responsible for supporting the technology. For example, one organization initially selected administrative clerks for HIE technology access, but over time moved access to nurse practitioners and physicians. The HIE technology continued to change in response to shifting organizational and user requests. The overall process of HIE and the technology supporting the process coevolved over time.

Impact of HIE Technology on the Information Ecology

HIE Technology Implementation

Figure 1 summarizes the Regional Health Information Ecology before HIE technology implementation. Information silos characterized the Regional Health Information Ecology, with limited health information availability outside of each parent organization. Information consumers such as physicians and nurse practitioners followed a formal and manual process to obtain data from external health care organizations. Information exchange facilitators including administrative staff and nurses bridged gaps between organizations, using fax machines and phone calls to convey information requests. Information repositories within medical records departments at each organization controlled external access to health information. An informal data exchange process facilitated by informal connections among resident physicians coexisted with the formal manual data exchange process.

HIE technology created a centralized information resource. Automated approaches to information exchange shifted roles and responsibilities and created new forms of interorganizational connections (Figure 2). The technology-supported information exchange process substantially changed how organizations exchanged information. Information consumers were able to directly access external health information. The roles of information exchange facilitators and information repositories were minimized in the new automated approaches. Availability of HIE technology fundamentally altered the Regional Health Information Ecology.

However, limited access to and adoption of the HIE technology resulted in both manual and automated information exchange processes coexisting. Availability of HIE technology did not fully replace the manual information exchange process. The Regional Health Information Ecology structures shown in Figures 1 and 2 both existed after HIE technology implementation. An overview of the study and its results can be found in Multimedia Appendix 1.

Figure 1. Regional Health Information Ecology, before HIE technology implementation.

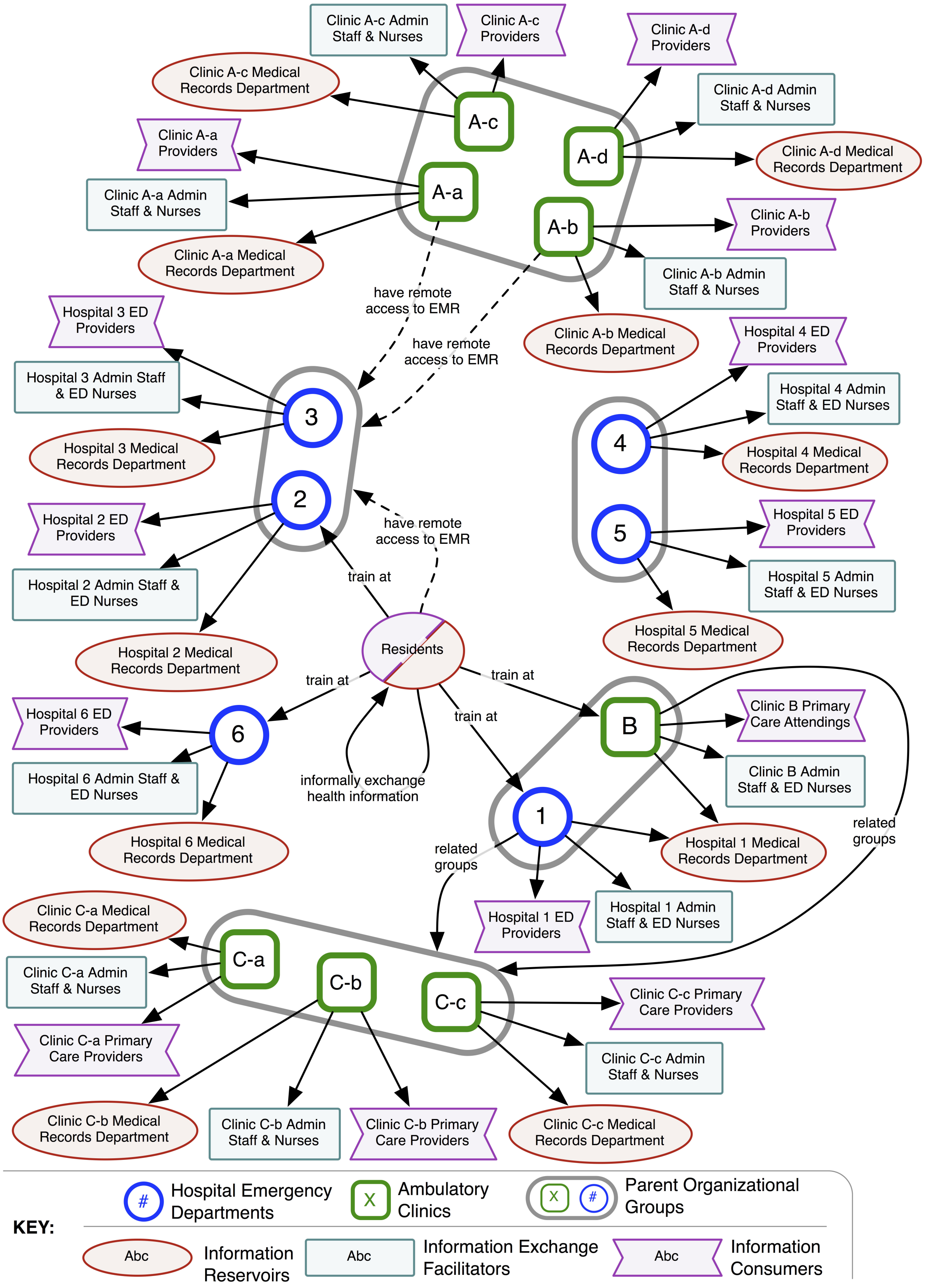
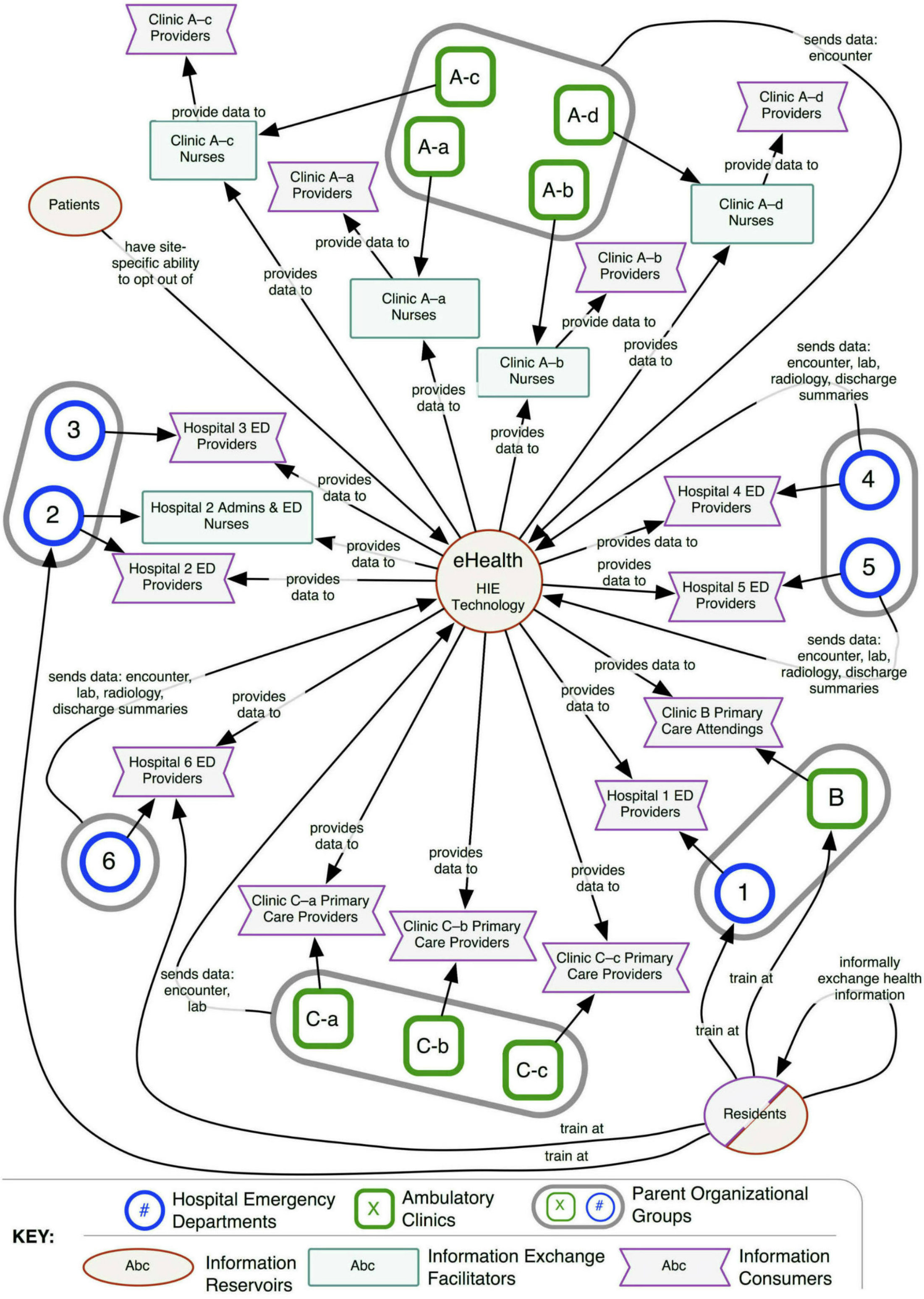


Figure 2. Regional Health Information Ecology, after HIE technology implementation.



We identified three categories of changes to the Regional Health Information Ecology with the introduction of HIE technology:

1. Moving from health information fragmentation toward unification, characterized by a shift from separate information silos and information fragmentation toward a more cohesive view of patient health.
2. Reduced time to obtain health information, created by streamlined processes to access information and a reduction in the role of information exchange facilitators.

3. Improved interorganizational communication among information technology departments, indicated by a shared sense of knowledge about health information technology practices in the community.

We will discuss each of the three categories in detail.

Moving From Health Information Fragmentation Toward Unification

Observation of both technology-supported and manual HIE processes illustrated the highly fragmented nature of each patient's individual health information. Even in a hypothetical scenario where a patient only visited clinics and hospitals sharing common information repositories, some external health transactions like filling prescriptions would occur outside that shared information environment. Observed patient situations were far more complex than this hypothetical scenario. Patients visited multiple clinical sites and health care organizations for primary and specialty care. We also observed a lack of intraorganizational information exchange within some organizations. In one organization, electronic health record systems used in their hospital and their ambulatory clinic group did not share data, introducing difficulty in following up after patients were discharged from the hospital. In other organizations, the ED information system was unable to share data with the hospital's electronic health record, creating information gaps when patients moved from the ED to inpatient care. Paper-based documentation processes further contributed to information fragmentation. Health care providers noted that the information available through HIE technology did not provide a complete record of all of the patient's health care information, but that the HIE technology improved information availability. As one ED physician stated,

> *For the first time, we've become more like a doctor in an office type practice, where we have that sort of continuity of care information that's never been available. It'll never be on par with a doctor's office, but we're getting a whole lot closer.*

Reduced Time to Obtain Health Information

Manual information exchange processes resulted in delays of information availability, described by providers as waiting for "hours" or "days" to receive requested records and sometimes never receiving them. Information exchange delays were particularly challenging in the ED setting. One ED physician described these challenges by saying,

> *Before, if I was working during the day, I could at least still contact the medical records department of another facility, get the patient to sign a consent form, fax the information over, and then hope that someone would fax it back to me. That wasn't always foolproof, but at least during the day, there was some chance of it happening. But if I worked the evening or overnight shift, I was just frustrated, because most medical records departments aren't open for outside help overnight.*

Delays in information availability affected not just providers but also patients as noted by one technology manager,

> *We'd been waiting for like three hours for one of the hospitals to fax over discharge summaries and stuff for somebody who was referred. As soon as [the providers] looked into eHealth they could get all that information right then and the patient didn't have to sit in the waiting room for another hour or two. They could be seen, right then and there.*

Availability of HIE technology increased the ability of health care providers to access health information, regardless of day or time, and had potential to improve patient health care experiences. The HIE technology also impacted medical decision making, by making information available immediately. One ambulatory physician noted, "Now, I can make a decision… having access to tests right now makes a big difference as far as making choices at the bedside." An ED physician described the impact of information obtained through the HIE technology, "Everything you do, it helps narrow the field on what you're having to deal with."

Increased Provider Awareness of Patient-Health System Interactions

Our previous grounded analysis of our data explored trust-related use of the HIE technology and provider use of HIE technology to identify individuals seeking narcotic medications [23]. Use of the HIE technology also increased provider awareness of patient interactions with other health care organizations. For example, ED providers could quickly identify if patients had a recent visit to another ED in the region. Knowledge of patient visits to other hospitals and procedures performed elsewhere changed how providers moved forward with medical decisions, as described by one ED physician,

> *Again, oftentimes it will just be that they just were at another hospital and had this complete workup done; they didn't share that with you. When you confront them with that, "Hey, you just left [another hospital], what did they tell you?" Then it just totally changes, changes what you do.*

Another ED physician discussed the impact of HIE technology on continuity of care,

> *The only thing we had before eHealth was sort of the continuity of the same doctors at the same place and as you kind of got to know patients a lot of times you can root some of this [information] out, but this helps earlier in the process now, you don't have to wait until you have some kind of personal experience with them. You've expanded your personal experience with them.*

ED providers also used the HIE technology to identify individuals possibly using the ED for primary care and attempt to redirect those individuals to ambulatory care resources, as described by one ED physician,

> *With frequent ER visits, I'm looking to see if they use the ER instead of going to clinics, use the ER for minor health issues, so that I can encourage them to find a primary care physician and maybe try to hook them up with a clinic they can use.*

The HIE technology also assisted primary care physicians with understanding recent hospitalizations or other health care interactions. The type of information available through the HIE technology provided greater depth than patient-provided information. An ambulatory physician described one patient scenario,

> *I had a patient who was hospitalized and when I checked the record [in eHealth], the discharge summary mentioned they had HIV as part of their diagnosis and they just didn't tell me that. They had fifteen other things that went wrong and when I called her, she said "Oh, yeah, I remember that… I just forgot and didn't mention it."*

Improved Interorganizational Communication Among Information Technology Departments

HIE technology also impacted health information technology specialists in the region. Implementing and supporting the technology required communication among information technology (IT) support groups across organizations. Working with IT support at different organizations allowed communication that previously was not common in the region. One IT manager described this shift in thinking about IT support by saying,

> *It's too bad that not every community, especially for IT, people at my level, to be able to talk to other people in real life, you're not alone… so that even if our best practices aren't industrial best practices, we can say that they're regional health care IT best practices.*

Implementation of the HIE technology fundamentally shifted how health care providers and IT support staff viewed other organizations in the region. Patient involvement in the design and implementation of the HIE technology was, however, quite limited. Patients were less aware than providers of the evolving process for information exchange among organizations, resulting in surprise for some patients when providers had access to information they had not disclosed.

The Paradox of Nonuse and the Regional Health Information Ecology

Regardless of how frequently an individual used the HIE technology, health care providers uniformly described HIE as a useful contribution to health care. An ED physician who frequently used the HIE technology expressed how much she valued the system for providing patient care:

> *I think eHealth is quite useful to me. eHealth to my ability to treat patients is like a cell phone is to now. You know, if you look back, you say "How did I ever survive without a cell phone?" but somehow we managed to do it. It's like now with eHealth, "How did I ever take care of patients without eHealth?" It has made a big difference.*

Even providers who were only sporadic HIE technology users uniformly described how useful the technology was, with comments like "When we use it, it's great."

Integration of the HIE technology into health care practices varied across sites and among providers. Substantial inter- and intrasite usage variability presents an intriguing paradox that researchers previously described with other types of health information technology [63]. If providers value HIE technology, why was it used so infrequently? How does this paradox of nonuse impact the evolution and future of the Regional Health Information Ecology?

Previous research examined questions of HIE technology use and nonuse through quantitative approaches [64,65]; our research adds a complementary rich layer of description to the understanding of usage questions through qualitative approaches.

Inconsistencies in the amount of information and the types of information available through the HIE technology created a barrier to use. Participating organizations determined information sharing policies for their own organization. Some organizations provided both raw data (eg, laboratory reports) and summary data (eg, discharge summaries), while others provided only raw data or demographic data. Although some providers expressed concerns about information overload, more commonly providers stated that there was too little information available through the HIE technology. Providers identified discharge summaries as especially important, with one provider stating "Accessing labs and radiology is nice, but pulling up the discharge summary is the cherry on the cake."

The HIE technology evolved over time as more hospitals and clinics contributed data and as the types of available data increased. For example, the HIE technology was initially directed only at EDs, but rapidly expanded to ambulatory clinics. The amount of data shared by ambulatory clinics was limited however, due to technology infrastructure barriers and ongoing organizational change. Despite efforts to communicate the availability of additional data, providers often seemed unclear on what data were available. Some providers, frustrated by initial data limitations early during implementation, stopped using the HIE technology altogether. Widely varying implementations of the HIE technology across organizations and specific sites increased the difficulty of reaching these providers.

Although providers uniformly discussed HIE technology as useful in general, some providers indicated it was not useful for their specific role. One ED provider stated, "I need to concentrate on life-threating illnesses. I don't have time to go looking through the chart looking for records." The same time pressure prevented some providers who used the HIE technology from understanding the full functionality of the tool. According to one ED provider,

> *I'm not sure if I'm using eHealth to its full potential. I've got in my little rut that I go through just because of repetition. Whether there's a lot more to offer from it, I don't know… I guess if I sat down and played with it, but I'm usually on it literally a few seconds at a time or a minute at a time and then I turn it off. Maybe there's some unlocked potential there that I'm not even aware exists.*

Our research also identified missed opportunities related to participating organizations and potential users for HIE technology. Although the majority of hospitals in the region participated in the HIE, two hospitals did not, causing gaps in information availability. During data collection, we identified several different types of health care sites outside of ambulatory and ED environments that could benefit from HIE participating including assisting living and nursing home facilities, radiology centers, and specialty clinics.

Organizations determined who had HIE technology access within their organization. We observed multiple cases of sharing logins and looking information up for other providers without HIE technology access, indicating a potential need for broader access. Groups that did not have HIE technology access that could benefit based on observation and interviews included: nurses, resident physicians, hospitalists, specialty care providers, and pharmacists. Nurses at several sites had HIE technology access, but not at all sites.

Our research identified a complex interplay of factors contributing to the paradox of nonuse of HIE technology in this specific Regional Health Information Ecology. The impact of addressing one or more of the factors identified through our research as contributing to nonuse requires changes in policy, technology, and organizations and concomitant evaluation.

Discussion

Principal Findings

The exchange of health information is integral to health care delivery, but significant gaps in information availability present a long-standing and continuing challenge. The manual and formal information exchange processes that we observed resulted from a culture of “information silos”, where organizations tightly controlled access to their own data and health care providers had limited expectations of data availability. Our study demonstrated that HIE technology opened these “information silos” by bridging information gaps among competing organizations. When used, HIE technology allowed providers to directly access health data across contexts and organizations. Direct data access reduced frustration caused by restricted access to external information and improved interorganizational information flow. The new form of information availability resulting from HIE technology allowed providers to proactively seek patient health information, rather than relying primarily on patient self-reports.

The changes in information flow that we observed demonstrated how the Regional Health Information Ecology evolved in response to technology-supported data exchange. Health care providers at some sites significantly altered their health information practices and expectations of data access. Inconsistent adoption levels within and across organizations, however, resulted in many sites where health information practices of health care providers remained effectively unchanged. Limited adoption of the HIE technology revealed gaps in how HIE technology designers and implementers viewed work practices related to information exchange.

Our research also demonstrated how provider perspectives about health information from outside their organization affected HIE technology adoption. Perspectives on health information needed to shift for successful HIE technology implementation and adoption. From a management and technology support perspective, HIE technology requires organizations to relinquish proprietary interest in health data. HIE technology challenges how health care providers view information, broadening the scope of information available for medical decision making. Approaches that assist with changing organizational perspectives on health information ownership are needed. Support for demonstrating to health care providers how this broader information base can contribute to patient care may also improve adoption. Based on observation and interviews, successfully implementing HIE technology requires awareness of perspective shifts required of health care providers.

Based on our research, we hypothesize that greater evolution of information exchange across a Regional Health Information Ecology requires consistently higher rates of HIE technology adoption and inclusion of a broader range of health care organizations across the region, suggesting foci for future HIE technology efforts. Our research revealed barriers to and opportunities for continuing evolution of the Regional Health Information Ecology. Strategies to extend the reach of the HIE technology could include adding more types of health care organizations to the exchange and working with organizations to provide HIE technology access to more health care roles. Existing progress with the information ecology demonstrates, however, the challenges of communicating dynamic system information across organizations. Strategies are needed to overcome barriers to improving HIE technology support for the Regional Health Information Ecology.

Future interorganizational data exchange efforts can build on this research; organizers should examine the Regional Health Information Ecology during HIE technology design and implementation. During initial design stages, organizers could apply awareness of the existing interorganizational landscape and navigate challenges created by long-standing competitive relationships. Implementation planners could use information ecology knowledge to develop an evidence-based approach to implementing exchange technology across organizations, sites, and clinical contexts. System designers could also tailor HIE technology to specific components of local contexts, to best meet regional and local needs. For example, understanding the role of informal information exchange processes, like the residents in the Memphis case, could provide a basis for design of technology features to support different perspectives on health information. Awareness of components of the Regional Health Information Ecology could also help HIE technology implementers to identify potential challenges prior to implementation. Our research suggests the need for HIE technology efforts to provide cross-organizational expertise to help guide technology implementation in specific contexts. While leaders within organizations know their context well, they may have limited experience with identifying challenges to achieving widespread technology adoption and use. Most importantly, lessons about information ecology and applications of HIE technology across organizations can provide an evidence base for context-specific design and implementation strategies.

Limitations

Our research followed a rigorous protocol directed at ensuring confirmability of this qualitative research, but the study has several limitations. The research setting was one example of the application of a specific HIE technology approach to a specific regional context. We would expect specific details of a Regional Health Information Ecology to vary depending on multiple contextual factors, but the broader ecology concepts developed through this research are transferable to other settings and other HIE structures. A single researcher collected the data for this study, introducing the potential for observer bias. As with any observational study, the Hawthorne effect was a potential data confounder. Both the HIE technology and the regional health care environment changed during the course of the study. We addressed these potential limitations through multiple approaches. The data, data analysis processes, and outcomes of data analysis were discussed extensively with other members of the research team, formal and informal advisors specializing in ethnographic approaches, and a peer reviewer with extensive qualitative experience. Interviews with observation subjects and other exchange users provided member checking of observation analysis. The researcher asked probing questions throughout observation and interviews specifically directed at determining potential observer effects on work activities and potential researcher effects were carefully examined during data analysis. We incorporated information about changes to the HIE technology and to the regional health care environment in our data. We sought to address potential limitations of the study through these multiple approaches.

Conclusions

The goal of our research was to examine the impact of HIE technology on the Regional Health Information Ecology as part of developing an in-depth understanding of the context. The context in this case was the MidSouth eHealth Alliance and the Memphis region. The research introduced a qualitative and ethnographic perspective to the evaluation of technology-supported HIE. By applying the Information Ecology Framework to HIE, we moved beyond the local interaction level and captured a spectrum of the ecology from the highly localized and individualized level of detail to the broader community level. Our study demonstrated that the Regional Health Information Ecology is a complex, constantly evolving Web of relationships among organizations and individuals.

Examining the Regional Health Information Ecology provides a foundation for future HIE efforts and a pathway toward customization of HIE systems. Although contextual factors vary among HIE implementation environments, the patterns of HIE use identified through this research and the methodology we applied can serve as a starting point for design and implementation efforts elsewhere. Other HIE structures such as smaller private exchanges or directed exchange could use the Regional Health Information Ecology concepts as a starting point for analysis of their own specific ecological constructs and needs. The next phases of interorganizational data exchange must build greater awareness of the needs and perspectives of intended HIE system users to achieve wider technology diffusion and adoption.

Acknowledgments

This research was supported by NLM Training Grant #T15 LM007450 and by contract 290-04-0006 from the Agency for Healthcare Research and Quality. The authors thankfully acknowledge the contributions of Drs Madhu Reddy and Bruce Barry to the design of the overall research study and critiques of data collection and analysis. Dr Jacob Weiss served as an external peer debriefer throughout the research project.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Study and results overview.

[MP4 File (MP4 Video), 228MB - medinform_v1i2e3_app1.mp4]

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Abbreviations

ED: emergency department
HIE: health information exchange
IT: information technology

Edited by G Eysenbach; submitted 21.12.12; peer-reviewed by R Elmore, M Solomon; comments to author 27.04.13; revised version received 20.09.13; accepted 13.10.13; published 29.10.13.

Please cite as:
Unertl KM, Johnson KB, Gadd CS, Lorenzi NM
Bridging Organizational Divides in Health Care: An Ecological View of Health Information Exchange
JMIR Med Inform 2013;1(1):e3
URL: http://www.jmir.org/2013/1/e3/
doi:10.2196/medinform.2510
PMID:25600166

Publisher:
JMIR Publications
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Email: support@jmir.org