# e-Health monitoring applications: What about Data Quality?

Claudia C. Gutiérrez Rodríguez, Michel Riveill
I3S – CNRS - University of Nice - Sophia Antipolis
930 route des colles – BP 145
06902 Sophia Antipolis, France
+33 (0)4.92.94.27.05
{cgutierr, riveill}@i3s.unice.fr

## ABSTRACT
Data quality analysis remains a difficult issue on several domains (e.g. geographic, software, databases, etc.). This is particularly the case on e-Health monitoring applications for chronic patients, where the need of data quality to ensure correct decision making is very important. Patients monitoring refers to a continuous observation of patient's condition (physiological and physical) traditionally performed by one or several body sensors. In fact, significant actions and decisions are based on data coming from such sensors (e.g. remote diagnosis, consultations, hospitalization…). Providing high data quality helps to guarantee a correct processing and interpretation of information, as well as the appropriate intervention of medical services. In this paper, we explore the principles and issues of data quality in this particular domain providing primary research clues and motivation about this subject. We underline the necessity of the analysis of data quality on e-Health applications, especially concerning remote monitoring and assistance of patients with chronic diseases.

## Categories and Subject Descriptors
J.3 [**Computer Applications**]: Life and Medical Sciences – *Health;* K.6 [**Management of Computing Information**]: System Management – *Quality assurance*

## General Terms
Reliability, Measurement, Management

## Keywords
Data quality, e-Health applications, Remote medical monitoring, Medical assistance

## 1. INTRODUCTION
According to the WHO (World Health Organization) in 2020 most of the diseases worldwide will be due to chronic pathologies as diabetes, hypertension or cardiovascular diseases. Thus compounds the problems of obesity and intensify the activity monitoring (i.e. actimetry). The evolution of such pathologies requires numerous and expensive cares. Homecare associated to a remote medical monitoring and assistance becomes unavoidable.

Nowadays, the improvement of ICT (Information and Communications Technology) strongly helps to provide better quality of healthcare. For example, the use of high-technology body sensors (i.e. pulse, body temperature, ECG…), wired and wireless communications technologies, real-time data processing, interactive interfaces, etc. This improvement has been a motivation for new healthcare programs and approaches (i.e. Medic4you, Health Guide, Medmobile…) which attempt to better assist patients with chronic or genetic diseases. Such programs allow better quality and accessibility of healthcare systems and develop the information exchange between medical professionals. However, the management of data in this kind of systems is becoming increasingly complex. Frequently, decision makers (medical experts or professionals, medical services…) are confronted to inaccurate, incomplete or excessive information. As a result, more and more questions concerning data quality, security and privacy in this domain arise. Particularly, ensuring the data quality in healthcare domain remains an important issue. If data quality is ignored, collected data may have considerably negative impact on the achievement of the application and on the decision making.

In this research work, we claim that data quality in e-Health monitoring applications cannot be neglected and neither restricted to basic data quality approaches. We believe that a better understanding of the meaning of data quality issues improves also the quality of decision making and thus better will be the patient outcomes. Several features of data quality analysis over e-Health monitoring applications are illustrated in this paper by a scenario from a current research project – STM3: A solution for the medical assistance and monitoring in a mobile context - grouping industrial and academic research teams, as well as users and manufacturers from electronics, communications, and computer science domains. The project is supported by the French cluster SCS (Secure Communication Solutions).

The remainder of this paper is organized as follows: In section 2 we introduce e-Health applications and our interest on data quality over this kind of applications. We describe the main aspects which motivate our work. Section 3, describes our initial view of quality issues in this domain. In this section we depict the scenario used as a reference for this research. We also introduce a general analysis of data quality impact resulting from e-Health monitoring systems specificities and data quality aspects comparison. Such analysis is based on current data quality


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modeling approaches. We conclude and present our future work in Section 4.

# 2. MOTIVATION

In the last few years, technological improvement opens new possibilities to healthcare and medicine practice, but carriers some inherit risks and leaves decision makers with numerous unanswered questions about quality, security and other important matters. Some surveys and approaches have showed the importance of data quality of end-users, particularly in healthcare domain [23], [13].

E-Health monitoring applications have some particularities concerning the importance on data quality. On the one hand, successful healthcare delivery and planning strongly rely on data (e.g. sensed data, diagnosis, administration information); the higher quality of the data, the better will be the patient assistance. On the other hand, these applications are also particularly exposed to a contextual environment (i.e. patients' mobility, communication technologies performance, information heterogeneity…) that has an important impact on information management and application achievement. Motivated by these observations, we study the related data quality issues over the specificities of e-Health monitoring applications.

## 2.1 e-Health applications

Since data computing, networks and communications have move on, the multiplicity of e-Health applications have increased. The improvement on transfer rates over networks and data processing have removed must of the barriers to exchange medical data (i.e. physiological signals, medical imagery, etc.) According to [11], e-Health describes the combined used of electronic communication and information technology in the health sector and it is identified by the use of digital data transmitted, stored and retrieved electronically for clinical, educational and administrative purposes, both locally or at distance. Actually, e-Health is compared to terms like "e-learning, e-business…" in order to highlight the processing and management of digital data and the use of internet [17].

Our vision of a typical e-Health application comes from [10], where it is viewed as an end-to-end process whatever the cultural or national context. In Figure 1, we illustrate a typical example, where a patient is related to a work station like a home PC or any medical module oriented to process medical data (i.e. telemetry) and at which medical professionals have totally access (remotely or locally) in order to plan and provide healthcare.

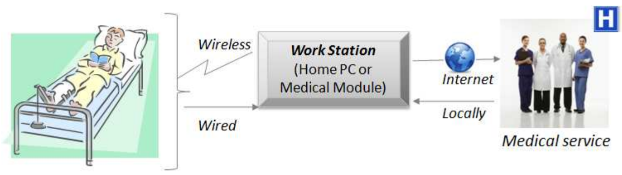


**Figure 1. Typical e-Health monitoring application**

Recently, more and more patient-centric approaches and programs have been proposed for such kind of applications [3], [15], [5]. These programs increasingly exploit pervasive and ubiquitous infrastructures allowing patients to be more autonomous and medical services to better monitor and assist patients [9], [10], [25]. We are especially focused on approaches, especially oriented to monitoring the condition of patients with chronic diseases as STM3 project. In this kind of approaches, the monitoring of a patient is possible by continuously recording and processing their vital signs and/or activity every day. Here, data coming from patients body sensors are traditionally transferred (at real or differed time) via wired or wireless communication to a server; being also analyzed, monitored and managed by medical professionals. Such approach enables to capture more precisely atypical patient symptoms or activities at anytime. Also enable to guarantee accessibility to healthcare independently of the location of the patient.

## 2.2 Data quality and medical information

As retrieved data grows, users and providers are more and more concerned about data quality [27]. Data quality remains an important aspect of information management and becomes a research domain increasingly active. Specific research approaches and well established quality managements programs as Six Sigma and Total quality Management [27], [19] have been adapted to data quality assessment.

Data quality often takes several perspectives (i.e. user view, product view …), in the literature there is no single definition of data quality accepted by researchers or specialists [13], [14]. Recently, data quality was better defined as "contextual". This means that the user (i.e. quality analyst) defines their own perspective of quality for each proposed use of data and within its particular context of use according to the application domain and goal [20], [24]. Thus, according to [21] high-data quality appears when data fits its intended use in operations, decision-making and planning. *Data are "fit-for-use" if they are free of defects and possess desired features.*

Generally, the quality of information is described by several attributes, dimensions, factors or criteria. Such aspects allow qualifying data delivered to users (e.g. accuracy, completeness…) as well as the processes that transform such data (e.g. reliability, security…). They are associated to quality requirements and explained at different level of characteristics in quality models. A quality model is generally viewed as a schema to better explain quality perception. Quality models depict the relation between all quality aspects as elements, characteristics, metrics, measures, etc. A great number of quality criteria and their relation with data have been proposed [19], [4].

In Medical Information Systems, there is an especial care about the reliable and timely delivering of medical information, especially held in databases or other electronic repositories [16]. Generally, the approaches in this domain focus on a qualitative and quantitative evaluation of medical repositories [12], [8] and lately, an interest on the quality analysis of medical data over the web has also emerged [2].

Medical information systems generally process and manage large volumes of heterogeneous data (i.e. medical images, medical records). Thus, typical quality problems in this context concern the lack of generic process to manage all kinds of data, the amount of data to be treated, being aware of human interventions (i.e. uncertain inputs, wrong data, accidental delete, etc.), privacy and security (e.g. control of information access). To address these issues, several approaches concerning data quality management have been proposed [3], [28]. Such approaches provide several quality criteria in order to qualify data, as: *accuracy* (data compared with a data referential), *completeness* (percentage of data missing at a given points), *timeliness* (delay from a given event described by data to its availability on the information system), *relevance* (impact of specific data on the decisions or actions of the user), *legibility* (data have to be concise, readable and understandable), *accessibility* (data have to be available to the right person at the right moment), *usefulness* (data have to be relevant and useful to decision making), *confidentiality* (data have to be confidential and secure).

We have identified more recently work describing additional data quality factors that influence decision making in this context. For instance the impact of distributed data collection and application through new technologies such wireless and the Internet [22], [7], [14]. This kind of approaches generally lead too much information responsibility at medical side, where personal are not always a data quality expert. However, such approaches propose and interesting strategy as "step-by-step" process to data management as the Information Product Mapping (IMAP, [22], [26]). This strategy allows tracking data quality throughout their life cycle. Other approaches, more focused on the qualification of sensor data streaming as [14], propose interesting criteria to evaluate the quality of sensor data associated to some metadata.

As we can see, a lot of effort has been developed in order to provide better healthcare. However, the management of information in this domain is becoming increasingly complex. Patient's mobility, huge volumes of data, decisions under time pressure, etc., frequently expose decision makers (medical experts or professionals, users…) to inaccurate, incomplete or too much information. We observe that ensuring the quality of data in this domain stills a critical aspect. If data is ignored, collected information may have a considerable negative impact on the achievement of the application and decision making. As a result, more and more questions concerning data quality in this kind of applications arise, for instance: Which are the principal issues of data quality in this kind of applications? Which aspects can impact data quality? Under which criteria data quality has to be evaluated? Etc.

In this paper, we attempt to introduce the first clues of data quality analysis in this particular domain. We base our study on an applicative scenario allowing us to identify data quality issues and associate them with the standard view of data quality. Next section, describe these aspects.

# 3. DATA QUALITY ANALYSIS ON E-HEALTH MONITORING APPLICATIONS

Traditionally, in a healthcare environment, data quality is illustrated by ensuring data accuracy. However, thanks to technology improvement, the representation of quality evolves to an adaptable and real definition. Data quality is now attempting to ensure that data are reliable, accurate, timely and consistent enough for organization goals. This means that data have to be as perfect as possible to the organization or/and goal requirements.

The goal of our research is oriented to explore the data quality problems, particularly in remote healthcare monitoring and assistance applications. In this section, we address our monitoring scenario and discuss our vision of data quality based on the applications specificities, the general quality requirements for healthcare, the current data quality approaches and the importance to support decision makers.

## 3.1 E-Health patients monitoring scenario

Our research is based on a scenario related to STM3 project. This project proposed a medical monitoring application for patients with chronic pathologies requiring continuous surveillance and medical assistance (Figure 2). This project proposes to integrate a secure medical monitoring using and developing new IMDs (Implant Medical Devices) with wireless transmission allowing a complete mobility of the patient (i.e. using a Smartphone). Also, it intends to develop a *data hub* (i.e. MicroSD card) used as a gateway, and implement dedicated Human Machine Interfaces (HMIs) to assist patients and medical services. Such goals open new application and research perspectives for e-Health monitoring applications.

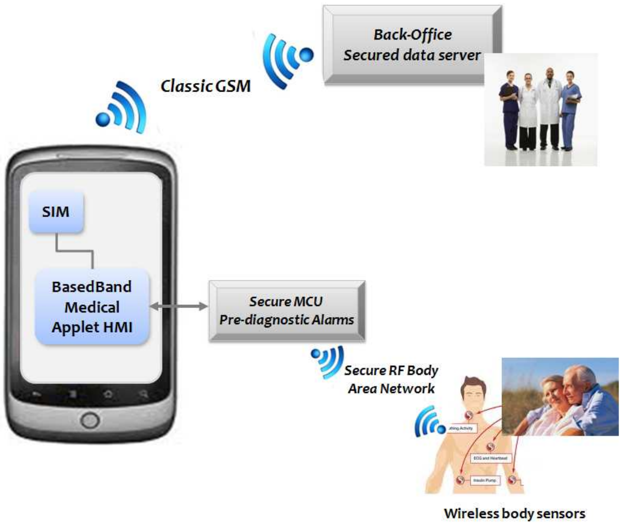


**Figure 2. STM3 medical assistance and monitoring application**

As we show in Figure 2, the general framework for this project is composed by four principal parts: 1) *medical sensors* including storage and pre-processing capacity as well as a secure wireless transmission; 2) *receptor* on-board to a Smartphone (i.e. MicroSD card) where an embedded software allows the pre-processing of acquired body sensor data; 3) a generic *Smartphone* including an optimal HMIs managing the interoperability with the receptor; and 4) a *data server "back-office"* oriented to store, process and manage all data, and also conceived to provide interesting medical services or application managing and communicating medical information.

This project is focused principally on two application cases, one oriented to monitor patients with hearing problems (using a cochlear IMD) and another one oriented to patients with cardiac problems. In this paper, due to the criticality of the scenario, we explore the second scenario illustrated in Figure 3.

For this scenario, in order to activate the patients monitoring, it is necessary to establish first a communication between the IMD and the external programmer at medical center (hospital or clinic) during the IMD implantation. This communication is essential in order to set-up the device and prepares it to follow-up data (FU – data collection). In fact, during the implantation the parameters of the IMD are fixed allowing the device to monitor correctly. Next, in this particular scenario, two kinds of monitoring are considered: one in real-time which can be continuous, triggered or on-demand, and a second one in differed-time (at FU, for instance). In both cases, the sensed data can be pre-stored and pre-processed at implant side, several warning and pre-diagnosis can be programmed at this point. Afterwards, collected data is transferred via 3G/GSM/WiFi (in real-time or *a posteriori*) to a back-office server for much complex analysis, processing and storage.

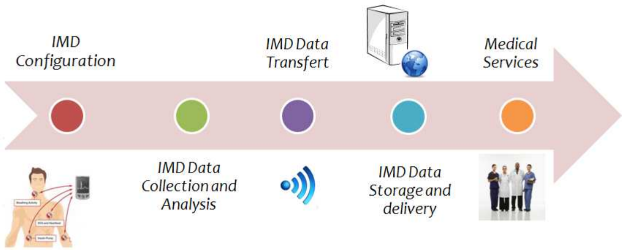


**Figure 3. Scenario process for cardiac monitoring application**

Moreover, several medical consultations over the year are scheduled. These consultations (routine, trigged by warning or on-demand) are principally oriented to follow-up data, control de implant and verify the condition of the patient. Regarding traditional healthcare applications, these consultations can be performed remotely associated to a constant monitoring.

As we can observe in this scenario, the introduction of IMDs, mobile devices, wireless communication and other technological improvements offers new opportunities to provide better healthcare. Nevertheless, as we state before it also comes with some quality concerns. We discuss hereafter several data quality issues on this kind of scenarios.

## 3.2 Data quality issues on e-Health monitoring applications

To correctly identify data quality issues, we must recognize the source of quality problems, analyze its impact and, where possible, propose a solution. In our particular application domain, there are many contextual reasons why it is difficult to maintain a good quality of data. Some difficulties are related to technology (i.e. equipment, body sensors, QoS – Quality of Service), to human intervention (wrong manipulation, input errors, misunderstanding…), or to process of data transformation (i.e. optimal analysis and processing).

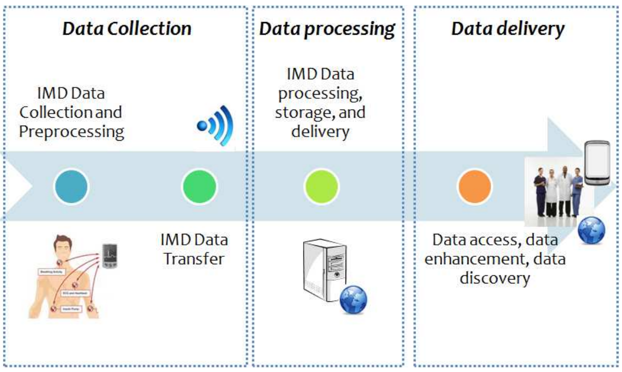


**Figure 4. Data management, processing and delivery levels on e-Health monitoring application**

To tackle this aspect, mainly focused on STM3 project scenario, we study at first the characteristics of this kind of applications according to data flow (from data source until destination). We try to identify where, when and how an impact over data quality occurs. For this, we define three main levels of data management and process over the system (Figure 4), defined as: *Data collection, Data processing and Data discovery.*

We refer as *Data collection level* all the processes related to the acquisition of data coming from body sensors. We take into consideration the pre-processing process performed at IMD side or at data hub side, as well as the transfer of data collected from implant to data hub, from data hub to server and also from data hub to medical services (i.e. Doctor's Smartphone).

At *Data processing level* we consider all the processes that transform, complete, integrate or modify collected data, together with their storage and delivery. Such collected data must be integrated with other medical data as EPRs (Electronic Patient Records), medical images, ECG (ElectroCardioGrams), etc.

Finally, *Data discovery level* represents the use of all the information available in the system. At this level, data discovery and use by users are performed via Web, locally or with a mobile device (3G, Wi-Fi). This level integrates also the communication between the back-office and the end-users as well as the communication between patient and medical services.

Our study according to these three data management levels allow us to conclude that the context in which data is collected (i.e. Data collection level) is a crucial aspect to be considered for data quality assessment. At this level, the quality of data can be impacted by several factors, such as data collection rate (very high or very low acquisition frequency), the performance of body sensors (battery, life time, settings…), the quantity of data to be pre-processed and transferred (i.e. respecting data quote) as well as the quality of communication (i.e. broadband, frequency…). We estimate that at this level it is necessary to implement a quality procedure in order to validate or qualify data and its context (rather than eliminate data), before they arrive to back-end servers or before they are discovered by users. For example, if several warnings are triggered from a critical pre-diagnosis at patient's side, we have to ensure as accurate and reliable as possible that the data transmitted to medical services or to the patient. In our scenario, patient can be also allowed to monitor himself in real-time, and thus any information with poor quality can impact his behavior.

Regarding data processing level, more analysis and data enhancement can be performed. As we show in Figure 4, the processes are executed at back-office server which is also considered as a data repository. Sensed data are then integrated with more heterogeneous data as EPRs, medical images or videos, etc. which are normally provided by distributed sources as medical services. In such a case, we are confronted with more information often provided with inaccurate or incomplete information. It is also important to guarantee data accessibility and the respect of privacy constraints at this level. Besides, data have to be as available and fresh as possible in order to provide a performing monitoring and verify the access to data. We believe that current quality approaches at the domain of Data Integration Systems (DIS) or Data Warehousing (DW) (e.g. [6], [1]) can be used as reference to evaluate and control data quality at this level.

Finally, at data discovery level, the system has to guarantee a good decision making based on reliable, understandable and secure information. Thus, we estimate that important to control the quality of data communicated to the users as well as the quality of information representation (i.e. consistency, understanding, etc.). Users (not always experts) can be confused with excessive information and by the way as information is represented and communicated.

After the review of potential data quality issues in this kind of applications, we attempt hereafter to analyze them according to the current approaches of data quality modeling.

## 3.3 Data quality modeling over e-Health monitoring applications

Our vision of data quality concerning e-Health monitoring applications is inspired on exiting data quality approaches as [26], [24], [23], [22]. We argue that the data quality can be defined according to several perspective or categories (Figure 5). Such categories can be defined according to several views of quality over the system [19], [18]. In our particular analysis, each view refers to each data management and processing levels depicted in Section 3.3 (data collection, data processing, data delivery). With this, we try to preserve a "product view" of the quality allowing a more clearly quality issues tackle. We estimate that these views are not exhaustive and they can be extended or modified according to systems characteristics and quality goals.

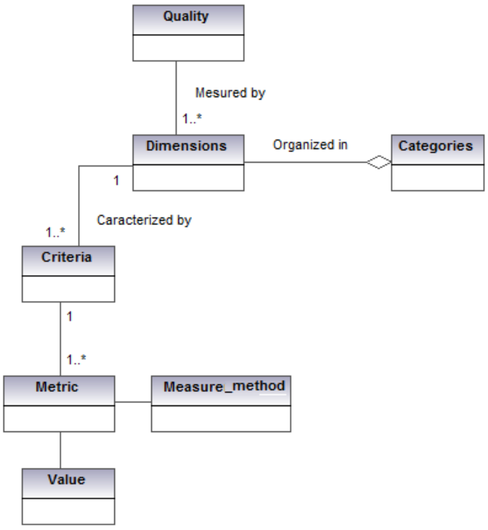


**Figure 5. Conceptual model of quality**

Data quality can be measured by a set of quality dimensions. Each dimension refers to one or several quality criteria (factors or attributes) representing the characteristics which data has to meet. Also, each quality criteria is evaluated by a quality metric and being measured applying measure methods (qualitative or quantitative). A quality measure enables to specify the set of quality indicators that are used to control, maintain or improve and information system. All these quality elements are related to a quality evaluation procedure, traditionally developed as a framework.

In our case of study, we observe that the big picture of data quality is generally illustrated by the accuracy and reliability of data. The more accurate and reliable data is, more confident and relevant decision will be taken by the actors (patients, medical experts, medical services…). However, as we state before, other complementary perceptions of quality are also necessary in our context. Thus, in order to define the optimal data quality criteria, we decide to analyze, at first place, the pertinence and usefulness (or applicability of the basic and most used quality criteria in the healthcare domain [23]. Such criteria are: *Accuracy, Precision, Accessibility, Currency or Freshness, Consistency, Relevancy, Comprehensiveness.*

Reviewing the specificities of e-Health monitoring applications and the goal of each quality criteria ensures that all relevant characteristics of the data are taken into consideration. Our study found some important correlations and clues about these aspects. In this paper, we underline several quality criteria correlations over data collection and we describe them with some examples.

- Considering accuracy, it is necessary to specify how valid or error free is data coming from body sensor, particularly to ensure integrity, consistency and reliability of all (or several) collected data.

- Precision contributes to complete data validation. Data can be not accurate but precise enough to ensure data reliability. For example, some ranges and categories can be defined to determine this aspect.

- Accessibility must ensure to provide right and legal data access according to users description, goals, etc. Doctors, emergency service and patients have to be allowed to access data at anytime, only for that data for they are allowed.

- Currency guarantees data-up-dating. Definitions for currency or freshness for each type of data must be determined (e.g. data are up-dated and usable within 2 seconds, 2 hours, 2 days). This aspect is very important in order to better manage critical situations.

- Regarding the characteristics of sensed data (raw and pre-processed), the consistency to data specifications and goals has to be ensured also before users' access. As we describe before, patient is sometimes allowed to monitor himself and thus a verification of consistency at patient side is suitable.

As we observe, most of the basic quality criteria have an important relation with our case of study. We estimate these clues as an important beginning for our future research and contributions, concerning specially the definition of a data quality evaluation process and modeling.

# 4. CONCLUSIONS AND FURTHER WORK

This paper describes an opening research dedicated to analyze data quality issues in a critical domain as e-Health monitoring. We note that this is a first attempt to analyze data quality issues in this kind of applications, and naturally this aspect requires further investigation. For example, we observe that the quality criteria presented previously are the core of data quality approaches but they are not exhaustive. Since the most part of quality criteria depends on the specificities of the environment and the user requirements, we plan to include other perspectives of quality as Quality of Service (QoS) and context-awareness, especially linked to data collection level. We also consider necessary to model user and system quality requirements and associate them to optimal procedures, metrics and measures. One or several quality evaluation methods, algorithms and procedures must be correlated. For the definition and application of such procedures, we consider important to take into consideration the granularity of data to be evaluated, in order to control the volume of data to be processed, transmitted and communicated. Also, we are particularly concerned about: Which are the preferences of medical and industrial experts on quality criteria? At which level of granularity the experts consider interesting to ensure the quality of data; only considering one data or a dataset, or several datasets? At which frequency will this evaluation be performed, continuous or episodic? Etc. A survey with medical and industrial experts is being prepared.

## 5. ACKNOWLEDGMENTS

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