TOWARDS A FRAMEWORK FOR REALIZING HEALTHCARE MANAGEMENT BENEFITS THROUGH THE INTEGRATION OF PATIENT'S INFORMATION

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Abstract

Business Intelligence (BI) applications, including customer relationship management systems, decision support systems, analytical processing systems, and data mining systems, have captured the attention of practitioners and researchers for the last few years. Health care organizations, which are data driven and in which quality and integration of data is of paramount importance, have adopted BI applications to help and assist healthcare managers in improving the quality of the information input to the decision process. Based on preliminary data collection results, it is found that high quality data is essential to successful BI performance and that technological support for data acquisition, analysis and deployment are not widespread. Yet, business organizations are not investing in improving data quality and data integration.

In this paper the authors propose a framework for evaluating the quality and integration of patient's data for BI applications in healthcare organizations. In doing so, a range of potential benefits is highlighted. Even though this framework is in an early stage of development, it intends to present existing solutions for evaluating the above issues. The authors conclude that further research needs to be carried out to refine this framework, through model testing and case studies evaluation.

Keywords: Data Quality, Data Integration, Business intelligence (BI), Healthcare Information Management.

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1 INTRODUCTION

Business intelligence (BI) is a strategic approach for systematically targeting, tracking, communicating and transforming relevant data into actionable information on which strategic decision-making is based. Business Intelligence is a new term which has replaced the old terms such as; decision support, executive information systems, and management information systems (Thomsen, 2003). Business intelligence systems combine operational data with analytical tools to present complex and competitive information to planners and decision makers. Their objective is to improve the timeliness and quality of the input to the decision process (Negash and Gray, 2003). Demand for Business Intelligence (BI) applications continues to grow remarkably (Negash and Gray, 2003; Soejarto, 2003; Whiting, 2003).

The healthcare field is highly specialized. Patient visits various organizations or units within organization to get proper treatment. Enterprise systems such as, Enterprise Resource Planning (ERP) systems, Customer Relationship Management (CRM) systems and Data Warehousing programs are deployed in healthcare for various purposes such as information sharing, strategic decision-support analysis (see Figure 1), data quality, data integration and the integration of hospitals internal systems (Khoumbati et al., 2003; Ball, 2003; Lee et al., 2003). The adoption of these systems in healthcare is making data management technologies even more critical (Alshawi et al., 2003; Grimson and Grimson, 2000; Hakkinen et al., 2003). The ability to support both business-to-business and business-to-consumer efforts often rests on a foundation of database systems, along with standards and Web-deployment technologies to ensure connectivity (Payton, 2001).

Health care industry includes many types of organizations, which are data driven and in which quality and integration of data is of paramount importance. Organizations such as, National Health Services (NHS), government health agencies, and pharmaceutical companies have data quality and integration problems. For example, the effect of poor data quality and integration in the public health sector can be seen in death certificate data (Altman, 1998). These data quality and integration issues are exacerbated by transferring data of less than optimal quality and integration from transaction processing into data warehouses or database systems. The data are then readily available to decision-making managers.

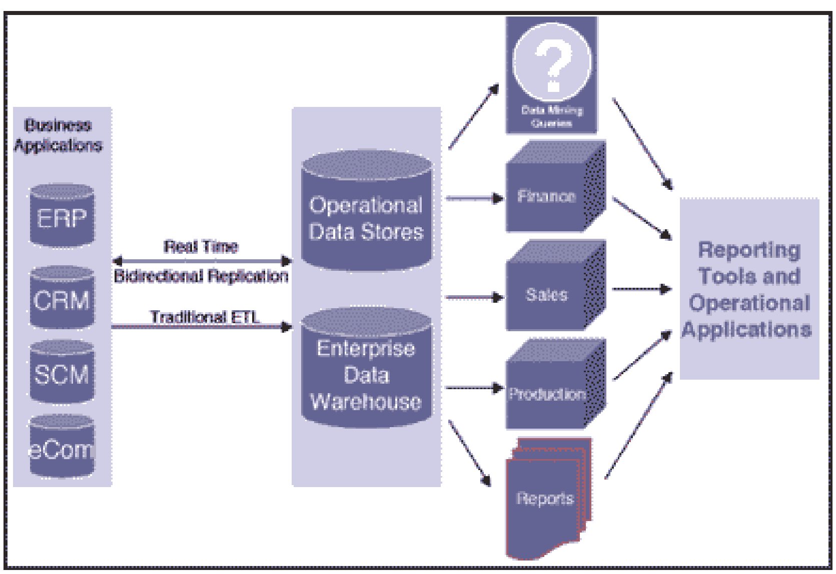

Figure 1. An example of Decision-Making Environment.

The decisions made by these managers reverberate throughout the organization as the decisions are operationalized. Implementation strategies are developed and policies and procedures for various corporate activities result. For these activities to be of value to the business, the quality of the decisions is based on the quality of the data and information used in making the decisions (Ballou and Tayi, 1999b). Thus, it becomes very clear on today's healthcare organization to ensure that quality and integration of patient's data are available and used in corporate decision-making.

Although many healthcare organizations have successfully implemented certain aspects of BI systems, an integrated approach to BI in Healthcare organizations remains to be developed. This paper is concerned with exploring and optimizing the available data quality and data integration issues that can be used by BI enabling tools in healthcare organizations. The main objective is to develop a well-defined, generic, and stepwise framework that encapsulates the different data quality and data integration processes necessary to satisfy the patient data requirements of a healthcare organization's BI system. The proposed framework architecture comprises four main evaluation and integration levels, and deals with both internal and external acquired patient information. The methodology is based on performing sequential analysis that progress from simple tests of data quality and integration to more rigorous, complex and extensive tests, which gives a comprehensive and complete assessment of the existing tools, and exposes and quantifies both strengths and weaknesses of these tools. The generic architecture enables the framework to support and utilize any type of available software product ranging from off-the-shelf packages developed for a general consumer database, through projects commissioned by a consumer, to embedded software. This concept also supports technology changes without needing modification of the basic structure of the framework. The work will then be expanded to develop and test progressive levels of the proposed framework using an evolutionary approach. Accordingly, a case study will be used as part of the research strategy.

2 PATIENT'S INFORMATION

Patient's data is usually spread throughout healthcare organizations' departments on different systems. Some of these are the operational systems, which run the healthcare business. Others are used for reporting purposes and healthcare business intelligence, such as data marts, data warehouses, and OLAP systems, where all patient information is acquired, stored, and accessed. Data warehouse is a separate store of transactional data that provides a single integrated view of the patient, and a strategic infrastructure for decision support (Newing, 2000). Data marts are subsets of a data warehouses, they are designed to support the requirements of a particular department or business function for Online Analytical Processing (OLAP). OLAP is the dynamic synthesis, analysis, and consolidation of large volumes of multi-dimensional data (Connolly and Begg, 2001).

Most operational systems have the ability to export patient data. Over the past few decades, healthcare personnel have been gathering patient data into healthcare organizations' databases to make better informed healthcare decisions (Henderson, 1995). Statistical modeling, campaign management and data mining tools are but some of the ways to segment patient information and prospects into lists that allow for the optimum expenditure of time, people and money (Kenyon, 1993). Often patient data is stored in a relational database, such as Oracle, Informix, Sybase, DB2, or SQL Server. Data can also be in flat files, log files, or other file structures (Connolly and Begg, 2001). Data mining is a natural extension to this effort. Data mining techniques typically take place on a separate platform, requiring that patient data be imported from other systems. Data mining is the process of exploration and analysis, by automatic or semi-automatic means, of large quantity of patient's data in order to discover meaningful patterns and rules (Rud, 2000; Berson et al., 2000).

Patient data associated with the above mentioned tools are the foundation upon which any successful BI strategy is built. The master tool, however, is the patient database. Databases as described in Connolly & Begg (2001), are shared collections of logically related data (and description of this data), designed to meet the information needs of healthcare organizations (see Figure 2.1). The database is the central repository for all of the information pertaining to the relationship of a healthcare organization and its patients. Analyzed patient data for BI use comes from both internal and external sources. Internal sources such as administrative, medical, and pharmacy departments. External sources, such as syndicated, government, demographic, geographic data, as well as externally purchased business data, such as local user-generated data, graphical and map-based data, statistical data, Web-based data, click-stream data, call centers, direct mail, and key government-produced economic indicators.

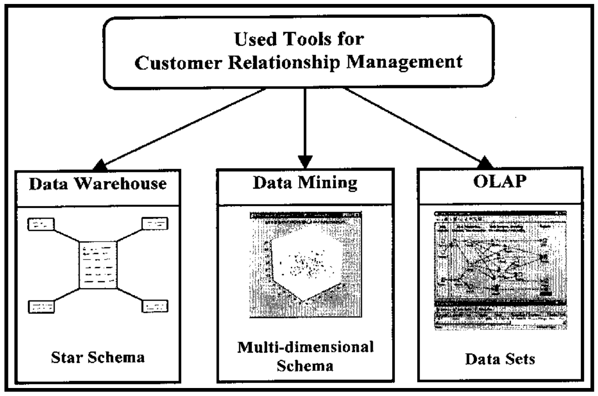

Figure 2.1. Examples of Data Types Required for BI Tools.

BI systems may use all the above and other tools and applications to analyze patient's information and to drive health marketing initiatives, based on observed regularities of patient behavior (Berson et al., 2000). Some of the tools used to accomplish this are patient profitability analysis, marketing analysis, campaign management and sales contact management. These tools applied to the BI database, enable healthcare organization to develop theories about how patients might respond to initiatives and then to track their actual responses and use this experience in future efforts.

3 DATA QUALITY AND DATA INTEGRATION ISSUES

Data quality and data integration issues have been a continuing concern to those in the information systems profession and research. Over time techniques and procedures have evolved, designed to leverage and make sure that the level of data required by the traditional transactions processing systems is of appropriate level of quality (Ballou and Tayi, 1998; Ballou and Tayi, 1999a; Leiheiser, 2001).

Data quality has become increasingly important to many healthcare organizations as they build data warehouses and focus more on BI applications. Significant effort has gone into defining what is meant by data quality (Ballou and Tayi, 1999b; Inman, 1996; Khalil and Harcar, 1999; Redman, 1998; Leiheiser, 2001). The issue of data quality concerns arise when one wants to correct anomalies in a single data source (e.g., duplicate elimination in a file), or when one wants to integrate data coming from multiple sources into a single new data source, such as data warehouse (Morgan, 2001).

At the strategic level, poor data quality has the potential for putting companies at a competitive disadvantage by making it more difficult to execute strategies in areas such as data warehousing, customer relationship management (CRM), and e-business (Eckerson, 2002).

In the healthcare environment, processes are built around collecting patient information from transactions. Patient information enters these systems through many touch points, such as the Internet, call centers, direct mail pieces, sales systems, and orders (Stern et al., 1998). These data collection points in the primary operational systems become the gateways for patient data to enter the healthcare organization. If defective data enters at this point, it can spread throughout all of the shared operational systems as well as the decision support systems. Healthcare organizations are realizing how expensive it can be to correct patient information after it has been entered into the healthcare database system. Furthermore, decisions are only as good as the data on which they are based. It follows, then, that improving results requires improving the quality of data.

English (1999) observes that bad data can cost businesses as much as 10 to 20 percent of an enterprise’s total budget through lost revenue, and as 40 to 50 percent of an IT department budget may be spent correcting errors caused by bad data. The best way to avoid these excessive costs is to focus on the prevention rather than the correction of defects. Preventing an error can cost ten times less than fixing it. This is the concept behind data quality program, which is actually a process for managing quality that involves perpetual improvement.

Data quality initiatives begin at the data warehouse entry phase (English, 1999). Data entry validation becomes the first line of defense in the battle against bad data (Kim et al., 2003). Today, technology makes it possible to clean data in real-time as it enters the enterprise (Galhardas et al., 2000). Many healthcare organizations today have legacy systems, and every line has its own patient database, and the information in these disparate databases is never shared across all healthcare departments. This approach creates an environment that breeds poor data quality, which leads to a poor understanding of the nature of patients’ information in the healthcare organization. Loss of data integrity, in the other hand, results in an invalid or corrupt data, which may seriously affect the operation of the healthcare organization (Spriestersbach et al., 2001).

Healthcare organizations moving toward full BI Strategy, know that the process of discovering who their patients are and what they really want begins with patient data integration. Patient data integration is essential for a unified view of the patient’s information, and for successful healthcare organization (Spil et al., 2002; Sujansky, 2002). With out a complete picture of patient interactions with the healthcare organization, it is impossible to generate maximum results. Ideally, patient data integration must occur in real time to meet the increasing demands of patients and to take advantage of healthcare management opportunities. Different operational systems and third-party data providers format data differently. One system may carry dates in a *month/day/year* format, while another system may carry dates in a *day/month/year* format. Different operational systems use different codes for the same data point. One may use a *1* to represent a male, while another uses an *M*. Without a painstaking examination and analysis of each source data point, data can not be integrated from the multitude of patient contact point operational systems (Berry and Linoff, 2000).

A BI healthcare organization simply must have immediate access to timely, accurate data if its BI programs are to be successful. With their internal databases integrated and functioning as a single information resource, healthcare organizations will have the ability to understand their patient’s needs far better and, consequently, tailor their services more effectively to meet patient's needs (Duke et al., 1999). Integration, also, means a BI healthcare organization can combine information on all products and services used by a patient and share that information across all delivery channels and point of contacts. As BI healthcare organizations accelerate their investments in alternative delivery channels, the integration problem is becoming more difficult (Spil et al., 2002; CPM White Paper, 2003).

4 THE FRAMEWORK

The proposed framework (see the diagram in Appendix A), is designed to assist healthcare organizations in supporting their BI enabling tools with high-quality and properly integrated patient data. This involves various operations in terms of quality data collection, cleansing, standardization, enhancement and consolidation (see Figure 4.1).

Evaluation is conducted through a well-defined, step-wise architecture which, to achieve flexibility, is based on four data quality evaluation and data integration levels. Each level is designed to analyze the quality of the data from a different perspective using appropriate criteria to identify the various types of data quality and integration problems that may be present. The analysis provides a structured framework in which to plan, organise and perform a systematic assessment as shown in the diagram (appendix A).

The analysis is designed to address relevant types of data quality and integration problems, and requires that appropriate quality and integration criteria are to be available or established. Hence, existing data quality and integration conditions are measured against those criteria. Analyzing each level in sequence is important because it is useful in understanding the problems at one level and how they can have a compounding effect on the results at a higher level of analysis.

The methodology is based on performing sequential analysis that progresses from simple tests of data quality and integration to more rigorous, complex and subtle tests. By following this methodology, the data quality and integration analysis results in a comprehensive and complete assessment of the existing tools, and exposes and quantifies both the strengths and weaknesses.

With data quality and data integration technology in place, healthcare organization will benefit a significant competitive advantage over traditional organizations. In head-to-head competition, the consumer-centric, or BI healthcare organizations will prevail because of their ability to quickly integrate meaningful patient information and then use the findings in their planning, marketing and decision efforts. Data integration technology represents a quantum leap forward. It will offers BI healthcare organizations a revolutionary opportunity to significantly improve patient acquisition and retention, dramatically enhance healthcare services, increase patient loyalty and preference, and maximize the lifetime value of each patient.

5 THE FRAMEWORK ARCHITECTURE

This section introduces the architecture for the framework, a data quality and integration model for BI applications (see diagram in Appendix A), which includes the following levels:

- Level 1: Identifying sources of patient data,
- Level 2: Data quality matching and comparison phase,
- Level 3: Data integration process,
- Level 4: Data quality Final Checks; Evaluation, Monitoring, Archival and Distribution phase.

Level 1: Patient information for BI use is collected from both internal and external sources (see Figure 4.1). Internal sources such as administrative, medical and pharmacy departments. External sources such as syndicated, government, demographic, geographic, as well as externally purchased business data such as local user-generated data, graphical and map-based data, statistical data, Web-based data, click-stream data, call centers, direct mail, and key government-produced economic indicators.

To ensure that patient data in the BI system supports fact-based decision-making, our recommended approach for incorporating data quality into the BI data warehouse, comprises these key stages:

- Define data quality expectations and metrics **-** Describe the quality of data that is required to support each major BI application.
- Identify poor data and its limitations **-** Forecast how the data made available through the BI data warehouse can fail to meet expectations.
- Assess data quality limitations **-** Implement appropriate data defectors and reporting mechanisms to help clarify data quality problems and decide whether to keep the data, and how to improve quality.
- Improve data quality **-** Take action to minimize bad data entering BI system.

The best methods of ensuring data quality, involve both the human experts and state-of-the-art tools. Assuming that we have identified the functionality provided by leading edge data quality and integration tools, that the appropriate tools to extract, transport and clean the data have been used, and insuring the quality of data regarding the way it is going to be used. Data quality problems are identified early during this phase, on day-to-day basis operations, which will reduce the likelihood of an event and the severity of its impact. Defining the user's expectations for the data, these expectations are defined using metadata and data quality metrics that measure the characteristics of data appropriate for each use. Several processes are used, such as accuracy, completeness, consistency, relatabilty, timeliness, uniqueness, and validity. This process will specify quality requirements for measuring the actual quality achieved within the BI healthcare organization.

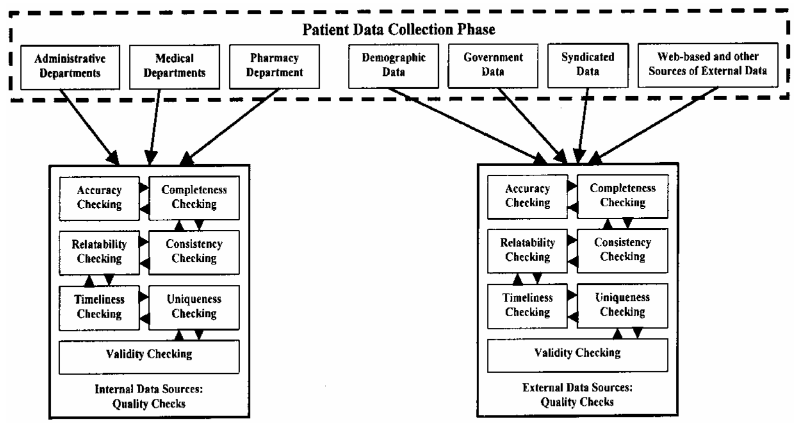

Figure 4.1. Patient's information Collection Phase.

When dealing with accuracy of data, each field must be looked at independently as well as dependently, especially if the data in question was originally from multiple sources. The values within one field may appear correct until associated with another field such as date, source, product, etc. Also, consider the source when investigating data inaccuracy. The degree of accuracy of any one data set is highly correlated to its source.

One of the finest companions of accuracy is completeness. Conversely, there may be nothing more frustrating than having 99.9 percent accurate data, only to have 40 percent blank or missing data (English, 1999). Often, this is unavoidable, such as the case of appended demographic data. But in other cases, it is the result of lost data or non-capture before a certain time or by a certain source. There may be nothing to do but identify the problem and fix it at the source. Similarly, consistency can be a challenge because it requires discipline over time. Again, problems must be fixed at the source and protocol must be established so to avoid mentioned problems in the future. A business will change and so will data input. It may be a new Web channel, a new telemarketing program or a new business partner.

Relatability is the agreement or logical coherence that permits rational correlation in comparison with other similar or like data. By timeliness, we mean the data that is not available when a decision needs to be made or the shelves need to be stocked (late data will hurt business). Another data quality issue is Uniqueness, where data values are constrained to a set of distinct entries, each value being the only one of its kind. Finally, the data quality process validity, which is the conformance of data values that are edited for acceptability (e.g. reducing the probability of errors). This procedure is, also, performed at the various phases of the data quality life cycle, and this is called the first phase of the data quality maintenance and archival procedure.

Level 2: Is the data quality matching and comparison phase. Patient information is collected from both internal and external sources (see Figure 4.2), data quality procedures are further used. This time is to measure the high characteristics of the data quality imported into the BI System against the internal ones, and compares the results to the expected quality of data defined by the standards mentioned above.

In this phase, the analysis of the data (from previous level) should be coupled with secondary sources that can supplement existing data or complete missing data. Information, such as demographics and credit ratings help to better describe the patient/consumer. Thus, help BI healthcare organizations (for example) to better predict future trends. Information that enhancement adds to a record may include data such as age, presence of children, and educational level for individuals. Parsing, correction, standardization, and enhancement ensure that all of the necessary data is present. Once a quality patient record exists, matching should become part of the data quality analysis to eliminate redundancies. Matching searches existing patient's data records using specific business defined criteria to look for similar records. Using match standards and specific business rules eliminates any doubt as to whether two records refer to the same individual patient or entire household.

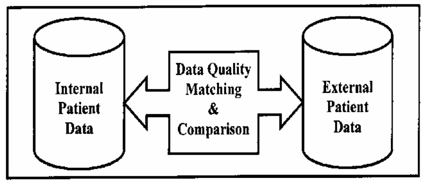

Figure 4.2. *Data Quality Matching and Comparison Phase.*

Level 3: The data integration process (see Figure 4.3). In order to add value to the healthcare organization's internal patient information, the picture of the BI healthcare data management is enhanced through the integration of data, which as discussed previously, generated from internal and external sources. Consequently, many healthcare organizations have significant data integration challenges, others use different data integration tools and techniques. Our approach will review and investigate these challenges, and suggests a consolidated data integration architecture as a solution.

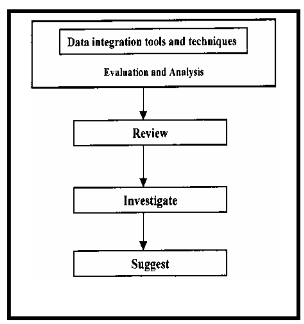

Figure 4.3. *Data Integration Process*

Consolidation uses the data found during matching to combine all of the similar data into a single consolidated view of each patient. This is a critical component of effective BI business decisions and successful one-to-one marketing campaigns. In good data quality environments, consolidation also goes one step further. It identifies the relationships between patients. Business grouping combines business records that share information such as business name, address, department, or title.

Level 4: The data quality final checks, evaluation of the results monitoring and archival phase (see Figure 4.4). Once complete, the integration of patient data into the healthcare organization's BI system provides a unified patient profile that allows the healthcare managers to enhance every patient-related decision. Archival phase is used to protect obsolete data from misuse, and record the success or failures of attempts to use the data for various BI applications while the data was active. Patient data is now ready to be distributed to BI healthcare organizations' servers (e.g. OLAP servers, mining servers, data marts, and other servers).

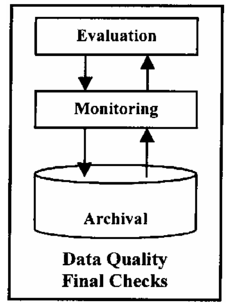

Figure 4.4 : Data Quality Final Checks

6 CONCLUSION

The discussion has focused upon the difficulties faced by existing healthcare data management infrastructures regarding the implementation of BI strategies, to help and assist healthcare managers in improving the quality of the information input to the decision process and support their patients' database systems. In this paper the authors proposed a framework that encapsulates the different data quality and data integration processes to satisfy the requirements of healthcare organization's BI system.

The methodology is based on performing sequential analysis that progress from simple tests of data quality and data integration to more rigorous, complex and extensive tests and analysis. Evaluation is conducted through a well-defined, step-wise architecture which, to achieve flexibility, is based on four data quality and data integration evaluation levels. The use of such architecture will support technology changes without the need to modify the basic principles of the framework. The standardization of the detailed processes within these levels is beyond the scope of this paper, and requires further research and design refinement through model testing and case study evaluation.

Furthermore, creating a common infrastructure for data acquisition, validation, integration and distribution into the healthcare information management will insulate the decision support infrastructure from operational systems infrastructure changes, such as re-engineering, re-platforming or re-mediating.

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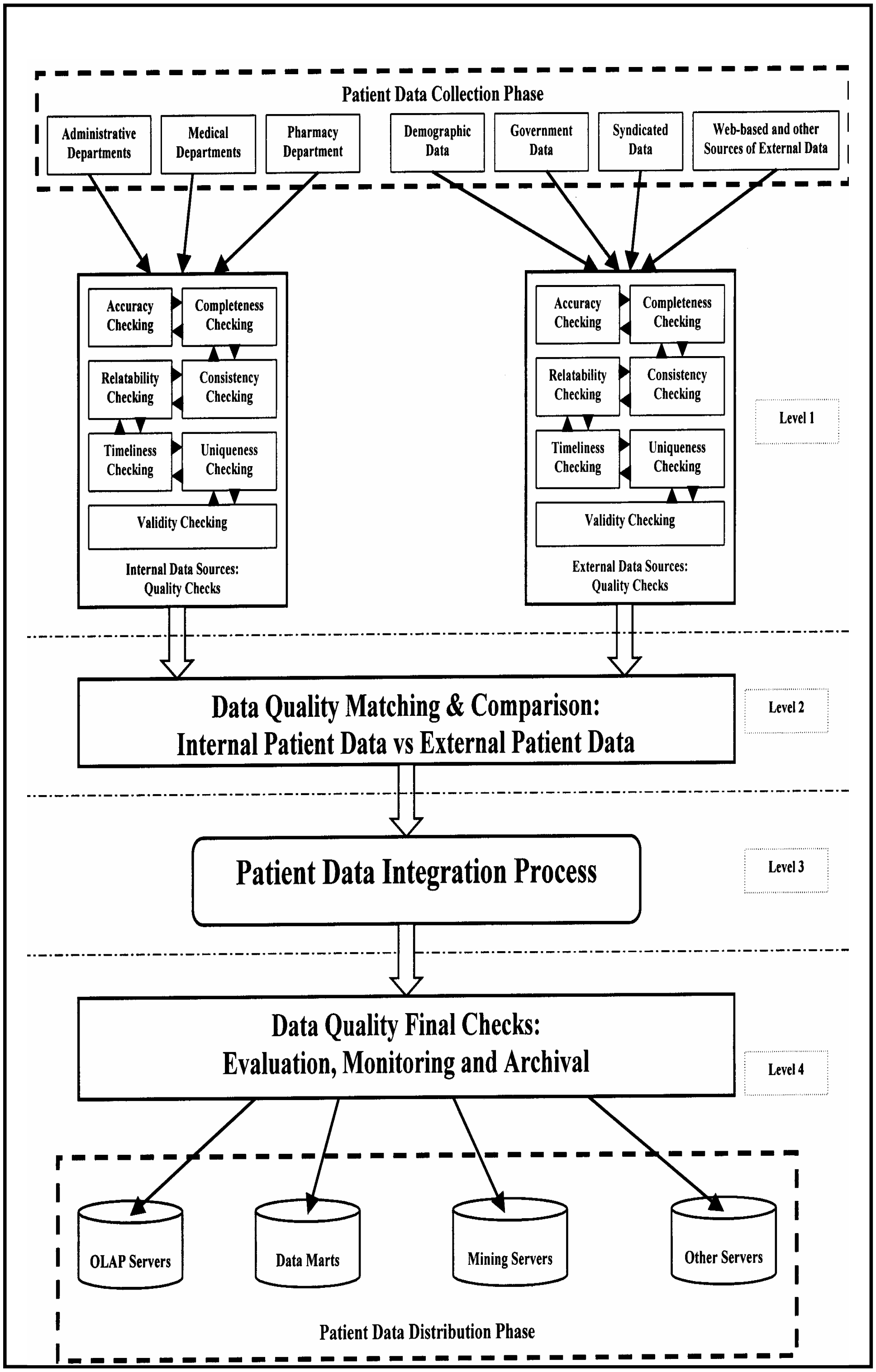
Appendix A:



Patient Data Collection Phase
Administrative Departments
Medical Departments
Pharmacy Department
Demographic Data
Government Data
Syndicated Data
Web-based and other Sources of External Data
Accuracy Checking
Completeness Checking
Relatability Checking
Consistency Checking
Timeliness Checking
Uniqueness Checking
Validity Checking
Internal Data Sources: Quality Checks
Accuracy Checking
Completeness Checking
Relatability Checking
Consistency Checking
Timeliness Checking
Uniqueness Checking
Validity Checking
External Data Sources: Quality Checks
Level 1
Data Quality Matching & Comparison:
Internal Patient Data vs External Patient Data
Level 2
Patient Data Integration Process
Level 3
Data Quality Final Checks:
Evaluation, Monitoring and Archival
Level 4
OLAP Servers
Data Marts
Mining Servers
Other Servers
Patient Data Distribution Phase

Figure 4: Framework Architecture for Evaluating The Quality and Integration of Patient's Data for BI applications in Healthcare Organizations.