

Quality-of-Data Broker for Quality-of-Data-Aware Telemedicine Systems

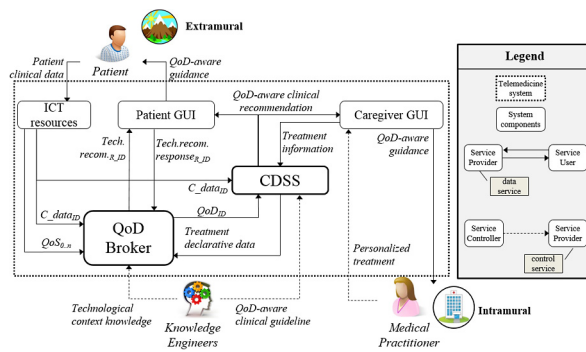
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Graphical abstract



Abstract

Purpose: Telemedicine systems must provide clinical data of sufficient quality (according to medical standards) to support safe treatment guidance of outpatients. Quality of clinical data (QoD) typically varies due to unstable performance of ICT-components of these telemedicine systems. Therefore, telemedicine systems that support treatment guidance of outpatients should be QoD-aware and must be able to appropriately adapt treatment guidance to QoD variations. Only in this way, the effectiveness of treatment guidance and the safety of outpatients can be guaranteed.

Methods: This paper follows a design science approach for the development of a functional architecture for QoD-aware telemedicine systems, with emphasis on one key component: the QoD Broker. Existing requirements elicitation methods were refined to deal with capturing QoD-specific requirements. Furthermore, an ontology-driven knowledge management method is proposed to enable the correct interpretation and manipulation of QoD within telemedicine systems. The functional architecture was validated using various methods, including prototype experiments and expert interviews.

Result: One of the key components of the proposed functional architecture is the QoD Broker, which is a novel component that adds QoD-awareness to telemedicine systems. The QoD Broker obtains quality of service data from ICT components within a given telemedicine system and uses different computational models to compute QoD. This paper presents the QoD Broker architecture and the QoD management techniques implemented in the QoD Broker: (1) QoD dimensions, (2) QoD evaluation (i.e. computational models), (3) QoD stratification models and (4) technological recommendations.

Discussion: The paper presents partial results of the validation that was performed in the context of the European MobiGuide project. The validation confirms that the proposed QoD Broker satisfies stakeholders' requirements and is considered useful to support stakeholders' goals.

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Both patients and medical domain experts found the role of the QoD Broker essential to guarantee the safety of patients when they are using telemedicine systems.

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1. Introduction

The continuous evolution of information and communications technologies (ICT) enables the ubiquitous availability of clinical data. For example, patients' physiological data (e.g. heart rate) and other case specific data (e.g. diet) are monitored remotely and processed by automated systems (e.g. clinical decision support systems) to safely guide a patient anytime and anywhere. Additionally, the clinical practitioner is able to access all clinical data and control patient treatment by modifying or adjusting treatment parameters (e.g. insulin dosage) from a distance. Ubiquitous clinical data availability drives the development of next generation telemedicine systems where personalized treatments are decoupled from intramural hospital settings and patients receive remotely supervised treatment at home. This may reduce the cost of healthcare, which currently is one of the major challenges in countries with an ageing population.

Our research addresses the problem of clinical data provision by telemedicine systems with variable data quality, which does not fulfill medical quality requirements to provide safe treatment guidance to outpatients. By using telemedicine systems, unavoidable and unpredictable performance disruptions of its ICT components may arise (e.g. noisy signals from poor quality electrodes, poor internet connections, low battery level of monitoring devices). These performance properties are characterized by a quality of service (QoS) of each ICT resource. Consequently, lower QoS may result in variable quality (e.g. 'poor') of clinical data that does not fulfill medical quality requirements. One of the research challenges is the development of a quality of clinical data aware telemedicine system that guarantees patient's safety when data quality varies. To accomplish this development, we need to determine which are relevant quality of clinical data (QoD) dimensions for telemedicine systems, compute these QoD dimensions and improve (when ever possible) QoD. In order to ensure patient's safety and treatment guidance efficacy, telemedicine systems should incorporate treatment adaptation mechanisms. These adaptation mechanisms enable safe treatment adaptation to varying QoD, considering patient needs and best medical practice. Hence, as discussed in [1], these adaptation mechanisms need to be specified by medical practitioners during the system design phase.

Several studies in healthcare [2–5] and in other fields [6–8] address the importance of providing data quality information to the decision-maker. Berner's study [2,3] shows that the QoD used in decision-making processes is a major determinant of impact on patient's safety and healthcare quality. Hence, this study identifies the necessity of including QoD mechanisms to guarantee patient's safety, but does not provide a solution.

In [5], Sriram et al. identifies the key challenges involved ensuring (and assessing) QoD, but they do not address a method to overcome the potential problems that occur in pervasive healthcare systems when QoD variation is unavoidable. In other studies, such as [6,7], they argue that QoD information needs to be provided to the decision maker to gauge the QoD based on his/her own requirements.

Other researchers focus on the study of data quality [9–11], quality of service (QoS) [12] and quality of context (QoC) [13], which is closely related to quality of sensor data. These studies are mainly focused on the factors that influence the data, service or context quality respectively, and the dimensions or indicators required to assess this quality. But they do not address how the QoD or QoC should be integrated in the application domain.

Hence, none of these studies provide a method or technique to bridge the gap between the impact of technological context on clinical data quality and how to overcome the potential negative impact on healthcare systems.

We present a cross-disciplinary study which provides a method to overcome these challenges by developing a QoD-aware telemedicine system that enables treatment adaptation in case QoD varies due to technological context performance variations. The system comprises a novel QoD Broker, which provides treatment context specific QoD and ICT based technological recommendations.

The rest of this paper is organized as follows. Section 2 introduces the design methods applied in our study. Section 3 presents the results, which include the details of the QoD Broker architecture and its main functionalities. Section 4 presents how this work has been implemented in the FP7 European project MobiGuide [14] and Section 5 discusses the results of this work with other studies. Section 6 summarizes the contribution of this work and outlines future directions.

2. Design method

In our study we applied a refined requirements elicitation (RE) method [15] in order to discover the implications of degraded QoD on a telemedicine system. This RE method results in the identification of the functional requirements for the QoD-aware telemedicine system architecture. Based on these requirements the system's functional architecture was developed but also the QoD-framework ontology, which is the foundation of the QoD-aware telemedicine system knowledge engine [16].

The system knowledge consists of two parts: 1) technical domain knowledge (ontology), which translates the technological context information into clinical data quality, and 2) clinical domain knowledge (ontology), which comprises clinical guide-

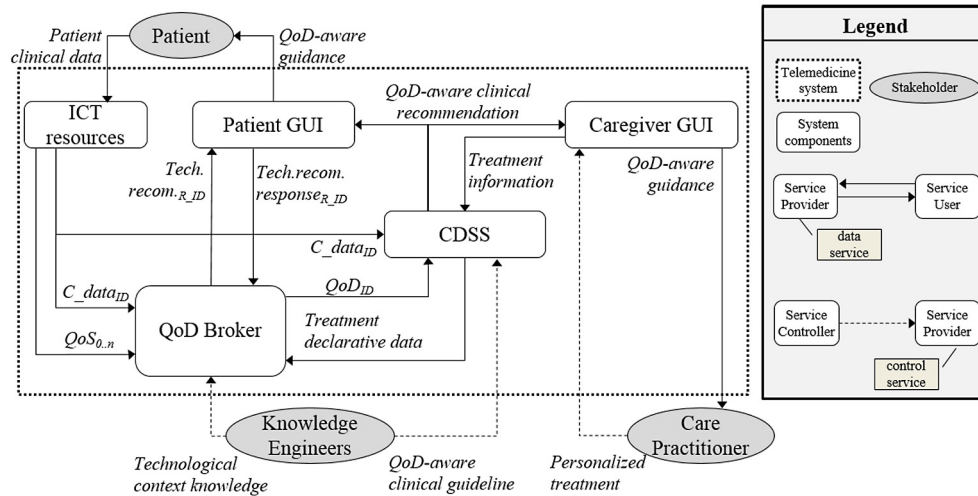


Fig. 1. QoD-aware telemedicine system architecture.

line knowledge and treatment adaptation mechanisms in order to adapt the treatment when QoD varies.

We describe the functional architecture of such a QoD-aware telemedicine system, which implements this system knowledge. This functional architecture gives also the rationale for the need of implementing the QoD Broker component.

2.1. QoD-aware telemedicine system architecture

First, we present the QoD-aware telemedicine system's stakeholders. Second, we summarize the functional requirements to develop such a system architecture. Next, we present the main components that contribute to QoD-awareness, and, finally, we briefly discuss the user–system interactions.

2.1.1. Telemedicine system stakeholders

We identified the following telemedicine system stakeholders:

- Knowledge engineering team: Consists of knowledge engineers and care professionals, in charge of formalizing a QoD-aware clinical guideline and treatment guidance logic. This team also includes QoD-experts to formalize QoD knowledge associated with the technological context for the QoD Broker and determine the QoD impact on the treatment together with medical practitioners.
- Patient: Consists of outpatients who provide their clinical data using ICT resources. They are also receivers of QoD-aware treatment guidance in the form of clinical and technological recommendations.
- Medical practitioner: Consists of domain specific practitioners in control of outpatient treatment specification, who can personalize and change treatment when needed, as well as a receiver of QoD-aware guidance.

We also identified a system engineer in charge of providing system configuration information (e.g. user access control). However, this user is not represented in Fig. 1 since it is not relevant for this paper's topic.

2.1.2. Functional requirements

The refined requirements elicitation method [15] results into the specification of the system requirements, which are used to identify the individual components. Here, we present a brief summary of the requirements and the components that would correspond to each of them.

- Shall compute QoD based on technological context information (QoD Broker)
- Shall provide QoD-aware guidance information to patient and guidance decision support to the medical practitioner (CDSS)
- Shall have an interface to interact with the patient and the medical practitioner (Patient GUI, Caregiver GUI)
- Shall monitor, process, and transmit patient clinical data and QoS information (ICT resources)

2.1.3. Telemedicine system components

Since QoD and its role in telemedicine systems is the main focus of this study, the following paragraphs briefly discuss the main QoD-aware telemedicine system components illustrated in Fig. 1:

- QoD Broker: Acquires quality related declarative data from the CDSS treatment and technological context knowledge (computational models and technological recommendations guidance) from knowledge engineers during design time. It also receives processed clinical data with its corresponding ID (C_data_{ID}) and QoS of technological resources ($QoS_{0..n}$) during runtime. These inputs are used to calculate and output QoD information associated with clinical data with the same ID (QoD_{ID}). Additionally, the QoD Broker also outputs technological recommendations (tech. recom. R_{ID}) to the patient via the patient GUI, which is identified with R_{ID} . The QoD Broker uses this recommendation ID in case of a patient response (tech. recom. response R_{ID}), whose response is also used by QoD Broker for QoD computation optimization purposes (see 3.2.4).

- **CDSS:** During design time, it acquires knowledge (QoD-aware computer interpretable clinical guideline capable of adapting the treatment when QoD degrades) from the knowledge engineers and medical practitioners [1]. During runtime, it receives processed clinical data with an ID (C_data_{ID}) and its associated QoD (QoD_{ID}). It uses this input to make QoD-aware decisions to support the treatment guidance.
- **Patient GUI:** Graphical user interface supporting patient–system interaction. These interactions include clinical recommendations from the CDSS and technological recommendations from the QoD Broker, and patient’s responses to these recommendations.
- **Caregiver GUI:** Graphical user interface supporting medical practitioner–system interaction. These interactions include the treatment personalization from the medical practitioner to the system and QoD-aware treatment guidance given by the system to the medical practitioner, among others.
- **ICT resources:** Monitors, processes and communicates patient’s clinical data (C_data_{ID}) and resources’ technical information ($QoS_{0..n}$) to other system components.

Data provided by these components may require secure storage. Accordingly, there is a secure clinical data storage component. However, its representation is not relevant for the topic of this paper and hence, not illustrated in Fig. 1.

2.1.4. User–system interactions

Fig. 1 illustrates the interaction (data transfer) between stakeholders (service user) and the system (service provider), which is done in two ways.

Firstly, the stakeholders receive information from the system, which includes QoD-aware guidance. Additionally, patient clinical data is transmitted from the patient (service user) to the system (service provider). Since ICT resources (e.g. sensors) can obtain clinical data unobtrusively, a patient need not interact with the system at all.

Secondly, the stakeholders (service controller) can make use of the control function provided by the system control interface in order to input knowledge required by the system.

The communication protocol uses a publish-subscribe pattern i.e., service providers broadcast data on a channel and service users subscribed to the channel access this data.

3. Design results

After presenting the QoD-aware telemedicine system knowledge and architecture, it is clear that such systems need to comprise a QoD component, named ‘QoD Broker’. In this section we present the novel QoD Broker architecture and its QoD management techniques.

3.1. QoD Broker – architecture

Fig. 2 illustrates the functional architecture of the QoD Broker, which is composed of three main functions, namely QoD

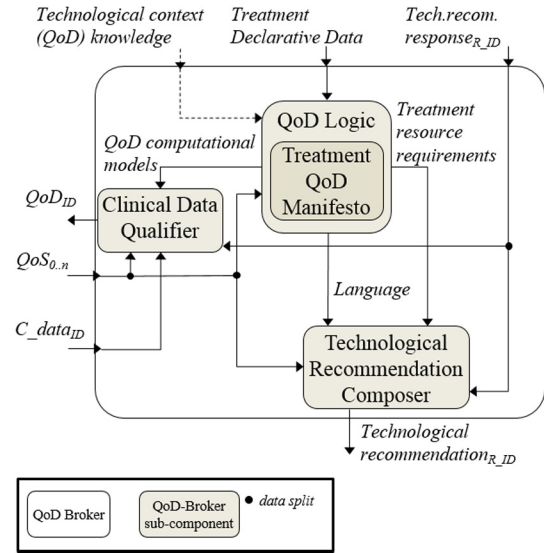


Fig. 2. QoD Broker functional architecture.

Logic, Clinical Data Qualifier and Technological Recommendation Composer.

- **QoD Logic:** Acquires QoD knowledge associated with the technological context from knowledge engineering team (data control) and treatment declarative data from the CDSS, which includes patient specific treatments requirements (e.g. duration) and language settings. It converts this information into the Treatment QoD Manifesto, implemented as an executable (XML) file and used by the other three QoD Broker components.
- **Clinical Data Qualifier:** Outputs clinical data quality (QoD_{ID}) associated with processed clinical data with ID (C_data_{ID}). QoD_{ID} computation is based on $QoS_{0..n}$ provided by ICT resources, clinical data under observation (C_data_{ID}), and quality of data computational models specified in the Treatment QoD Manifesto. This function also uses the patient’s response to technological recommendations for QoD computation optimization.
- **Technological Recommendation Composer:** Based on treatment resource requirements and $QoS_{0..n}$ provided by ICT resources, together with treatment resource requirements and language settings (e.g. Italian) from QoD Logic, it triggers a specific technological recommendation. For example, 24 hours treatment requires smartphone battery level above 80%. If the actual smartphone battery level is 50%, this function provides a technological recommendation “charge smartphone battery”.

3.2. QoD Broker – QoD management techniques

As reported by Batini et al. in [9], literature already provides a wide range of techniques to assess and improve QoD. However, our study is applied to healthcare domain (focused particularly on emerging telemedicine systems) and therefore, the method to approach these research areas differ from other studies.

In this section we present the main functionalities integrated on QoD Broker. These functionalities cover four main research areas in data quality studies: 1) define each quality dimensions, 2) evaluate data quality and 3) determine the relative data quality and 4) technological recommendations for QoD improvement and QoD computation optimization.

3.2.1. QoD dimensions

In order to determine the QoD dimensions to address, we combined the *intuitive*, *theoretical*, and *empirical* approaches [17]. Hence, first, we, as QoD researchers, studied potential relevant quality dimensions for the applied study [8,11,18,12]. Second, we focus on the dimensions that describe best the inconsistencies between the real world phenomena and the data obtained from the ICT resources. Finally, we discussed with medical practitioners the QoD dimensions that can cover their necessities and do not overwhelm the system with irrelevant information.

As a result of this process, five QoD dimensions have been implemented in QoD Broker: *Accuracy* (degree of correctness at which the attentive phenomena is represented by the data), *Dependability* (degree of certainty that data can be used for meaningful decisions regardless of speed or accuracy), *Timeliness* (time interval used to transport data from source to destination), *Cost* (amount of money required to obtain data for the decision-making process) and *Quality of Evidence* (degree of conformance with guidelines and rules of certification/legislation bodies and evidence based medicine).

As discussed before, in our study, QoS information is related to QoD and used to compute QoD (see 3.2.2). Therefore, QoS of technological resources may also be expressed in terms of the identified five quality dimensions. For example, an ICT resource's QoS accuracy specifies the degree of correctness of the resource's processed data, thereby preventing further errors in the output data.

3.2.2. QoD evaluation: computational models

As presented in [19], we use different computational models to quantify the five quality dimensions identified in Section 3.2.1. For our convenience, in this section, the terms QoD and QoS denote one of the five quality dimensions.

Quality of output data from technological resource i (QoD_i) depends on the resource's quality of input data (QoD_{i-1}) and it's provided quality of service (QoS_i): $QoD_i = f_i(QoS_i, QoD_{i-1})$, with transfer function ' f_i '. For example, if a data processing and delivery chain constitutes of two technological resources, the calculated quality of output data is: $QoD_2 = f_2(QoS_2, f_1(QoS_1, QoD_0))$ with two (potentially) different transfer functions f_1 and f_2 . Note that D_0 is input data (e.g. cardiac electrical signal) of the first technological resource (e.g. BioHarness (BH) sensing component [20]) in the data processing and delivery chain. The quality of D_0 is not directly measurable. Therefore, QoD_0 contributes to the QoS_1 of the first technological resource with a neutral impact.

A transfer function depends on each quality dimension and the QoS information we can obtain. For example, an arithmetic summation function can be used for Timeliness and Cost

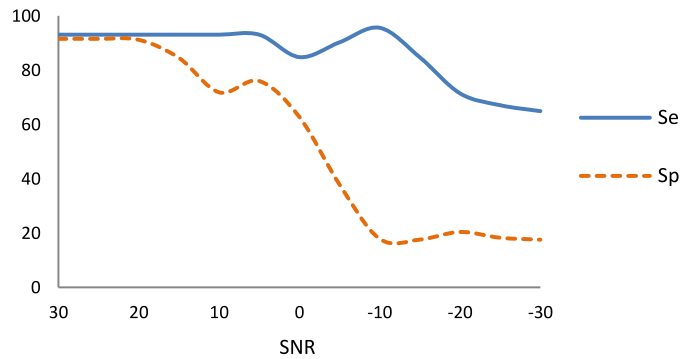


Fig. 3. AF algorithm's Se and Sp relation to input data's SNR [21].

quality dimensions calculation when we have time delay and monetary cost respectively. Boolean algebra can be used for the Quality of Evidence quality dimension calculation when we just check if the technological resources have the required CE certificate. In case quality dimension calculation is not straightforward, graph based mapping (Fig. 3), look-up tables or more advanced mathematical functions are required. In the sequel, we address four possible computational models and present an example for each. Notice, that additional computational models may also be required depending on the type of data, type of information system or other relevant aspects of the application.

1. Summation and multiplication arithmetic functions

The transfer function f_i of technological resource i is the arithmetic summation $SUM(x;y)$. Quality of output data of this resource i is calculated by: $QoD_i = SUM(QoS_i, QoD_{i-1})$. In a data processing and delivery chain of n technological resources with the SUM as the only transfer function, quality of output data is expressed by: $QoD_n = \sum_{i=1}^n (QoS_i + QoD_0)$. Similarly, for a multiplication transfer function $MULTIPLY(x;y)$, output data's quality of a chain of n technological resources with the same multiplication transfer function is expressed by: $QoD_n = \prod_{i=1}^n (QoS_i \times QoD_0)$. *Example:* Timeliness sub-qualifiers (e.g. delay) are calculated with the summation arithmetic function. In a delivery chain of concatenated technological resources of BH sensor, BH processor and Bluetooth technological resources (see Fig. 3), their delay contribution to timeliness is calculated by: $Timeliness = d_{BHsensor} + d_{BHprocessor} + d_{Bluetooth}$ (assuming the provision of the electrode signal is instantaneous). Hence, imagine a case where $d_{BHsensor} = 2$ s, $d_{BHprocessor} = 30$ s, $d_{Bluetooth} = 1$ s, the resulting scalar value of $Timeliness = 33$ s.

2. Boolean functions

The transfer function f_i of technological resource i is based on Boolean algebra, expressed in terms of Boolean variables and logical operators "AND", "OR" and "XOR". Accordingly, quality of output data of resource i can be expressed by for example, $QoD_i = AND(QoS_i, QoD_{i-1})$.

Example: Quality of Evidence is computed by the Boolean transfer function "AND". It uses Boolean sub-qualifiers like the availability (true) or non-availability (false) of a monitoring device's CE certificate to determine to overall

Quality of Evidence. For example, if one of the technological resources to obtain HR data does not have a CE certificate (e.g. the HR sensor), the Quality of Evidence of HR clinical variable may be negatively affected with Quality of Evidence = False [“0”] (scalar value).

3. Mathematical functions

Mathematical transfer functions are based on formulae from mathematical or statistical methods or theories. For example, arithmetic “mean” or utility functions applied to RQPs or quality dimensions’ sub-qualifiers.

Example: Accuracy of clinical data ‘AF episode’ can be calculated using a utility function and the AF detection algorithm’s Se and Sp values, which depend on preceding RQPs (see example below at Graph-Based Mapping Function). During design phase, the medical practitioner determines the utility function’s weight factor w to express his prevalence to true positives or true negatives. The accuracy’s utility function can be expressed by $Accuracy = Se \times w + Sp \times (1 - w)$, $w \in [0, 1]$. For example, when SNR = 0 dB (see Fig. 3), $Se \cong 88\%$ and $Sp \cong 63\%$. Hence, if $w = 0.5$ (determined by the medical expert), $Accuracy \cong 75.5\%$ (scalar value)

4. Graph-Based Mapping Functions

The use of graph-based mapping (implemented by lookup tables) is an alternative for deriving complex transfer function formulas. It captures the relation between variables based on prior experimental work. Quality dimension’s sub-qualifiers could be determined by graph-based mapping transfer functions. This approach is common in medical practice, since medical studies typically use empirical methods which yield tables or graphs of studied relationships.

Example: Values of the Accuracy sub-qualifiers Se and Sp are related to the robustness of a particular data processing algorithm to input data Signal to Noise Ratio (SNR). Fig. 3 shows an example of SNR effect on Se and Sp values of an AF detection algorithm [21]. Hence, we can make use of the graph as shown in the mathematical function example to obtain Se and Sp values for SNR = 0 dB.

The result of these computational models is an “objective” scalar value for each of the five quality dimensions of a clinical variable. Therefore, contrary to other studies reported in [9], we do not introduce questionnaires or “subjective” models in this step. However, in medical practice this value is relative and depends in patient and treatment context, as mentioned before. Therefore, QoD Broker introduces the QoD Stratification Model, which maps this scalar values to a quality grade.

3.2.3. QoD stratification model

In medical practice quality is usually represented by four quality grades: *High*, *Medium*, *Low* and *Very Low*, as identified by GRADE healthcare working group [18]. After validating with medical practitioners involved in MobiGuide, we adopted this in our approach, so that the scalar values of QoD dimensions (3.2.2) are stratified to one of these particular grades [19]. The underlying stratification model is based on a medical prac-

Table 1
Stratification model example for accuracy [19].

Clinical variable HR _{mon}	
Scalar ranges	Grade value
[0%, 69.9%]	Very low
[70%, 79.9%]	Low
[80%, 94.9%]	Medium
[95%, 100%]	High

itioner’s interpretation of the computed scalar values based on the patient and treatment context, also conforming to the medical way of working. This stratification model is represented as mapping tables, exemplified in Table 1, and they are part of the QoD Broker Treatment QoD Manifesto. Hence, QoD Broker is able to map the specific scalar value of a quality dimension to a QoD grade for each treatment context. Table 1 represents the stratification model for Accuracy quality dimension of scalar values of HR_{mon} clinical variables, which has been approved by the medical practitioner for the AF patients’ physical exercise treatment.

3.2.4. Technological recommendations

The technological recommendations provided by QoD Broker have two aims: 1) provide more reliable QoD information and 2) improve QoD:

- QoD is often difficult to compute since it may depend not only on the technological resources and treatment context, but also in the user context [10]. Therefore, we send technological recommendations to the patient in terms of surveys. The patient’s reply is used by QoD Broker to better understand his/her context and possible causes of degraded QoS. Consequently, QoD Broker may provide more reliable QoD information. For example, when QoS of an ICT resource (e.g. battery of the smartphone) does not fulfill the treatment requirements, the patient may be asked if the smartphone battery was recently charged. This supports the QoD Broker to determine more accurately the technological context: either the battery is low because the patient has not charged it, or the battery is damaged. Accordingly, the QoD Broker may take different action (e.g. QoD grade may be different).
- Alternatively, technological recommendations aim to improve the system performance in terms of QoS of the ICT resources and as a consequence QoD. In this case, technological recommendations will be notifications to the patient with system related information, which do not require patient’s reply. For example, one of the notifications may be to charge the smartphone battery or to re-enter the clinical data if QoD Broker detects that the values are of low quality. This is closely related with the process modeling addressed by Batini et al. [9], a strategy often used for QoD improvement in the analyzed studies of Batini.

We found studies that use technological recommendations in combination with QoD validation [10,4]. Vavilis et al. [4] propose to build a troubleshooting mechanism to determine the

impact of data qualifiers (or quality dimensions) on the overall quality of measurements. Accordingly, the system can investigate the cause of QoD degradation. In contrast, we acquire QoS information to determine QoD without patient's involvement in our study. We only consult the patient if additional patient context information is needed to understand the causes of a particular QoS degradation. Berti [10] proposes a multicriteria recommendation mechanism to obtain and present user information based on his/her preferences (e.g. provide data with higher freshness rather than data with higher credibility). In the medical practice however, medical practitioners are in charge of determining the most relevant QoD dimensions and quality grades based on patient and treatment context during the requirements elicitation phase (see Section 3.2.3).

4. Validation

To validate whether the proposed QoD Broker system design would adhere to stakeholder requirements, we designed and validated our study in the context of the MobiGuide European project [14].

MobiGuide (MG) aims to develop a telemedicine system that provides a context-aware clinical guideline based decision-support service to medical practitioners and patients. The implemented clinical decision support system (CDSS) provides recommendations for outpatient treatment guidance independent of time and location. These recommendations are adapted to medical, personal and technological context.

MG studies two clinical cases; each implemented in a different countries. The first case studies Atrial Fibrillation (AF) arrhythmia, which is the most common arrhythmia associated with an adverse prognosis. This case is directed by the Fondazione Salvatore Maugeri hospital in Italy. The second clinical case deals with Gestational Diabetes Mellitus (GDM), which is defined as glucose intolerance of various degrees that is first detected during pregnancy that can carry some risk to

both mother and the unborn child. This clinical case is directed by Sabadell hospital in Spain.

Our study focus is the functional validation of the QoD Broker as an operational subsystem of the prototype MG telemedicine system. We conducted two main validation activities: 1) use the pre-pilot (prototype) MG telemedicine system to validate QoD Broker functionality with healthy volunteers, and 2) use the pilot-ready MG telemedicine system to validate QoD Broker functionality with patients.

4.1. Test prototype with healthy volunteers

We deployed the QoD-aware MG telemedicine system in an operational setting. At the start of the '**pre-pilot study**', healthy volunteers were enrolled in the MG system. They received instructions together with the MG system prototype and tested all its functionalities. In several iterations, errors, unexpected behavior or a perceived missing functionality were reported to technical partners and consequently solved.

The medical practitioners were also involved in the pre-pilot to validate if the MG system was fulfilling the medical requirements. Particularly, the physical exercise treatment presented in Fig. 4 was the primary test scenario for the validation of the MG system's QoD-awareness; the outpatient guidance depends on monitored physiological data where QoD plays a key role.

During every system test cycle, user–system interaction data and MG components (including the QoD Broker) communication data was automatically collected. We studied these data to determine whether the functional requirements for the QoD Broker derived from the stakeholder requirements were satisfied.

The result of the pre-pilot was a pilot ready QoD-aware MG telemedicine system that fulfilled the stakeholder requirements, including the medical requirements. This version of the MG system was deemed to be mature enough to be used by patients.

The pre-pilot validation step guaranteed that all functionalities of the MG system, including the QoD Broker, were working satisfactory before given to patients (i.e. real end-users).

MobiGuide outdoor AF physical exercise treatment scenario demonstrates very well the application of QoD Broker in a QoD-aware telemedicine system. Some of the ICT resources needed for this scenario are an electrocardiogram (ECG) sensing resource, a HR processor, a smartphone capable of storing data and connect to the sensing and processing components. One of the technological contexts may be characterized by noisy ECG, which has an effect on the QoD and, hence, the treatment. The process starts with the ICT resources. The BH sensing resource outputs the HR_{mon} clinical variable and an ECG signal with associated QoS information (ECG amplitude and ECG noise RQPs), possibly influenced by patient motion artifacts. The QoD Broker uses this QoS information as input to calculate the SNR sub-qualifier (e.g. 0.7 dB). Thereafter, it uses look-up tables to obtain the Se and Sp values of the BH processing resource, for this case $Se = 85\%$ and $Sp = 60\%$. With these Se and Sp values and the use of a mathematical transfer function, the Accuracy quality dimension of HR_{mon} clinical variable is computed: $Acc. = Se \times w + Sp \times (1 - w)$. Considering a weight factor of $w = 0.5$ (determined by the care practitioner), the Accuracy quality dimension is 72.5%. This scalar value is stratified to a particular grade value $Acc.' = Low$ using the stratification model (Table 1). The CDSS processes the HR_{mon} clinical variable together with its QoD ($Acc.' = Low$) to provide QoD-aware safe guidance to patients. For example, in the context of MG's non-supervised AF physical exercise treatment, the augmented guidance specifies that the patient should lower his/her physical exercise intensity. As a result, the CDSS generates a recommendation for the patient (e.g. "slow down") to maintain safe guidance. This way medical practitioners (involved in the augmented guidance specification) ensure that the patient is safely guided, although at times could be at the cost of a less effective physical exercise treatment.

Fig. 4. Summarized example of an AF physical exercise treatment adaptation.

4.2. Test prototype with patients

In the final stage of MobiGuide project, we conducted a ‘pilot study’ by applying the QoD-aware telemedicine system prototype in an operational setting with 9 AF patients and 9 GDM patients for a period of 3–4 months (in average). Once completed, we collected feedback on user experience and studied the feedback in order to determine the contribution of QoD Broker in the clinical setting.

The applied validation methods were ‘technical action research’ (TAR) and ‘questionnaires’. The technical action research method makes use of a system prototype in a real-world problem (e.g. Atrial Fibrillation disease guidance) to help a user (e.g. outpatients and care practitioners) and to verify if the designed solution fulfills the expectations [22]. The user experience information was obtained by using questionnaires, with a set of QoD related multiple-choice questions, for patients and medical domain experts (medical practitioners and nurses) in charge of the patients. In this research, which primarily focuses on QoD Broker, we present the QoD related questions and results. The usage of the TAR in combination with ‘questionnaires’ allowed us to verify the QoD Broker prototype performance in the real-world environment and helped us obtain precise answers from the users.

Patients were questioned about their experience with the QoD-awareness system. These questions addressed two aspects: 1) the patients’ experience with technological recommendations and 2) the patients’ feeling of safety while receiving treatments when outdoors. These are basically the outcomes of QoD Broker and other MG components interactions.

The questions related to the clarity of the technological recommendations received “clear” or “very clear” responses from patients (average score 89%). The number of recommendations received was considered “appropriate” by most of the patients (average score 81.5%). However, 5.5% of patients found the number of recommendations “annoying”. For the questions regarding the usefulness of recommendations, half of the patients graded it as “neutral”, the other half considered them “useful” or “very useful” (average score 79.5%).

The patients, in general, also felt safer (average score 76%) with the guidance given in the context of QoD-awareness for outdoor treatments (e.g. AF physical exercise treatment example illustrated in Fig. 4). The patients who performed higher number of outdoor sessions replied with the higher scores. Nevertheless, some patients did not feel the additional safety measures implemented in the QoD-aware system. One of the reasons could be that QoD did not degrade and, hence, the system did not provide additional recommendations. In fact, some patients would have preferred more user–system interaction during the outdoor sessions even if the QoD was optimal.

Medical domain experts found the role of QoD Broker necessary, especially in autonomous patient guidance systems (e.g. AF physical exercise treatment illustrated in Fig. 4), as the treatment can be adapted to guarantee patients safety (average score 80%). They also concluded that QoD information presented to them is important since it may impact their treatment decisions (average score 85%).

5. Discussion

As discussed in Section 1, several studies are related to our research study, but differ in several aspects. [2,3] address the potential impact of QoD on healthcare systems, and some [4, 5] present approaches to address QoD in such systems. For example, [4] presents a semi-automated system to evaluate the quality of medical measurements taken by patients and [5] identifies the challenges to ensure and assess QoD. In our study, we integrated a QoD management component into a telemedicine system that is capable of providing useful (treatment context aware) QoD information.

A number of studies, although not in the healthcare domain, address the importance of data quality information for the decision-maker [6–8]. However, they do not present a method to integrate the QoD related knowledge into an automated decision-making process, so that the decisions are QoD-aware. In our study, we provide a complete QoD-aware telemedicine system solution, which augments clinical guidelines with QoD-awareness, so that the CDSS is capable of adapting the treatment decision when QoD degrades [1].

Other studies have focused on data quality [9–11] and quality of context (QoC) [13]. They address factors that influence the data or context quality and the dimensions or indicators required to assess data quality or QoC. In [17], we present a method to select the QoD dimensions for the specific application domain and, here, we provide the architecture and functionalities of QoD Broker that is integrated into the telemedicine system. Hence, besides, identifying the QoD dimensions and computational models, we address how QoD should be integrated in the application domain.

We can conclude from the study that we went one step further towards understanding the application domain and we designed and implemented, in a real-world setting, a QoD-aware telemedicine system that overcomes difficult situations that arise due to QoD degradation.

6. Conclusion

Telemedicine systems benefit from the availability of ubiquitous clinical data. Consequently, ambulatory patient treatment, including medical practitioner remote supervision, becomes feasible. Successful deployment of telemedicine systems in the healthcare domain may reduce pressure on human and economical resources. However, supporting a large population of outpatients using telemedicine systems depends on the acceptance of this new technology by medical practitioners [23]. A key success factor is the quality of clinical data (QoD) produced by telemedicine systems. Remotely obtained clinical data has to fulfill the specified medical data quality requirements, but there is a high probability that QoD degrades due to performance variations of ICT resources.

Traditionally, a clinical decision support system (CDSS) uses computer interpretable clinical guidelines that do not consider variation of technological context. We propose a QoD-aware telemedicine system architecture that encompasses a QoD Broker system and a CDSS. The combination of these sys-

tems enables treatment adaptation based on changing QoD with a focus on outpatient treatment safety. However, the CDSS is not polluted with technical specific information since the QoD Broker is in charge of this translation.

The novel QoD Broker uses available quality of service (QoS) information from the telemedicine systems' ICT resources to compute treatment context-aware QoD. The CDSS uses the QoD in combination with QoD-aware computer interpretable clinical guidelines. As a result, it provides QoD-aware guidance that maintains the safety of the patient even when technological disruptions occur. Thus, we address the problems encountered when there is a degradation of QoD, as pointed out in other studies [3].

Our solution has been implemented in a real telemedicine setting focusing on outpatients. Nevertheless, this novel QoD-awareness approach is also applicable in a broader setting, for example, in intramural settings (e.g. hospitals) and diverse clinical domains (e.g. primary care).

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