Quality of Data Computational Models and Telemedicine Treatment Effects

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***Abstract*—Clinical decision-support functions of telemedicine systems use patient's monitored clinical data to support treatment of outpatients. However, the quality of monitored clinical data may vary due to performance variations of technological resources inside a deployed telemedicine system. This paper discusses models to compute quality of clinical data affected by quality of service provided by technological resources along the data processing and delivery chain between the point of monitoring and point of decision. We discuss prospective effects of quality of clinical data degradation on outpatient treatment with medical practitioners, and implement these effects in the clinical decision-making process during design time. Consequently, the designed telemedicine system is technological context and quality-aware and preserves patient's safety and treatment efficacy.**

Keywords—Quality of Data; Quality of Service; Computational Models; Technological Context- and Quality-Aware Telemedicine

I. INTRODUCTION

The ongoing evolution of Information and Communication Technologies (ICT) drive the development of next generation telemedicine systems. These systems require remotely monitored patients' clinical data to enable individual treatment decoupled from monitoring (location) or clinical decision-making (time) points. Medical practitioners assume the quality of patients' clinical data at the point of decision-making is sufficient for medical practice, but in fact they are not aware of the real quality of clinical data. In telemedicine, Quality of Service (QoS) of supporting ICT infrastructures (addressed in this paper as technological resources) are often unpredictable and difficult to manage since they depend on many systems conditions (e.g. wireless data communication networks load). QoS variation of technological resources may undesirably influence the treatment's technological context, i.e. QoS information provided by a collection of technological resources (e.g. communication systems, sensor devices) that characterize the treatment of a patient [1]. Technological context has a direct effect on the monitored clinical data's quality at points of decision during the telemedicine treatment. In such cases, the treatment may need to prospectively adapt to maintain patient's safety and treatment's efficacy.

Therefore, a challenge in telemedicine system design is to make the system aware of technological context and clinical data quality variations, and to provide mechanisms to safely adapt patient's treatment to these variations. In this paper, we augment the ICT based telemedicine system by a Quality of Data (QoD) framework that enables treatment adaptation in case quality of clinical data degrades. We specify, via a layering technique [2], the functional (i.e. conceptual) and non-functional (i.e. qualitative) relation between clinical variables and its abstractions used for the treatments and the underlying technological variables associated to the supporting technology. The non-functional relation includes computational models to derive clinical variables' QoD from technological resources' QoS.

In this paper, we adopt the computational models discussed in [3], which presents the computation of quality of context data from QoS to select an optimal end-to-end resource configuration chain. Other studies [4, 5] address the effect of technological resources' performance on clinical data and its quality provision. In contrast to [3-5], this paper describes techniques and computational models to build the bridge between technological and clinical areas in telemedicine. Moreover, we present the potential QoD impact on the treatment, so the treatment adapts to technological disruptions.

Our work has been implemented in the European project MobiGuide (MG) [6]. MG develops a telemedicine system that provides context aware clinical guideline based decision-support service to medical practitioners and patients. The system decisions for patient guidance must be made available anytime and anywhere and adapted to the technological, medical and personal context. This paper exploits the technological context concern to make patient guidance of envisioned MG system resilient to technological resources disruptions.

The paper is further organized as follows. Section II describes the applied layering technique. Section III provides an introduction to QoD and QoS. In section IV, we discuss illustrative computational models and their application. Section V presents the procedure used for treatment adaptation to technological context. Section VI presents the current implementation status in MG and future work. Section VII closes with a brief discussion and conclusion of the results.

II. LAYERING TECHNIQUE

We separate medical from technological concerns during the requirements elicitation process [7]. This brings forth a

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layering technique [2] which enables capturing functional and non-functional relations between clinical variables and technological variables used in clinical and technological layers respectively (Fig. 1). Although dependent on functional relations, the computational models, part of the non-functional relation, are addressed in Section IV.

A. Functional Relation

In clinical decision making, medical practitioners are used to reason in high level clinical concepts, i.e. clinical abstractions [8]. These clinical abstractions are typically represented as temporal patterns of (a combination of) elementary clinical variables (e.g. heart rate) and lower-level clinical abstractions. Clinical variables are output technological variables of the end-to-end data processing and delivery chain at points of decision. These technological level variables are monitored patient data traversing the sensing, processing and communication chain of technological resources. Consequently, clinical variables act as an intermediate between clinical abstraction and technological level variables (Fig. 1a).

B. Non-Functional Relation

Based on the functional relation, including the configuration of the technological resources, the non-functional relation links the QoD of clinical abstractions and technical variables via QoD of clinical variables. QoD of technological variables is influenced by QoS of preceding technological resources along the end-to-end data processing and delivery chain [2]. Consequently, QoD of clinical variables is affected by the QoS of technological resources required for its provision at the point of decision-making. Additionally, clinical variables directly affect the higher-level clinical abstractions' QoD, whereas used technological layer variables' QoD and technological resources' QoS indirectly affect QoD of a higher-level clinical abstraction (see Fig. 1b).

C. Example

In MG, we develop an outpatient physical exercise training treatment for patients suffering from atrial fibrillation (AF). During the AF physical exercise treatment's elicitation process, medical practitioners describe the treatment in terms of clinical abstractions. For example, they describe a clinical abstraction on which AF patient's monitored heart rate (HR_{mon}) should reside within a predetermined target heat rate (THR) range for an effective training that potentially improves AF patient's condition, i.e. THR_{range}. The upper boundary of THR_{range} depends on the THR, which is based on patient's maximum heart rate (HR) during an exercise stress test [9], HR_{max}, lowered by an intensity factor percentage (I_{fact}). The lower boundary of THR_{range} is based on the upper boundary value lowered by a tolerance. Consequently, $THR_{range} := HR_{mon} \in [THR\text{-}Tolerance, THR]$, with $THR = HR_{max} \times I_{fact}$. The medical practitioner predetermines the HR_{max} clinical abstraction value during a supervised Bruce Protocol stress test [9], and the I_{fact} and Tolerance values are predetermined in relation to a prescribed patient specific training program. HR_{mon} (Fig. 1c) is a clinical variable used by the THR_{range} clinical abstraction and it is derived from technological variables (e.g. ECG raw, HR) of the end-to-end data processing and delivery chain (e.g. BioHarness (BH) sensor and processor [10]).

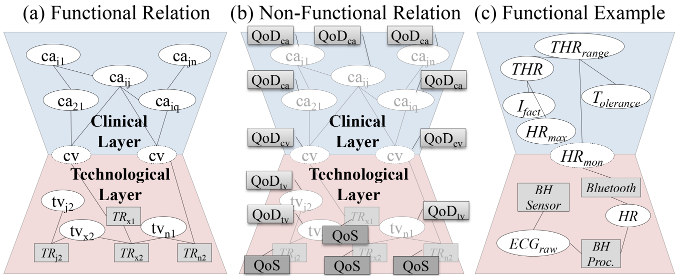

Fig. 1. Layering Technique [2]: (a) Functional relation: clinical abstractions (ca), clinical variables (cv), technological variables (tv) and technological resources (TR); (b) Non-Functional relation of QoD and QoS; (c) Example

Consequently, HR_{mon} clinical variable is the intermediate element between clinical and technological layer (Fig. 1c). Their non-functional relation is explained in Section IV-B.

III. QUALITY OF DATA AND QUALITY OF SERVICE

We adopt quality concepts of the literature [11-14] to express QoD by five quality dimensions: 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). These five quality dimensions represent often used qualifying characteristics in data quality [12] and healthcare [13] literature. We use these quality dimensions to describe QoD computational models (Section IV) and provide examples of telemedicine treatment adaptation (Section V). Quality dimensions may contain data sub-qualifiers. For example, Sensitivity (Se) and Specificity (Sp) are sub-qualifiers of Accuracy quality dimension as they qualify the probability of a data to correctly identify an observed phenomena or non-phenomena respectively (e.g. percentage of AF episodes correctly identified as being there and percentage of non-AF episodes correctly identified as not being there).

QoS of technological resources is also being expressed in terms of the five identified quality dimensions. In this case, each dimension represents the extent to which the output data's quality dimension is influenced by technological resource's QoS quality dimension. For example, a technological resource's QoS accuracy specifies the degree of correctness of resource processes data, preventing additional errors to the output data. We specify technological resource's QoS in terms of sub-qualifiers (as explained for QoD) and underlying Resource Qualifying Parameters (RQP). These sub-qualifiers and RQPs are either static (derived from technological resource manufacturer specified properties) or dynamic (derived from monitoring the technological resource's changing values properties). RQPs are the basic elements to compute the five quality dimensions values associated to the output data (i.e. technological variable or – at the point of decision – clinical variable) of a technological resource. Dynamic sub-qualifiers and RQPs may have an active influence on the quality dimensions values; in contrast, static sub-qualifiers and RQPs have a permanent influence.

In the MG project, we use the Zephyr BioHarness 3 (BH) [10] as a technological resource to monitor AF outpatient's HR remotely during physical exercise training treatment. The BH device captures, processes and transmits patient vital signs (e.g. ECG or HR) and associated QoS related information, i.e. RQPs and sub-qualifiers (Table I). The BH device has both static RQPs (e.g. CE certificate, HR range, ECG digital resolution) and dynamic RQPs (e.g. ECG amplitude, ECG noise, battery level). When the BH output suffers from external factors (e.g. motion artifacts induced by patient's activity) or technological disruptions (e.g. sensor malfunctioning or detachment), dynamic RQPs values change (e.g. ECG noise increases) as well as related sub-qualifiers (e.g. Se, Sp decrease), resulting in a HR_{mon} quality degradation at the point of decision (e.g. HR_{mon} accuracy decreases). Additionally, the dynamic RQP 'battery level', influences the degree of capability of the data to be available for meaningful decisions during the time span of the physical exercise treatment, influencing the dependability of HR_{mon}.

QoS variation affects QoD of technological variables and QoD of clinical variables and associated clinical abstractions at points of decision. This is the rational for the development of computational models (Section IV) that links QoS of technological resources to QoD of technological and clinical variables and QoD of clinical variables to QoD of clinical abstractions. Additionally, QoD degradation may have a harmful impact on patient's safety and treatment's efficacy. Therefore, in the requirements elicitation process, we consult medical practitioners to capture the requirements for a telemedicine system that adapts treatment (Section V).

IV. Computational Models

We use a scalar output of computational models to calculate quality of clinical data and apply these models to a single data processing and delivery chain.

A. Computational Models

We use different computational models to quantify the five quality dimensions identified in Section III for the data processing and delivery chain. We decompose each computational model into a set of technological resource transfer functions that determine the resource's QoS impact on quality of input data. For our convenience, 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 its 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. ECG sensing component) in the data processing and delivery chain. The quality of D_0 is not directly measureable. Therefore, QoD_0 contributes to the QoS_1 of the first technological resource with a neutral impact.

A transfer function depends on a quality dimension. For example, an arithmetic summation function can be used for Timeliness and Cost quality dimensions calculation and Boolean algebra for the Quality of Evidence quality dimension calculation. In case quality dimension calculation is not straightforward, graph based mapping (Fig. 2), look-up tables or more advanced mathematical functions are required. In the sequel, we address four possible computational models.

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 same transfer function, sum, 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).

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.

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 at *4 – 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 $Accuracy = Se \times w + Sp \times (1-w)$, $w \in [0, 1]$.

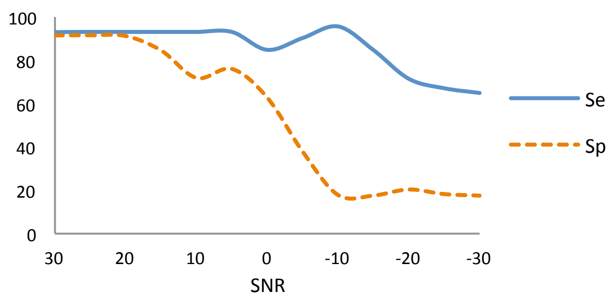

Fig. 2. AF algorithm's Se and Sp relation to input data's SNR [15]

4) *Graph-Based Mapping Functions*

The use of graph-based mapping (implemented by look-up 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. 2 shows an example of SNR effect on Se and Sp values of an AF detection algorithm [15].

B. *Computational Models Application*

Fig. 3 depicts a simplified system architecture of the MG system's mobile platform. A set of interacting technological resources creates a data sensing, processing and delivery chain. The start and end points of this chain respectively present the point of monitoring (PoM) and point of decision (PoD). Each resource outputs a technological variable (e.g. ECG, HR) and associated QoS values, whereas the last resource outputs the clinical variable (e.g. HR_{mon}) of discourse at the PoD, i.e. mobile Decision Support System (DSS). The QoD provider consists of the QoD Broker that uses aggregated QoS values to compute clinical variable's QoD (QoD_{HRmon}). The QoD Broker outputs QoD with a reference to a specific clinical variable to the mobile DSS (see Section V and Section VI). In this section we focus on the technological resource and QoD provider.

The BH is the technological resource of discourse. We model it as a chain of sensing, processing and communication resources (Fig. 3). The sensing resource outputs an ECG signal and associated QoS values (ECG amplitude and ECG noise), possibly influenced by motion artifacts. We use these QoS values to calculate the SNR and a graph-based transfer function to obtain the QoS values Se and Sp of the processing resource. With these Se and Sp values and the usage of a mathematical transfer function, the Acc. quality dimension of HR_{mon} clinical variable is computed: $Acc. = Se \times w + Sp \times (1\text{-}w)$ (see Section IV-A.3). Setting the weight factor to w = 0.5 (determined by the medical practitioner) the Acc. values for the ideal case (e.g. without motion artifacts) and non-ideal case (e.g. with motion artifacts) are 97.5% and 72.5% respectively (see also Table 1).

TABLE I. HR_{MON} QOD COMPUTATION

Case	**Technological resources QoS**		**QoD computational output**
	Sensing	***Processing***	
Ideal	SNR = 5.0 dB	Se = 98% Sp = 97%	Acc. =97.5%
Non-Ideal	SNR= 0.7 dB	Se = 85% Sp = 60%	Acc. =72.5%

Our computational models output a scalar value (e.g. Acc.= 97.5%) for each of the five quality dimensions of a clinical variable. However, in medical practice clinical variable quality is usually represented by quality grades *High*, *Medium*, *Low* and *Very Low,* as identified by GRADE healthcare working group [13]. Therefore, the computed scalar values of the quality dimensions must be stratified to a particular grade value. Graded data quality dimensions are denoted by ' (e.g. Acc.'=High). The underlying stratification model is based on a medical practitioner's interpretation of the computed scalar values and conforms to the medical way of working. Table II represents the stratification model for scalar values of HR_{mon} clinical variable's Acc. quality dimension, which has been approved by the medical practitioner for the AF physical exercise treatment. In collaboration with medical practitioners we associate scalar values to a grade values. On the other hand, a higher-level clinical abstractions' QoD are also affected by the QoD computation output. Clinical abstractions' quality dimensions grades are based not only on clinical variable's quality dimensions grades, but also on other lower-level quality grades of clinical abstractions. In Table II we stratify Acc. grades of the THR_{range} clinical abstraction with HR_{mon} clinical variable's Acc. grades, although it is also based on lower-level clinical abstractions' quality (e.g. THR, Tolerance). However, we do not consider these lower-level clinical abstractions for the THR_{range} quality grade computation because medical practitioners provide these values typically with a high quality.

V. TREATMENT ADAPTATION

Designing a telemedicine system that is resilient to technological disruptions requires treatment adaption to preserve patient's safety and treatment efficacy. During a treatment requirements elicitation session, we challenge medical practitioners to contemplate on quality of clinical variables degradation due to telemedicine system's technological resource (e.g. BH) performance disruptions in the context of a treatment scenario. Our aim is to collaborate with medical practitioners to determine prospectively the impact of changing technological context on quality of clinical variables and quality of clinical abstractions.

TABLE II. STRATIFICATION MODEL EXAMPLE FOR ACCURACY

Clinical Variable HR_{mon}		**Clinical Abstraction THR_{range}**
Scalar Ranges	***Grade Value***	***Grade Value***
[0%, 69.9%]	Very Low	Very Low
[70%, 79.9%]	Low	Low
[80%, 94.9%]	Medium	Medium
[95%, 100%]	High	High

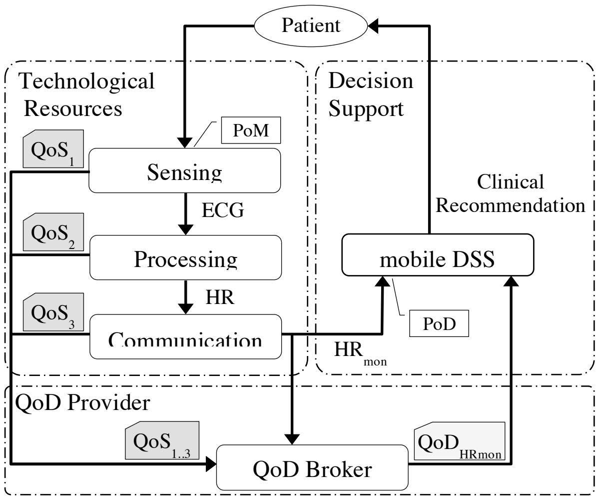

Fig. 3. Simplified system architecture of the MG system's mobile platform

In addition, we jointly determine the effect of (changing) QoD grades of clinical variables or clinical abstractions on the treatment. For example, we ask a medical practitioner in the context the AF physical exercise treatment to contemplate on the treatment effect of a "Low" Accuracy quality grade of the HR_{mon} clinical variable and the corresponding THR_{range} clinical abstraction. The medical practitioner considers the medical context (e.g. non-supervised physical exercise), treatment related clinical abstractions (e.g. THR_{range}) and patient medical condition (e.g. permanent AF) to determine required treatment adaptation. Collaboratively, we determine the required telemedicine system behavior for treatment adaptation in accordance to data quality associated to technological context in order to guarantee patient's safety (highest priority) and treatment's efficacy. This technological context- and quality-aware treatment adaptation process is part of the requirements elicitation methodology discussed in [2, 7].

Example: Table III shows the HR_{mon} and THR_{range} QoD stratification and its effect on the I_{fact} clinical abstraction. Stratification of HR_{mon} QoD computational output (see Table II) is collaboratively performed with medical practitioners to determine the specific quality dimension scalar value range to a grade value. When QoD of clinical variable HR_{mon} and QoD of its associated clinical abstraction THR_{range} degrades (e.g. Acc.' = *Low*), the medical practitioner determines the treatment effect. For example, the medical practitioner lowers the intensity factor I_{fact} clinical abstraction from 70%, which is used in normal practice [16], to 60%. The I_{fact} is a lower-level clinical abstraction used by THR_{range} and the THR_{range} is the clinical abstraction used by the telemedicine physical exercise treatment to guide the patient in a safe and efficient exercise intensity level (see Section II-C). The indirect effect of I_{fact} decrement on the treatment is the physical exercise intensity reduction. As a result, the decision-support function may generate a message to the patient (e.g. "slow down") when monitored HR is above the range, ensuring a lower physical intensity for safer patient's safety, possibly at the cost of a less effective training treatment.

TABLE III. HR_{MON} AND THR_{RANGE} STRATIFICATION AND ITS EFFECTS ON CLINICAL ABSTRACTIONS

Case	QoD comp. output	QoD HR_{mon}	QoD THR_{range}	Clinical Abstraction
Ideal	Acc.= 97.5%	Acc.'= High	Acc.'= High	I_{fact} =70%
Non Ideal	Acc.= 72.5%	Acc.'= Low	Acc.'= Low	I_{fact} =60%

VI. IMPLEMENTATION IN MG AND FUTURE WORK

We developed a QoD Broker prototype (Fig. 3) as a MG sub-system to compute QoD grades for clinical variables or clinical abstractions and provision of QoD information to the mobile DSS.

For every technological resource presented in Fig. 3, the QoD Broker uses their output QoS values (expressed in terms of sub-qualifiers and RQPs), transfer functions (see Section IV) and the initial cardiac electrical signal quality (QoD_{0}) to compute the QoD grade of technological resource's output data (QoD_{HRmon}). Note that QoD_0 contributes implicitly to the QoS_1 of the first technological resource with a neutral impact. The QoD Broker maps the HR_{mon} clinical variable's quality dimension scalar value to a corresponding quality grade by using the stratification model presented in Table II.

The clinical DSS of MG system's mobile platform is represented by the mobile DSS in Fig. 3. It uses clinical variable or clinical abstraction (e.g. HR_{mon}) and associated QoD (e.g. QoD_{HRmon}) to provide a patient with safe and quality aware (i.e. robust to technological-context and QoD variations) clinical recommendations. The mobile DSS uses a Computer Interpretable Guideline (CIG) which contains clinical concepts and rules relevant for the guideline based MG telemedicine services. To make the mobile DSS quality aware, we augment the CIG during design time with possible contexts that affect the clinical decisions expressed in treatment adaptation (see Section V). This results on a CIG-Customized-Contexts (CCC) [6].

The treatment adaption mechanisms are defined in the CCC and induced by either personal or technological context. The technological context is expressed in terms of QoD of clinical variables and its abstractions at point of decision. Hence, the CCC treatment adaptation is induced by quality of clinical data concerned to technological context (e.g. Table III). During telemedicine treatment execution, the QoD Broker acquires technological resources QoS values, computes QoD of the clinical variable at point of decision and stratifies the computed QoD to its corresponding quality grade. The mobile DSS uses the CCC as a knowledge base and obtains the clinical variable and associated QoD to make technological context- and quality-aware clinical recommendation (e.g. message to patient to slow down).

Future work encompasses the presentation of the elicitation process performed with medical practitioners aiming to augment both MG's Atrial Fibrillation (AF) and Gestational Diabetes Mellitus (GDM) guidelines with changing technological context. Additionally, in collaboration with medical practitioners we study the effects of all combinations of the five quality dimensions and their four grades on the mentioned treatments. The objective here is to avoid potential conflicts in recommendations for treatment adaptation caused by different treatment effects of each individual quality dimensions grades. Additionally, we study QoD temporal abstraction to prevent "nervous" behavior of a telemedicine system's DSS. For example, if medical practitioners evaluate clinical data episodes (i.e. temporal patterns) of 5 minutes before they make a clinical decision, it makes sense to temporal abstract QoD and present one QoD grade for each episode. Without clinical data episodes and QoD temporal abstraction, every clinical data sample (e.g. sample rate 1 Hz) is accompanied by QoD grades. If these grades fluctuate, the treatment adaption may be based on the same clinical sampling frequency (e.g. 1 Hz). This potentially creates "nervous" behavior of the telemedicine DSS, resulting in undesirable frequent and potentially conflicting clinical recommendations for patients or medical professionals.

VII. Discussion And Conclusion

Clinical decision-support functions of telemedicine systems use patient's monitored clinical data to support treatment of outpatients. However, the quality of monitored clinical data may vary due to performance variations of technological resources inside a deployed telemedicine system. We accept and deal with the consequences of "unavoidable" disruptions of technological resources that may affect the monitored clinical variables' quality during patient treatment. Our aim in this paper is not to make the technological resources of telemedicine systems more reliable or maximize QoD of clinical variables at points of decision. Technological disruptions and other external factors that can affect QoD are hard to avoid and sometimes they are unpredictable. Our goal is to make telemedicine systems technological context and quality aware to preserve treatment quality.

We presented a solution to determine the effect of changing quality of clinical variables and changing quality of clinical abstractions on telemedicine treatment. It uses static and dynamic QoS information of telemedicine system's technological resources and computational models to compute five QoD dimensions (each with four grades) of clinical variables and clinical abstractions at point of decision. The computation is performed by a QoD provider component; i.e. the QoD Broker. This QoD Broker uses aggregated QoS values of technological resources to compute clinical variable's QoD and outputs QoD and a reference to a specific clinical variable to the data quality aware mobile DSS. The mobile DSS provides patient treatment that is safely adapted to different clinical variable's quality variations. This adaptation prevents the potential quality deterioration of clinical recommendations, guidance and treatment provided to the patient. Potentially, safe treatment adaptation increases patient treatment compliancy. As a result, this solution makes it possible to design a technological context- and quality-aware telemedicine system design that ensures patient's safety and treatments efficacy.

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References

[1] A. K. Dey, "Understanding and Using Context," *Personal Ubiquitous Comput.*, vol. 5, pp. 4-7, 2001.

[2] N. Larburu, I. Widya, R. G. A. Bults, and H. J. Hermens, "Making medical treatments resilient to technological disruptions in telemedicine systems," in *Biomedical and Health Informatics (BHI), 2014 IEEE-EMBS International Conference on*, 2014, pp. 285-288.

[3] I. Widya, B. J. van Beijnum, and A. Salden, "QoC-based Optimization of End-to-End M-Health Data Delivery Services," in *Quality of Service, 2006. IWQoS 2006. 14th IEEE International Workshop on*, 2006, pp. 252-260.

[4] S. Vavilis, N. Zannone, and M. Petkovic, "Data reliability in home healthcare services," in *Computer-Based Medical Systems (CBMS), 2013 IEEE 26th International Symposium on*, 2013, pp. 377-380.

[5] M. Shin, "Secure remote health monitoring with unreliable mobile devices," *Journal of Biomedicine and Biotechnology*, vol. 2012, 2012.

[6] MobiGuide. Available: http://www.mobiguide-project.eu/ (last view 3-5-2014)

[7] N. Larburu, I. Widya, R. G. A. Bults, H. J. Hermens, and C. Napolitano, "Early phase telemedicine requirements elicitation in collaboration with medical practitioners," in *Requirements Engineering Conference (RE), 2013 21st IEEE International*, 2013, pp. 273-278.

[8] C. Combi, E. Keravnou-Papailiou, and Y. Shahar, *Temporal Information Systems in Medicine*: Springer Publishing Company, Incorporated, 2010.

[9] R. A. Bruce, "Exercise Testing for Evaluation of Ventricular Function," *New England Journal of Medicine*, vol. 296, pp. 671-675, 1977.

[10] Z. Technology. *BioHarness 3 Medical Data Sheet*. Available: http://www.zephyranywhere.com/products/bioharness-3/

[11] R. Y. Wang, H. B. Kon, and S. E. Madnick, "Data quality requirements analysis and modeling," in *Data Engineering, 1993. Proceedings. Ninth International Conference on*, 1993, pp. 670-677.

[12] Y. Wand and R. Y. Wang, "Anchoring data quality dimensions in ontological foundations," *Commun. ACM*, vol. 39, pp. 86-95, 1996.

[13] G. H. Guyatt, A. D. Oxman, R. Kunz, Y. Falck-Ytter, G. E. Vist, A. Liberati, *et al.*, "Going from evidence to recommendations," *BMJ*, vol. 336, pp. 1049-51, May 10 2008.

[14] I. Widya, R. Stap, L. Teunissen, and B. Hopman, "On the end-user QoS-awareness of a distributed service environment," *Protocols for Multimedia Systems*, pp. 222-237, 2001.

[15] N. Larburu, T. Lopetegi, and I. Romero, "Comparative study of algorithms for Atrial Fibrillation detection," in *Computing in Cardiology (CinC), 2011*, 2011, pp. 265-268.

[16] P. S. Osbak, M. Mourier, J. H. Henriksen, K. F. Kofoed, and G. B. Jensen, "Effect of physical exercise training on muscle strength and body composition, and their association with functional capacity and quality of life in Patients with Atrial fibrillation: A Randomized controlled trial," *Journal of Rehabilitation Medicine*, vol. 44, pp. 975-979, 2012.