Future Generation Computer Systems 96 (2019) 297–308

Contents lists available at ScienceDirect

Future Generation Computer Systems

journal homepage: www.elsevier.com/locate/fgcs

Missing data resilient decision-making for healthcare IoT through personalization: A case study on maternal health

Iman Azimi [a,*], Tapio Pahikkala [a], Amir M. Rahmani [b,c], Hannakaisa Niela-Vilén [d], Anna Axelin [d], Pasi Liljeberg [a]

[a] Department of Future Technologies, University of Turku, Turku, Finland
[b] Department of Computer Science, University of California Irvine, Irvine, CA, USA
[c] Institute of Computer Technology, TU Wien, Vienna, Austria
[d] Department of Nursing Science, University of Turku, Turku, Finland

HIGHLIGHTS

- A personalized missing data resilient decision-making approach is proposed.
- The approach is presented for a real human subject trial on maternal health.
- Personalized models are defined, exploiting medical and context data.
- A personalized pooling method is introduced to deliver health decisions.
- The proposed approach is evaluated in terms of accuracy of the health decisions.

ARTICLE INFO

Article history:
Received 11 July 2018
Accepted 11 February 2019
Available online 20 February 2019

Keywords:
Missing data
Long-term monitoring
Health monitoring
Internet of Things
Maternity care
Personalized decision making

ABSTRACT

Remote health monitoring is an effective method to enable tracking of at-risk patients outside of conventional clinical settings, providing early-detection of diseases and preventive care as well as diminishing healthcare costs. Internet-of-Things (IoT) technology facilitates developments of such monitoring systems although significant challenges need to be addressed in the real-world trials. Missing data is a prevalent issue in these systems, as data acquisition may be interrupted from time to time in long-term monitoring scenarios. This issue causes inconsistent and incomplete data and subsequently could lead to failure in decision making. Analysis of missing data has been tackled in several studies. However, these techniques are inadequate for real-time health monitoring as they neglect the variability of the missing data. This issue is significant when the vital signs are being missed since they depend on different factors such as physical activities and surrounding environment. Therefore, a holistic approach to customize missing data in real-time health monitoring systems is required, considering a wide range of parameters while minimizing the bias of estimates. In this paper, we propose a personalized missing data resilient decision-making approach to deliver health decisions 24/7 despite missing values. The approach leverages various data resources in IoT-based systems to impute missing values and provide an acceptable result. We validate our approach via a real human subject trial on maternity health, in which 20 pregnant women were remotely monitored for 7 months. In this setup, a real-time health application is considered, where maternal health status is estimated utilizing maternal heart rate. The accuracy of the proposed approach is evaluated, in comparison to existing methods. The proposed approach results in more accurate estimates especially when the missing window is large.

1. Introduction

Remote health monitoring systems broadly extend the boundaries of everyday healthcare access particularly for at-risk population groups including pregnant women [1] and senior adults [2] who may require additional observation. These systems are very promising in the healthcare domain as the individuals can be continuously monitored for early detection, preventive care, and early intervention. The key function of such healthcare systems is to ubiquitously observe and analyze users' health conditions, and subsequently deliver medical early-warning as well as health and wellness coaching.

* Corresponding author.
E-mail address: imaazi@utu.fi (I. Azimi).

https://doi.org/10.1016/j.future.2019.02.015

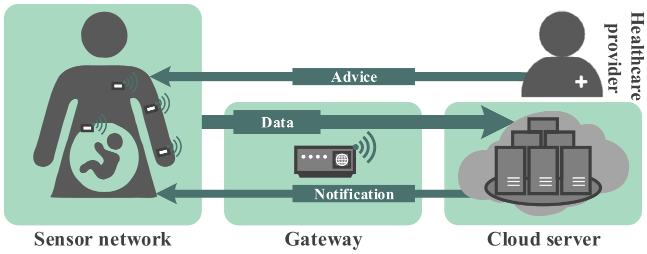

Fig. 1. An IoT-based system for remote health monitoring.

Fortunately, recent advances in Internet-of-Things (IoT) technologies have paved the way for enabling such monitoring services with 24/7 availability. IoT is a growing network of interconnected objects that envision a shared knowledge for smart and autonomous decision-making and actuation [3–6]. In the healthcare domain, IoT systems leverage different sensing, computing and communication resources.

As illustrated in Fig. 1, the architecture of IoT-based systems can be partitioned into three main tiers [7]. First, a *Sensor network* includes wearable and mobile sensors (i.e., Body Area Network) recording health and context data, by which the user's condition is perceived. Second, a *Gateway* acts as a bridge between the *Sensor network* and remote servers. Such a device (e.g., an access point) mostly performs data transmission and conventional services such as protocol conversion. However, alternative network infrastructures (e.g., smart e-health gateways) are proposed to incorporate intelligent techniques into the edge of the network [8–10]. Third, a *Cloud Server* offers broadcasting, data storage and a wide range of data analytic techniques (e.g., machine learning), through which healthcare services and applications are obtained [11].

In the real-world domain, missing data is one of the biggest challenges among the IoT-based health monitoring systems. Missing data refers to an entry in data where no value is available. Such missingness often occurs over the process of health monitoring, in particular long-term screening, due to failure in data collection and data transmission, as the sensor(s) might detach from the skin, lose connections with gateway devices or run out of batteries. Moreover, in case of long-term monitoring, the user might refuse or forget to use wearable sensor(s) all the time. This inconsistent and incomplete data collection leads to failure in decision making and consequently the mission of the application.

There is a large body of literature on the analysis of missing data in databases [12,13]. However, most of the conventional techniques are insufficient for real-time health monitoring systems since they neglect the variability of the missing data in estimations. This issue is especially significant in primary vital signs (e.g., heart rate) as the variations are considerably large, influenced by different factors such as health conditions, physical activities and surrounding environment. Clearly, these techniques generate biased estimates and subsequently cause high error rates in health applications. In consequence, a missing data resilient method is required to consider a wide range of parameters while minimizing the bias of estimates. We believe such a solution can be realized for real-time health monitoring systems by holistically leveraging IoT-enabled concepts such as multi-modal data collection and personalization.

In this paper, we present a personalized missing data resilient decision-making approach to continuously deliver health decisions despite missing values. This approach uses a Multiple Imputation method [12,13] reinforced with various data resources (e.g., context information) in IoT-based systems to estimate missing values. Subsequently, a personalized pooling method is introduced to provide an acceptable decision according to states of the user and monitoring system. Our approach is proposed for a real human subject trial on maternal health where 20 pregnant women were remotely monitored for 7 months (i.e., 6 months of pregnancy and 1 month postpartum) beside normal check-up visits in maternal health clinics. In this case study, we concentrate on a real-time health application, in which maternal health status is remotely estimated using maternal heart rates. Major contributions of this paper are as follow:

- A personalized missing data resilient decision-making approach is proposed to continuously deliver health decisions despite missing data.
- The approach is presented for a real human subject trial on maternal health, focusing on a real-time health application where maternal health statues are remotely estimated.
- Personalized models are defined and used exploiting maternal (medical) history and context data to impute the missing values.
- A personalized pooling method is introduced to fuse the values and deliver health decisions leveraging user's data.
- The proposed approach is evaluated in terms of accuracy of the health decisions, in comparison to existing missing data analysis methods.

The remainder of the paper is organized as follow. In Section 2, we outline background and related work of this research. Section 3 describes the proposed solution. The demonstration and evaluation are provided in Section 4; and finally, Section 5 concludes the paper.

2. Background and related work

In this section, we first present our case study on maternal health monitoring, including a maternal health indicator to remotely estimate health conditions of pregnant women. Then, we delve into the missing data concept and possible techniques of dealing with this issue.

2.1. Maternal health monitoring

The maternal body undergoes a variety of changes throughout pregnancy, particularly in the cardiovascular system. Cardiac output and compliance elevation is an example, which is reflected by different vital signs such as stroke volume and heart rate [14,15]. These changes are parts of physiological adaptations during pregnancy and are mostly normal. However, they are affected by pre-pregnancy and pregnancy conditions and complications. On the one hand, diseases and serious conditions such as maternal obesity, diabetes and depression considerably impact pregnancy and elevate vital signs (e.g., heart rate and blood pressure), increasing risk factors for various health problems in the mothers and their future offspring. On the other hand, a healthy lifestyle consisting of an adequate diet and regular physical activity engagement could be beneficial [16,17].

To investigate such physiological changes in pregnancy, long-term monitoring and studies of pregnant women are desirable [18,19], assessing their health conditions and providing efficient recommendations and guidelines. In this context, we conduct a real-time maternal monitoring and concentrate on heart rate variation and physical activity of pregnant women. This study includes 7 months monitoring of 20 pregnant women, in which heart rate, steps, hand movements, sleep level and ascending/descending stairs are continuously collected via a smart wristband. The parameters should be mapped into an abstracted level of data (i.e., a health score) to continuously and explicitly indicate her maternal health status.

Therefore, a maternal health indicator is selected to remotely estimate the health condition while the user is engaging in various physical activities in everyday settings. This indicator leverages a set of guidelines, rules and recommendations that state the target ranges of heart rate in different phases of pregnancy [14,16,17,20–22]. In our case study, this rule-based indicator tailors continuous monitoring of heart rate, physical activity, personalized data (e.g., baseline heart rate values at the beginning of the monitoring) and meta-data (e.g., gestational week and maternal age) to estimate the health decision. The decision is a warning sign ranging from 0 to 3, where 0 indicates a normal health condition and 3 shows the highest health deterioration [23,24].

2.2. Missing data

In the first place, it is important to understand the properties and patterns of the missing values for developing effective methods in real-world applications. Various missingness mechanisms cause missing values in the health monitoring systems, interrupting real-time decision-making. As proposed by Rubin et al. [12,13,25], such missingness mechanisms generally stand into three main categories. (1) *Missing Completely At Random (MCAR)*. The missing value is independent of the data values. For example, unpredictable data loss occurs during the monitoring in case of sensor failure or loss of Internet connection. (2) *Missing At Random (MAR)*. The probability of data to be missing is related to available information. However, the missingness does not depend on the missing values. For instance, the vital signs are more likely to be missing in the evening, as the sensors are disconnected to be charged when the user is at home. (3) *Not Missing At Random (NMAR)*. It occurs when the missingness depends on the missing values. For example, a pregnant woman removes the wearable devices while she is smoking, obscuring the direct effect of smoking on the vital signs.

There is a broad variety of missing data analysis methods in the literature, aiming to provide estimates with acceptable bias (i.e., distance between the estimate and the true value) for missing values [13,26–29]. Such analysis methods have their own strengths and restrictions. They are selected according to target applications with different requirements (e.g., desired accuracy) and limitations (e.g., the amount of missing data and the missingness mechanisms). In the following, we outline various missing data analysis methods available in the literature.

Deletion methods are the most straightforward approaches for handling missing data, where records with missing values are eliminated. Listwise deletion is one of the methods where a record is dropped out from the analysis if it has at least one missing attribute. This method results in a complete dataset although it reduces the amount of data. Similarly, Pairwise deletion is another method in which a record is omitted on an analysis-by-analysis basis. This method minimizes the deletion, in contrast with the Listwise deletion, as records with missing values are kept if their under-analysis attributes are not missing. Such deletion methods are restricted to MCAR, otherwise they produce biased estimates [28,30–32].

Despite the deletion methods, imputation-based methods fill-in the missing values exploiting available (i.e., observed) data. There are different imputation methods in the literature including mean imputation, Last Observation Carried Forward (LOCF) imputation, regression imputation, hot-deck imputation, cold-deck imputation and K-Nearest-Neighbor (KNN) imputation [12,33–35]. Unfortunately, such single imputation methods might lead to biased estimates, as they neglect the variability of the missing values. Additionally, Multiple Imputation (MI) is a modern missing data imputation method that complete the dataset, considering imputation uncertainty [12,13,36–38]. MI includes three main steps as *Imputation*, *Analysis* and *Pooling*. First, different estimates ($n \geq 2$) for the missing values are created via different procedures (e.g., linear regression and hot-deck). Second, the completed datasets are analyzed. Last, the results are integrated into one final output. In contrast with single imputation methods, MI is applicable for both MAR and MCAR.

In addition to the imputation-based methods, model-based methods create a model of the observed data to estimate the missingness. For example, Maximum Likelihood Estimation (MLE) method utilizes available data to approximate parameters (e.g., mean and standard deviation of a log-likelihood function) that fits the data [13,39,40]. Missing values can be estimated via the obtained model. MLE provides unbiased estimates for MAR and MCAR. Furthermore, there are model-based methods such as pattern-mixture, selection models and shared-parameter models, that are able to yield estimates for NMAR. Such methods are appropriate for studies where data are recorded repeatedly through time [41–44].

Moreover, machine learning-based methods tailor available data (i.e., attributes) to provide a hypothesis (i.e., classifier). The hypothesis could assign new values to missing attributes. Thus far, different approaches including Artificial Neural Networks (ANN), Support Vector Machine (SVM) and Generic algorithms have been evaluated for missing data estimations [45–50]. On the other hand, some machine learning-based methods handle missingness in a dataset without imputing values. In such methods, a classifier is trained by observed data including missing values, and subsequently decision making is performed. However, the missingness and poor correlation between available attributes might decrease the performance of the methods. These learning-based methods (e.g., Decision Tree) have been investigated in different studies [51–54].

In addition, there are studies to investigate missing data in IoT devices and wireless sensor network, featuring a multi-sensors data collection. In this regard, a probabilistic method has been proposed to estimate the missing value considering similarity in neighboring sensors data [55]. Similarly, missing, corrupted and late-reading data has been tackled in streaming data [56–58].

3. Missing data resilient decision-making approach

In this section, we tackle the missing data issue in IoT-based health monitoring systems, which are incapable of providing services when sensory data are unavailable or unreliable. In this regard, we, first, outline which missing data analysis techniques can be suitable for these systems. Then, we present the definitions and functions of our personalized decision-making approach via a case-study on maternal health monitoring.

As mentioned in Section 2.2, there is a wide range of methods available for missing data estimations, targeting different applications and missingness mechanisms. Many of the available techniques are, nevertheless, inappropriate for real-time decision-making of IoT-based health monitoring systems. Deletion methods are not applicable in such systems as the decision making is interrupted while there is a missing input. Moreover, the decision making is vulnerable to biased values when single imputation methods are exploited. LOCF imputation is also a straightforward method used for longitudinal studies, which fills in missing values leveraging the pattern of gradual changes in observed data. This method is inappropriate, due to underestimating the variation of the missing values. In addition, conventional multiple imputation, model-based methods (e.g., Maximum Likelihood Estimation) and machine learning-based methods are other possible alternatives. In health monitoring systems, these methods are insufficient for data with high variations such as heart rate, which highly depends on different factors.

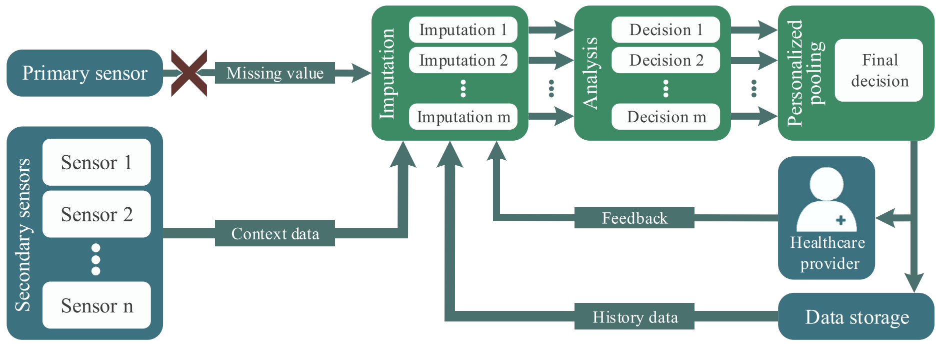

Fig. 2. Health decision making while the primary data (from primary sensor) is missing. In this setup, context data (from Sensor 1 to Sensor n), history data and user's feedback are utilized in the computation.

In contrast, auxiliary information can be utilized in missing data analysis techniques to mitigate the bias of the estimates [59–62]. Auxiliary information is additional data or meta-data that correlates with the value of interest (i.e., missing value). The use of such information in a missing data analysis technique is suitable for IoT-based monitoring systems due to their capability of heterogeneous data collection. Moreover, this information is very promising in real-time health decision-making as the missingness mechanism might be MAR or NMAR.

The IoT-based systems provide a great opportunity to record such auxiliary information, also named as context, along with the primary data collection throughout the monitoring. Context is the information that describes the environment and condition of the system [63]. Context-awareness in computing enables the IoT-based systems to observe and understand the sensory data and to be aware of their own states and surrounding environment, providing robust and adaptive behavior in different conditions [64,65]. In addition, other meta-data such as medical records and user feedback can be manually added to the computations to improve the system's performance.

To incorporate context-awareness into our missing data resilient decision-making approach, we believe that Multiple Imputation (MI) method can be an appropriate alternative. In this regard, the computation of this decision-making approach is partitioned into three main components as *Imputation*, *Analysis* and *Personalized Pooling*, estimating a real-time health score while the sensory data is missing. This function is depicted in Fig. 2, where the data collected from one sensor is missing. In the rest of this paper, we entitle this sensor as primary sensor and its data as primary data; and other sensors are named as secondary sensors which acquire context data and other information including other vital signs.

We thoroughly present these three components in the following and clarify the definitions and functions of our approach via a case study on maternal health during pregnancy. In this context, we concentrate on a maternal health indicator (see Section 2.1) which remotely estimates the degree of maternal health condition while the pregnant woman is engaging in various physical activities in everyday settings. This indicator tailors sensory data and meta-data to estimate the health score (i.e., warning sign). However, its functionality is limited to the availability of the real-time heart rate value (i.e., primary data). The proposed decision-making approach allows this health indicator to acceptably operate even if the heart rate is missed due to interruptions in data collection or data transmission.

3.1. Imputation

A number of different methods are exploited to impute the missing value (i.e. maternal heart rate in our case) m times, where $m \geq 2$. Therefore, m values are estimated leveraging different resources, each of which holds a considerable correlation with the primary data that is missing. The method of selection depends on the nature of the data and the type of auxiliary information. In the following, we outline methods to impute maternal heart rate values throughout the monitoring.

3.1.1. Short-term data

First, short-term history of data (i.e., preceding neighbors) can be utilized for the data imputation. These values correlate strongly with the missing value, particularly when the context situation and the individual condition are constant. Autoregressive models [66] are conventionally used for such a sequence of data, in which the current value is estimated from n preceding values. The autoregressive model of order n is defined as:

$$\begin{aligned} x_t &= f_s(t, \beta) \\ &= \beta_0 + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \cdots + \beta_n x_{t-n} \end{aligned} \tag{1}$$

where $x_{t-1}, x_{t-2}, \ldots, x_{t_n}$ are the previous n data, and $\beta_0, \beta_1, \ldots, \beta_n$ are the parameters of the model estimated.

In our case study, non-missing heart rate values from previous weeks are selected as the training data to estimate the parameters via a regularized least-square (i.e., ridge regression) desired to minimize:

$$\sum_{i=1}^{k} [x_i - f_s(t, \beta)]^2 + \lambda \sum_{j=0}^{n} \beta_j^2$$

where k is the number of training data, x_i indicates the actual heart rate, $f_s(.)$ estimates the heart rate from preceding data, and $\lambda > 0$ is a regularization parameter [67,68]. The model is periodically updated to consider variation of maternal heart rate throughout pregnancy.

The estimated value is added to the heart rate set, so it is considered as a preceding neighbor for the next iteration. When a considerable number of data items are missing, the estimates become unreliable in this imputation as the errors are accumulated. Root-mean-square error (RMSE) of the heart rate estimates for a pregnant woman is shown in Fig. 3. As indicated, the RMSE values increase when a large portion of data is missing. In a similar manner using neighboring heart rate values, the unreliability of heart rate estimation when the missing window is large is investigated in [69]. In consequence, this imputation is appropriate only when the amount of missing data is small.

3.1.2. Context data

Associations between the primary data and context information can be exploited to impute the missing values. This can be indicated as:

$$x = f_c(t, \gamma) \tag{2}$$

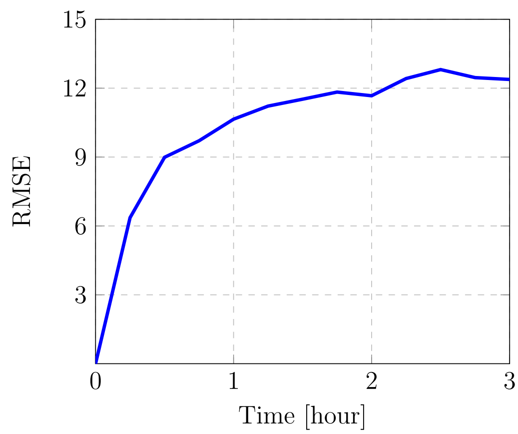

Fig. 3. RMSE of the estimates of a pregnant woman's heart rate (1714 iterations) using the autoregressive model.

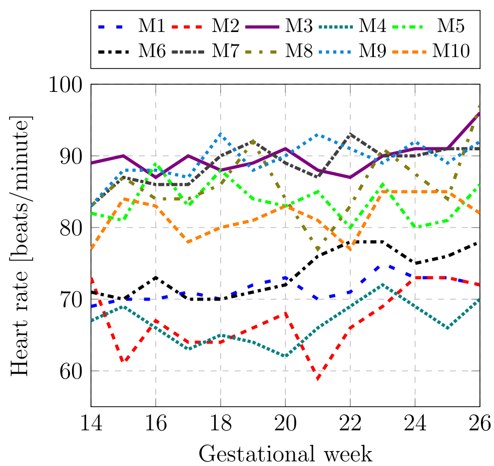

Fig. 4. Weekly average of maternal heart rate values of 10 pregnant women during sedentary time in the second trimester.

where γ is the context-related data and $f_c(.)$ is the function that approximates the heart rate value. In our case study, context data are the maternal physical activities, including 7 states as light sleep, deep sleep, sedentary, very light activity, light activity, moderate activity and vigorous activity. They are specified via steps and hand movements of the user [70,71]. Such physical activities are associated with the heart rate values and their variations.

However, this association is specific for each individual, so a personalized model is required. To show the differences in maternal heart rate, we select data from 10 pregnant women as examples. Weekly average heart rate values of these women during the sedentary time in the second trimester (i.e., gestational weeks 14–26) are illustrated in Fig. 4. As indicated, the heart rate ranges are not overlapped in some cases. Average heart rates of $M4$ vary from 62 to 72 beats/min although $M3$ average heart rates are between 87 and 96 beats/min. Moreover, such a model should be dynamically updated frequently (e.g., every week or every two weeks) because conditions of each pregnant woman are changing as the pregnancy advances. Fig. 5 illustrates such variations in average heart rates of one pregnant woman in different activities from gestational week 14 to postpartum week 4.

In our context, Eq. (2) can be defined as:

$$x = \gamma(t)^T H \tag{3}$$

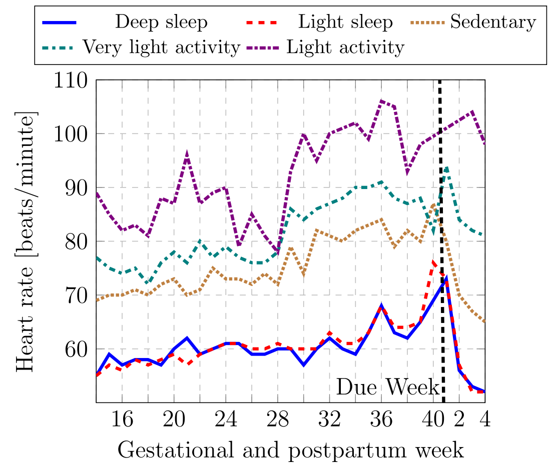

Fig. 5. Weekly average of maternal heart rate values of a pregnant woman in different activities from week 14 to postpartum week 4.

where $\gamma(t) = [p_1(t), p_2(t), \dots, p_7(t)]$ represents which of the 7 physical activities is allocated to t, where $p_k(.)$ is either 0 or 1 and:

$$p_1(t) + p_2(t) + \cdots + p_7(t) = 1$$

$H = [h_1, h_2, \dots, h_7]$ also indicates the most probable heart rate value in each state. This vector is uniquely defined for each individual according to non-missing data of previous weeks of monitoring.

3.1.3. Lifestyle data

Similarity in heart rate patterns due to repetitive habits (i.e., user's lifestyle) is another resource to impute missing values. These patterns could be manually added by users (feedback) or automatically extracted from the data. This is significant in the monitoring particularly when the context data is incomplete or not fine-grained enough. For example, we access to the physical activity of the pregnant women, but no information is available regarding eating and drinking habits (e.g., time and duration of meals), which affect user's heart rates [72]. With this intention, the missing value can be obtained via a function as:

$$x = f_l(\phi) \tag{4}$$

where ϕ holds history data and/or feedback.

In our case, non-missing heart rate values of the current time window are compared with previous time windows, and the window with the most similar heart rate pattern is extracted. Then, the imputation is fulfilled using heart rates of the most similar window. In this regard, Eq. (4) can be determined as:

$$x = x_k \tag{5}$$

where x_k is the corresponding heart rate value of the window k, which has the least distance to the current window. Hence, k is specified via:

$$\operatorname*{argmin}_{k \in \phi} dist(k)$$

which $dist(.)$ is a distance function defined as:

$$dist(k) = \sum_{i=1}^{n} \|x_{i0} - x_{ik}\|^2$$

where n is the window length, and x_{i0} and x_{ik} are available heart rate values in the current window and window k, respectively.

Moreover, additional information can be manually collected to select the most similar heart rate pattern. Such information includes self-reported physical activities or events marked in user's calender, from which similar windows are selected to perform data imputation. For instance, the user participates in a certain exercise course every odd day from 2 pm to 4 pm Heart rate data of this exercise can be leveraged if the heart rate value is missed in this activity in the future.

3.2. Analysis

The rule-based maternal health indicator is implemented, mapping the sensor data into an abstracted decision. It repeats m times per iteration, as m versions of the missing value are estimated in the *Imputation* part. Therefore, m decisions are generated in each iteration. m equals to 3 in our case study as the missing heart rate value is filled via the 3 imputation methods. However, the decisions might be diverse due to inaccuracy and uncertainty in the imputation methods.

The rule-based indicator generates a warning score between 0 and 3 for each heart rate value. Similar to a typical obstetric Early Warning Score (EWS) [23,24], different ranges are defined for the heart rate value to obtain the score. The ranges are defined for each pregnant woman according to personalized data such as baseline heart rate at the beginning of the monitoring. In addition, a set of guidelines and rules are utilized [14,16,17,20–22]. For examples, heart rate should not exceed 140 (beats/min) while the mother engages moderate and vigorous activities; it should not be less than 40 (beats/min) during sleep and sedentary time; and heart rate likely rises 20% till the end of pregnancy. Note that this function is assumed to indicate the functionality of the proposed approach, and it can be replaced with other classifiers.

3.3. Personalized pooling

A pooling method is performed to integrate the m decisions into a final decision (i.e., d_{final}). An arithmetic mean is a conventional method in this case. However, it might be inappropriate as the decisions with different errors are treated equally, even if some decisions hold high error rates.

We propose a *personalized pooling* method to alleviate the impact of the errors in the final decision. In this regard, a weighted arithmetic mean is exploited to pool the decisions, in which the weights become personalized throughout the monitoring leveraging user's data. In each iteration, the weights are determined and selected according to the states of the user and monitoring system. The final decision is obtained via a dot product of the vectors of the m decisions and the personalized weights that satisfies:

$$w_1 + w_2 + \cdots + w_m = 1$$

When the primary data is available, the weights are calculated by the squared error between actual and estimated values. However, as conditions of the user and system are highly dynamic (e.g., state of the user and size of the missing window), general weights are insufficient, minimizing the sum of squared errors over all time points. In this regard, we define different states for each imputation and calculate the sum of squared errors over the corresponding points in each state. In the following, we outline how states and weights are defined in our case study with the 3 imputation methods.

The first imputation is related to the short-term data. The error of the imputation highly depends on the portion of missing data, as indicated in Fig. 3. Therefore, the weights should be determined for different missing window sizes. A missing window refers to the interval between the current point and the last point that heart rate data was recorded. When the missing window size is i, the last i value(s) of heart rate data including current heart rate and previous values are removed; the current heart rate is imputed; and the weight is determined using the errors in this iteration and previous iterations. This process is repeated n_1 times with different sizes of missing window, where the maximum missing window size is n_1. In consequence, a set of weights (i.e., $W_1 = \{w_{1,1}, \ldots, w_{n_1,1}\}$) is obtained for the n_1 missing windows.

The second imputation is associated with the context data. The uncertainty of the heart rate is significant in this imputation as the most probable heart rate is selected (see Section 3.1.2). This uncertainty (e.g., variance) are diverse in different physical activities. For instance, in most cases, the variance of deep sleep heart rate is considerably less than the variance of heart rates of vigorous activity. Therefore, the squared errors should be severally calculated for each physical activity to obtain weights—i.e., $W_2 = \{w_{1,2}, \ldots, w_{n_2,2}\}$ where n_2 is the number of physical activities. As there are 7 physical activities, n_2 is 7 in this monitoring.

The third imputation is related to the lifestyle data. Meta-data including the weekly schedule of the user is considered to define different time states (i.e., n_3 states). For example, the weight for weekend-days (as a time state) is defined, considering the squared error of the time points during weekend days. In this regard, a set of weights (i.e., $W_3 = \{w_{1,3}, \ldots, w_{n_3,3}\}$) is calculated for the n_3 time states in the monitoring.

The three weights vectors, W_1, W_2 and W_3, are dynamically updated in iterations that the heart rate data is available. The dynamic weights determination of the *personalized pooling* method when the heart rate is available is illustrated in Fig. 6.

In contrast, in the iterations with the missing heart rate, the heart rate is imputed by the 3 imputation methods, and the health scores (i.e., d_1, d_2 and d_3) are calculated. The corresponding weights (i.e., $w_{i_1,1}$, $w_{i_2,2}$ and $w_{i_3,3}$) are selected from the three weights vectors according to the current missing data size, physical activity and time state, respectively (see Fig. 7). Finally, the health decisions are pooled using the selected weights as:

$$d_{final} = w_{i_1,1}.d_1 + w_{i_2,2}.d_2 + w_{i_3,3}.d_3 \tag{6}$$

Algorithm 1 also indicates the function of the *personalized pooling* when the heart rate is available and is missing.

4. Demonstration and evaluation

In this section, we present our case study on maternal health, where 20 pregnant women have been remotely monitored for seven months. First, we outline the study design and recruitment in this monitoring. Next, we represent the setup, data collection and data analysis in our IoT-based system. Moreover, the proposed approach is tested and evaluated by comparing the approach with conventional methods. Finally, strengths and weaknesses of the approach are discussed.

4.1. Study design

The monitoring was conducted on primiparous pregnant women who visited one of two maternity outpatient clinics in Southern Finland between May and September 2016. Pregnant women in Finland are provided a free of charge ultrasound examination at the end of the first trimester. The pregnant women were recruited in this appointment considering the following criteria.

1. The participant expected her first child.
2. The participant was at least 18 years old.
3. The pregnancy was singleton.
4. The pregnancy was less than 15 gestational weeks
5. The participant understood Finnish or English
6. The participant owned a PC, tablet or Smartphone to be able to synchronize the smart wristband

Consequently, twenty participants were selected as the sample size was appropriate for a pilot study [73].

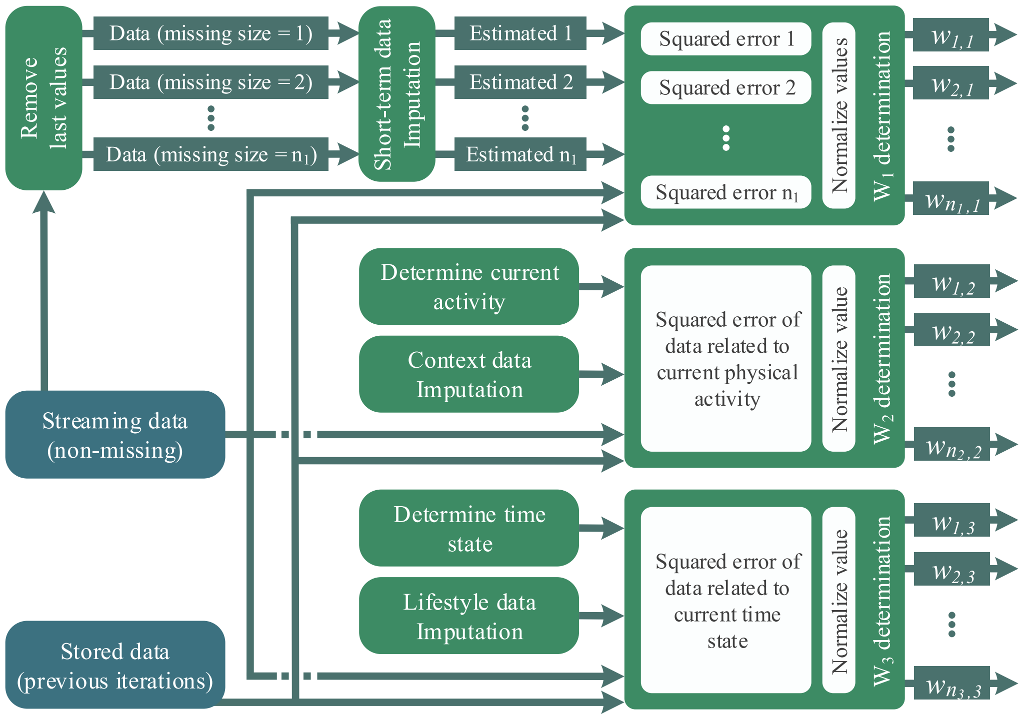

Fig. 6. The *personalized pooling* when heart rate is available (weights determination).

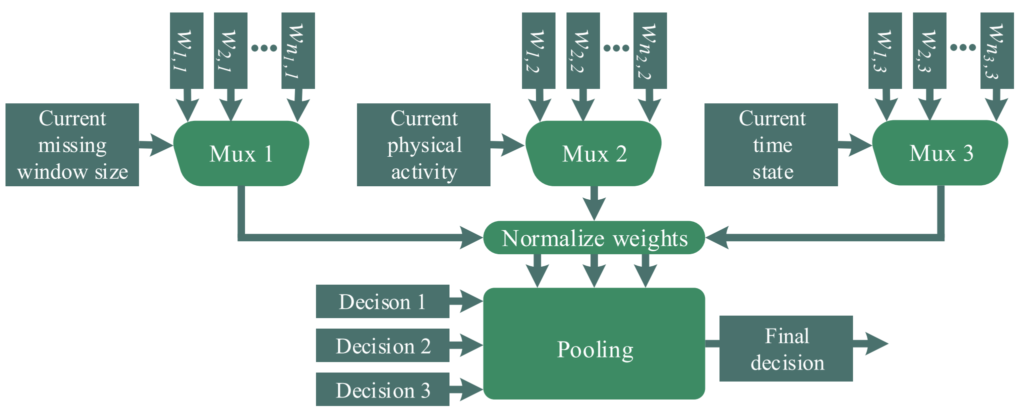

Fig. 7. The *personalized pooling* when heart rate is missing (weights selection).

After the ultrasound examination, the eligible women were met face-to-face once and after signing the informed consent, the device and instructions were provided. Background information was collected via a questionnaire. Some background information is represented in Table 1. Afterward, Garmin Vivosmart® HR [74] as the selected wristband for this study along with instructions has been delivered to the pregnant women. During the follow-up, the participants were interviewed via telephone.

4.2. Setup

An IoT-based system was tailored for this study, determining the Garmin wristband as the sensor device, by which physical activity and heart data were collected. The Garmin wristband is a small and light water-proof band with considerable battery life [74], so it can be an appropriate choice considering the feasibility of the monitoring. More details regarding the feasibility of this study can be found in [75].

The wristband includes one built-in optical-based sensor to record a photoplethysmogram (PPG) signal enabling real-time heart rate measurements [76] Moreover, it consists of an inertial measurement unit (IMU) to track steps, stair ascending/descending and hand movements. In our setup, the data collection rate was set as 1 sample per 15 min, so a new data record was available in every 15 min. A 24-h sample of such data with non-missing values collected from one pregnant woman is illustrated in Fig. 8 (a,b,c,d).

The pregnant women were asked to periodically send the data to remote servers through a gateway device, which was a smartphone or a PC. Most of the data analysis was performed in the cloud servers, amalgamating sensor data to extract new information such as health status and physical activity [77]. For the data analysis, we used a Linode virtual private server (VPS) [78] with two 2.50 GHz Intel Xeon CPU (E5-2680 v3), 4 GB memory and SSD storage drive. Fig. 8 (e,f) shows such information abstracted from the data in Fig. 8 (a,b,c,d). As indicated, the health score was

Algorithm 1 The function of the *personalized pooling* throughout the monitoring.

Initialize:
  $n_1 \leftarrow$ maximum missing window size
  $n_2 \leftarrow$ number of physical activities
  $n_3 \leftarrow$ number of time states
  $\{w_{1,1}, ..., w_{n_1,1}\}$, $\{w_{1,2}, ..., w_{n_2,2}\}$, $\{w_{1,3}, ..., w_{n_3,3}\}$
while monitoring is Active **do**
  $x_{true} \leftarrow$ data from the heart rate sensor
  if $x_{true} \neq NULL$ **then**
    $d_{final} \leftarrow \text{HealthIndicator}(x_{true})$
    for i_1 = 1 to n_1 **do**
      remove last i_1 value(s) of heart rate data
      $x_1 \leftarrow f_s(t, \beta)$
      $e_{i_1,1} \leftarrow$ squared error of the corresponding heart rate data
      $w_{i_1,1} \leftarrow 1 - Normalize(e_{i_1,1})$
    end for
    $i_2 \leftarrow$ determine the current physical activity
    $x_2 \leftarrow f_c(t, \gamma)$
    $e_{i_2,2} \leftarrow$ squared error of the corresponding heart rate data
    $w_{i_2,2} \leftarrow 1 - Normalize(e_{i_2,2})$
    $i_3 \leftarrow$ determine the current time state
    $x_3 \leftarrow f_l(t, \phi)$
    $e_{i_3,3} \leftarrow$ squared error of the corresponding heart rate data
    $w_{i_3,3} \leftarrow 1 - Normalize(e_{i_3,3})$
  else
    $x_1 \leftarrow f_s(t, \beta)$, $x_2 \leftarrow f_c(t, \gamma)$, $x_3 \leftarrow f_l(t, \phi)$
    $d_1, d_2, d_3 \leftarrow \text{HealthIndicator}(x_1, x_2, x_3)$
    $i_1 \leftarrow$ determine the current missing window size
    $i_2 \leftarrow$ determine the current physical activity
    $i_3 \leftarrow$ determine the current time state
    $Normalize(w_{i_1,1}, w_{i_2,2}, w_{i_3,3})$
    $d_{final} = w_{i_1,1}.d_1 + w_{i_2,2}.d_2 + w_{i_3,3}.d_3$
  end if
end while

0 when the subject was sleeping. However, it varied between 0 to 2 while she engaged in different physical activities.

Table 1
Background information of the twenty selected participants.
âĂÍ

Statement	Type	Value
Age at pregnancy (years)	–	25.7 ± 4.96
Gestational age at recruitment (weeks)	–	12 ± 2.1
Pre-pregnancy Body Mass Index	–	25.0 ± 6.45
Quantity of pre-pregnancy physical activity in week	Once or less	3 women
	Sometimes	5 women
	Almost daily	12 women
Quality of pre-pregnancy physical activity in week	Light	8 women
	Moderate	11 women
	Vigorous	1 woman
Employment status	At work	13 women
	Student	5 women
	Unemployed	2 women
Smoking status	Pre-pregnancy	7 women
	In-pregnancy	5 women

The proposed decision-making approach was implemented with a Python service in the cloud server to estimate health status of 15 pregnant women. Five of the pregnant women were dropped out of this analysis because the missing data was too large (i.e., no data for at least 50% of the monitoring days). A view of heart rate with missing values and estimated health scores for one day of monitoring is depicted in Fig. 9. The heart rate values are missed in two time windows with lengths of 75 and 180 min. The blue circles in Fig. 9(b) are the scores when the heart rates are available; and the red trinagles indicate estimated health scores while the heart rates are missing. Note that, this approach is not restricted to the cloud layer settings and can be pushed to the fog layer to enable local decision making.

In addition, manual data collection was implemented to enrich the aforementioned data collection and decision making. In this

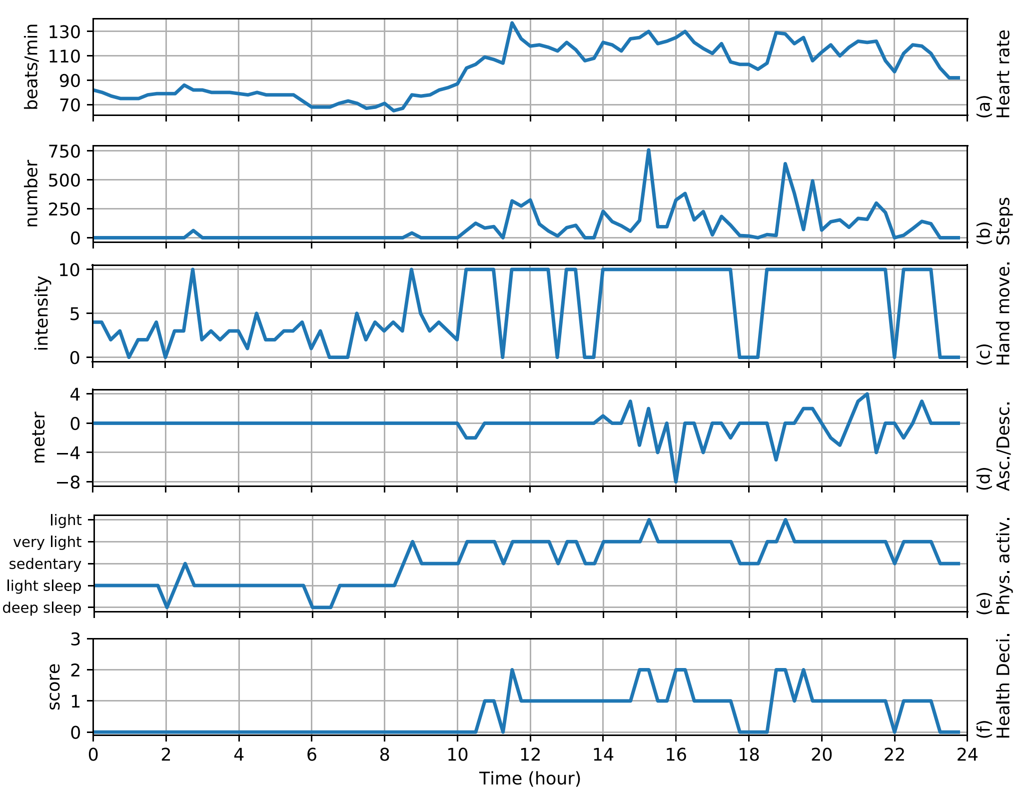

Fig. 8. A 24-h sample of (non-missing) data collected from one pregnant women in gestational week 34 (day 244th). (a), (b), (c) and (d) indicate the variables collected via the wristband; and (e) and (f) are the physical activities and health decisions calculated in the cloud server.

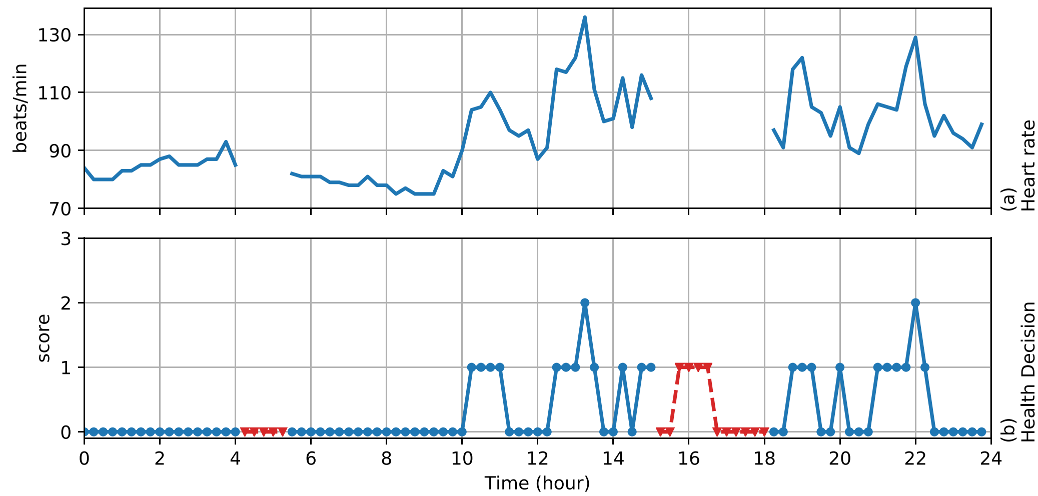

Fig. 9. A 24-h sample of heart rates with missing values and estimated health scores. The blue circles (solid line) represent the health scores obtained from the available heart rates while the red triangles (dashed line) indicate the estimated scores when heart rates are missing.

regard, semi-structured phone interviews were fulfilled once or twice in a month. Such interviews contained a set of questions to indicate the self-report physical activity on a scale 1 to 5 and certain events that considerably influence their sleep or activities. Pregnancy-related data including blood pressure, weight gain and oral glucose test were also obtained from the maternity card and hospital patient records.

4.3. Ethics

The monitoring was performed in accordance with the code of ethics of the World Medical Association (Declaration of Helsinki) for experiments involving humans. Moreover, it was approved by the joint ethics committee of the hospital district of Southwest Finland (35/1801/2016) and Turku University Hospital (TYKS). In addition, the permission to employ Garmin Vivosmart® HR (Garmin Ltd, Schaffhausen, Switzerland) in this monitoring was acquired from the manufacturer Garmin Ltd.

4.4. Accuracy assessment

We validate the performance of our personalized decision-making approach in terms of accuracy. In this regard, a cross-validation technique is used to discard a window of the heart rate and estimate the health score. The estimated score is compared with the actual score obtained via the actual heart rate value.

To evaluate the proposed approach, other existing methods are selected to impute missing heart rate values and extract the health scores. First, the KNN as a single imputation method is utilized, where the missing heart rate is estimated from the k preceding non-missing values by weights proportional to the inverse of the distance to the missing value. Second, the autoregressive model is used leveraging preceding neighbors. Third, the MLE as a model-based method is used, in which the missing value is extrapolated via a Sigmoid function. Fourth, the SVM (with an RBF kernel) as a machine learning-based method is tailored, imputing the missing value from the variation of the history of data (i.e., last two-weeks data). The methods are implemented using the SciPy [79] and Scikit-learn [80] libraries in Python.

In the first evaluation, we investigate the distance (i.e., RMSE) between the estimations and actual health scores with different windows of missing heart rate. The RMSE values are illustrated in Fig. 10 while the missing window (i.e., x axis) varies from 15 min to 6 h. As indicated, when the missing window is small, the proposed method, autoregressive and KNN have the lowest RMSE; and the RMSE values of the SVM and logistic MLE methods are higher. In contrast, in large missing windows, the RMSE values of the autoregressive and logistic MLE and KNN methods are significantly high, whereas the RMSE of the proposed method is the lowest.

In addition, we evaluate the performance of the methods by determining the C-index (i.e., concordance index) [81] of estimations in different missing windows. C-index represents how well health scores are estimated considering the correct rank/order of outcomes. In this experiment, the scores as well the outcomes are in ascending order, varying from 0, as the normal health status, to 3, as the highest health deterioration. The C-index is defined as:

$$\frac{1}{|\{(i,j)|y_i > y_j\}|} \sum_{y_i > y_j} H(\hat{y}_i - \hat{y}_j)$$

where y_i and $\hat{y}_i$ indicate the actual and estimated decisions (i.e. scores), respectively; and $H(.)$ is the Heaviside step function.

For 15 pregnant women monitoring data, the estimation process is randomly repeated in 2040 iterations, in which the health scores are obtained considering different missing windows. Eventually, the C-index values of the 5 methods are determined. As illustrated in Fig. 11, the proposed method's C-index is approximately 0.82 when the missing window is small, and it decreases to 0.7 when the missing window is considerably large. On the contrary, C-index of SVM and logistic MLE are less than the proposed method's C-index in all cases; and the C-index of the autoregressive and KNN methods drop to less than 0.55 while the missing window is large.

4.5. Discussion

The proposed approach results in more reliable and more accurate estimates compared with the conventional methods. As aforementioned, deletion methods are unfit for real-time decision making. Moreover, traditional imputation methods, model-based methods and machine learning based methods underestimate variability of the missing heart rate values, delivering estimates with high error rates. This is in accord with our findings in the previous section. In contrast, the proposed approach considers this variability in data using context information, minimizing the bias of estimates. This enhancement is particularly significant when there is a high correlation between context and the missing heart rate.

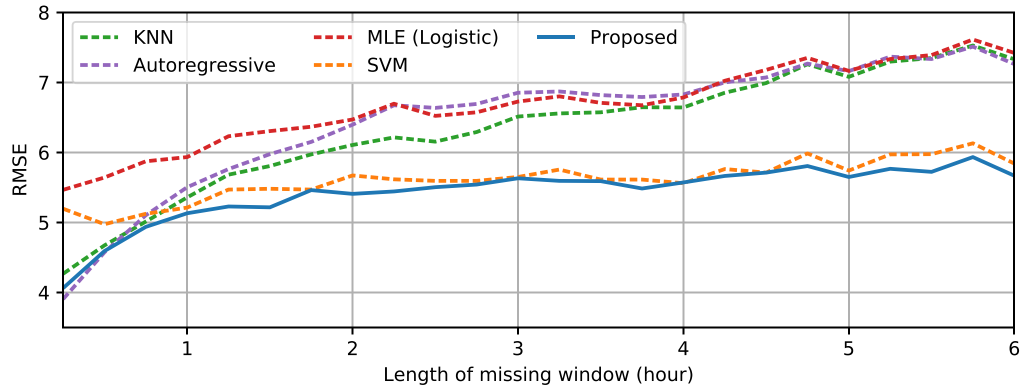

Fig. 10. RMSE values of the health scores estimations with different methods while the missing window varies from 15 min to 6 h.

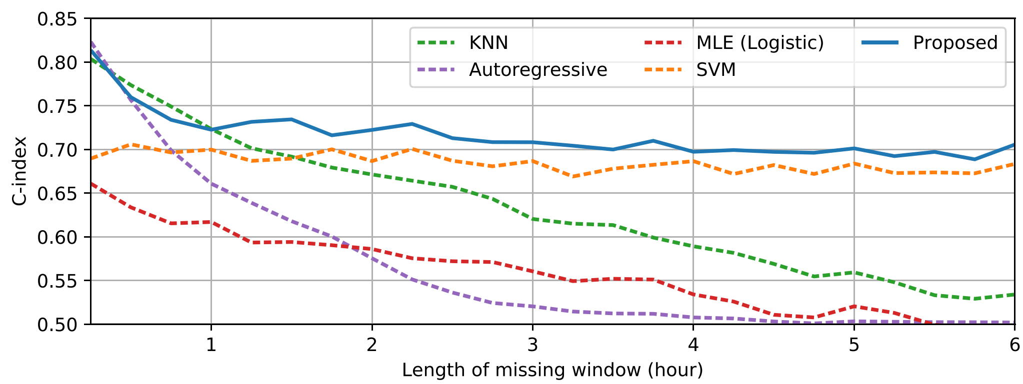

Fig. 11. C-index of the estimations with different methods while the missing window varies from 15 min to 6 h.

One of the major concern of using auxiliary information is a low correlation between context information and the missing data. As a result, the estimates could be biased, reducing the precision of the output [61]. The proposed approach mitigates such a problem in decision makings through the personalized pooling method. In this regard, a small value is allocated to the related weight when the correlation is insignificant.

Another issue in multi-sensor health IoT systems is the occurrence of missingness in more than one variable. In such cases, the *imputation* of the proposed approach is repeated $n \times m$ times, where n is the number of missed variables and m is the number of different imputation methods for each variable. In each imputation, one missed variable is considered as the primary data, and other non-missed variables are the secondary data (i.e., auxiliary information). Next, $n \times m$ decisions are generated, and consequently the decisions are pooled.

In addition, the proposed approach is capable of handling additions or changes in the health monitoring, adding new imputations to the approach or updating the existing imputations. This modular approach, first, suits IoT systems where the context of the user might change; and various sensors are added with respect to needs in the monitoring. Second, the approach can be distributed into the 3 layers of IoT systems (i.e., sensor network, gateway and cloud server) according to health application requirements. Moreover, adding new data resources can improve the performance of the system, removing ambiguity in the context information. This disambiguation is important when the missingness mechanism is NMAR, and the variability of missing data is invisible in available information.

Estimating health status with only one vital sign is the limitation of this study, where unexpected health deterioration with no prior history cannot be estimated when the heart rate value is missing. Therefore, the health indicator in this monitoring only targets real-time health coaching and preventive purposes, but not health deterioration detection. However, this health indicator is a proof-of-concept for the proposed decision-making approach; and inclusion of different vital signs could alleviate this problem.

As the future work of this study, we are going to extend our work, targeting real-time health deterioration in pregnant women. We will use an obstetric Early Warning Score (EWS) [23,24] as a standard manual tool in clinical settings to early-detect patients' health deterioration. This tool will be developed for remote health monitoring through IoT-based systems [82,83]. In this regard, five warning scores ranging from 0 to 3 are generated from five vital signs which are heart rate, body temperature, blood oxygen saturation, respiration rate and blood pressure. The aggregation of these scores represents the level of health deterioration.

5. Conclusion

Missing data is a prevalent problem among IoT-based health monitoring systems, where data collection and data transmission may be interrupted in long-term scenarios. This problem mostly leads to failures in decision making and subsequently health applications. Conventional missing data methods are inappropriate for such systems as these methods underestimate variability of the missing values. This is important when the vital signs such as heart rate are being missed, as heart rate variations could be considerably large. In this paper, we proposed a personalized missing data resilient decision-making approach tailoring data resources in IoT systems to enable continuous health decision making despite missing values. This approach exploited the Multiple Imputation method reinforced with auxiliary information obtained via the IoT-based system. In this regard, first, the missing values were estimated via different methods using various resources. Second, the decision-making method was implemented, and decisions were obtained from different estimates. Eventually, the final decision was extracted using a personalized pooling method. We demonstrated the proposed approach via a real human subject trial on maternity health. The accuracy of the proposed approach was compared with existing methods. We indicated that the proposed approach leads to more accurate decisions, especially when the missing window is large.

Acknowledgments

This work was partially supported by the Academy of Finland grants 313448 and 313449 (PREVENT project) and grants 316810 and 316811 (SLIM project).

References

[1] WHO. Maternal mortality, Retrieved on 2019. http://www.who.int/mediacentre/factsheets/fs348/en/.
[2] WHO. Ageing and health, Retrieved on 2019. http://www.who.int/mediacentre/factsheets/fs404/en/.
[3] L. Atzori, et al., The internet of things: a survey, Comput. Netw. 54 (15) (2010) 2787–2805.
[4] J.A. Stankovic, et al., Research directions for the internet of things, IEEE Internet Things J. 1 (1) (2014) 3–9.
[5] J. Gubbi, et al., Internet of things (iot): A vision, architectural elements, and future directions, Future Gener. Comput. Syst. 29 (7) (2013) 1645–1660.
[6] R. Mieronkoski, et al., The internet of things for basic nursing care—a scoping review, Int. J. Nurs. Stud. 69 (2017) 78–90.
[7] A. Al-Fuqaha, et al., Internet of things: a survey on enabling technologies, protocols, and applications, IEEE Commun. Surveys Tutor. 17 (4) (2015) 2347–2376.
[8] A.M. Rahmani, et al., Exploiting smart e-health gateways at the edge of healthcare internet-of-things: A fog computing approach, FGCS 78 (2) (2018) 641–658.
[9] F. Bonomi, et al., Fog computing and its role in the internet of things, in: MCC'12, 2012, pp. 13–16.
[10] A.M. Rahmani, et al., Fog Computing in the Internet of Things Intelligence at the Edge, Springer, 2017.
[11] J. Lin, et al., A survey on internet of things: architecture, enabling technologies, security and privacy, and applications, IEEE Internet Things J. 4 (5) (2017) 1125–1142.
[12] R.J.A. Little, D.B. Rubin, Statistical Analysis with Missing Data. Wiley Series in Probability and Statistics, Wiley, 2014.
[13] A.n Baraldi, C.K. Enders, An introduction to modern missing data analyses, J. Sch Psychol 48 (1) (2010) 5–37.
[14] S. Hunter, s, C. Robson, Adaptation of the maternal heart in pregnancy, Br. Heart J. 68 (6) (1992) 540–543.
[15] M.E. Hall, et al., The heart during pregnancy, Rev. Esp. Cardiol. 64 (11) (2011) 1045–1050.
[16] K. Melzer, et al., Physical activity and pregnancy, Cardiovascular adaptations, recommendations and pregnancy outcomes, Sports Med. 40 (6) (2010) 493–507.
[17] K.R. Evenson, et al., Guidelines for physical activity during pregnancy: Comparisons from around the world, Am. J. Lifestyle Med. 8 (2) (2014) 102–121.
[18] D.S. Feig, et al., Continuous glucose monitoring in pregnant women with type 1 diabetes (conceptt): a multicentre international randomised controlled trial, Lancet 390 (2017) 2347–2359.
[19] L. Underwood, et al., A longitudinal study of pre-pregnancy and pregnancy risk factors associated with antenatal and postnatal symptoms of depression: evidence from growing up in new zealand, Matern Child Health J. 21 (4) (2017) 915–931.
[20] J.F. Clapp, Maternal heart rate in pregnancy, Am. J. Obstet. Gynecol. 152 (6) (1985) 659–660.
[21] M.G. Moertl, et al., Changes in haemodynamic and autonomous nervous system parameters measured non-invasively throughout normal pregnancy, Eur. J. Obstet Gynecol. Reprod Biol. 144 (2009) S179–S183.
[22] P.K. Stein, et al., Changes in 24-hour heart rate variability during normal pregnancy, Am. J. Obstet. Gynecol. 180 (4) (1999) 978–985.
[23] G.B. Smith, et al., Vital signs and other observations used to detect deterioration in pregnant women: an analysis of vital sign charts in consultant-led uk maternity units, Int. J. Obstet. Anesth. 30 (2017) 44–51.
[24] C. Carle, et al., Design and internal validation of an obstetric early warning score: secondary analysis of the intensive care national audit and research centre case mix programme database, Anaesthesia. 68 (4) (2013) 354–367.
[25] D.B. Rubin, Inference and missing data, Biometrika 63 (3) (1976) 581–592.
[26] J.L. Schafer, J.W. Graham, Missing data: Our view of the state of the art, Psychol. Methods 7 (2) (2002) 147–177.
[27] X. Zhou, et al., Applied Missing Data Analysis in the Health Sciences, John Wiley & Sons Inc., 2014.
[28] L.O. Silva, L.E. Zárate, A brief review of the main approaches for treatment of missing data, Intell. Data Anal. 18 (6) (2014) 1177–1198.
[29] P.J. Garcia-Laencina, et al., Pattern classification with missing data: a review, Neural Comput. Appl. 19 (2) (2010) 263–282.
[30] R.J.A. Little, Regression with missing X's: a review, J. Amer. Statist. Assoc. 87 (420) (1992) 1227–1237.
[31] H. Jelicic, et al., Use of missing data methods in longitudinal studies: the persistence of bad practices in developmental psychology, Dev. Psychol. 45 (4) (2009) 1195–1199.
[32] H.W. Marsh, Pairwise deletion for missing data in structural equation models: nonpositive definite matrices, parameter estimates, goodness of fit, and adjusted sample sizes, Struct. Equ. Model. 5 (1) (1988) 22–36.
[33] R.R. Andridge, R.J. Little, A review of hot deck imputation for survey non-response, Int. Stat. Rev. 78 (1) (2010) 40–64.
[34] C. Tsai, F. Chang, Combining instance selection for better missing value imputation, J. Syst. Softw. 122 (2016) 63–71.
[35] S.B. Woolley, et al., Last-observation-carried-forward imputation method in clinical efficacy trials: review of 352 antidepressant studies, Pharmacotherapy 29 (12) (2009) 1408–1416.
[36] D.B. Rubin, Multiple imputation after 18+ years, J. Amer. Statist. Assoc. 91 (434) (1996) 473–489.
[37] C.K. Enders, Multiple imputation as a flexible tool for missing data handling in clinical research, Behav. Res. Therapy 98 (2017) 4–18.
[38] Y. He, Missing data analysis using multiple imputation: getting to the heart of the matter, Circ. Cardiovasc Qual Outcomes. 3 (1) (2010) 98–105.
[39] I.J. Myung, Tutorial on maximum likelihood estimation, J. Math. Psych. 47 (1) (2003) 90–100.
[40] I. Myrtveit, et al., Analyzing data sets with missing data: an empirical evaluation of imputation methods and likelihood-based methods, IEEE Trans. Softw, Eng. 27 (11) (2001) 999–1013.
[41] P. Diggle, et al., Analysis of Longitudinal Data, OUP Oxford, 2002.
[42] R.J.A. Little, Modeling the drop-out mechanism in repeated-measures studies, J. Amer. Statist. Assoc. 90 (431) (1995) 1112–1121.
[43] J.G. Ibrahim, G. Molenberghs, Missing data methods in longitudinal studies: a review, Test (Madr) 18 (1) (2009) 1–43.
[44] M.L. Bell, D.L. Fairclough, Practical and statistical issues in missing data for longitudinal patient-reported outcomes, Stat. Methods Med. Res. 23 (5) (2014) 440–459.
[45] F.V. Nelwamondo, et al., Missing data: A comparison of neural network and expectation maximization techniques, Current Sci. 93 (11) (2007) 1514–1521.
[46] M. Abdella, T. Marwala, The use of genetic algorithms and neural networks to approximate missing data in database, in: IEEE 3rd International Conference on Computational Cybernetics, 2005.
[47] I.B. Aydilek, A. Arslan, A hybrid method for imputation of missing values using optimized fuzzy c-means with support vector regression and a genetic algorithm, Inform. Sci. 233 (2013) 25–35.
[48] I.B. Aydilek, A. Arslan, A novel hybrid approach to estimating missing values in databases using k-nearest neighbors and neural networks, Int. J. Innovative Comput. Inf. Control 8 (7) (2012) 4705–4717.
[49] W. Wei, Y. Tang, A generic neural network approach for filling missing data in data mining, in: IEEE International Conference on Systems, Man and Cybernetics, 2003.
[50] E. Silva-Ramirez, et al., Missing value imputation on missing completely at random data using multilayer perceptrons, Neural Netw. 24 (1) (2011) 121–129.
[51] K. Pelckmans, et al., Handling missing values in support vector machine classifiers, Neural Netw. 18 (5–6) (2005) 684–692.
[52] S. Tsang, et al., Decision trees for uncertain data, IEEE Trans. Knowl. Data Eng. 23 (1) (2011) 64–78.
[53] M. Juhola, J. Laurikkala, Missing values: how many can they be to preserve classification reliability?, Artif. Intell. Rev. 40 (3) (2013) 231–245.
[54] G. Wang, et al., Tackling missing data in community health studies using additive ls-svm classifier, IEEE J. Biomed. Health Inf. 22 (2) (2018) 579–587.
[55] B. Fekade, et al., Probabilistic recovery of incomplete sensed data in iot, IEEE Internet Things J. (2017).
[56] M. Halatchev, L. Gruenwald, Estimating missing values in related sensor data streams, in: International Conference on Management of Data, 2005.
[57] P. Zhang, et al., SKIF: a data imputation framework for concept drifting data streams, in: ACM international Conference on Information and Knowledge Management, 2010.
[58] N. Jiang, L. Gruenwald, Estimating missing data in data streams, in: Advances in Databases: Concepts, Systems and Applications, 2007.

[59] C. Wang, C. Hall, Correction of bias from non-random missing longitudinal data using auxiliary information, Stat Med. 29 (6) (2010) 671–679.
[60] L.M. Collins, et al., A comparison of inclusive and restrictive strategies in modern missing data procedures, Psychol Methods. 6 (4) (2001) 330–351.
[61] J. Hardt, et al., Auxiliary variables in multiple imputation in regression with missing x: a warning against including too many in small sample research, BMC Med. Res. Methodol. 12 (184) (2012).
[62] J.G. Ibrahim, et al., Using auxiliary data for parameter estimation with nonignorably missing outcomes, Appl. Statist. 50 (2001) 361–373.
[63] G.D. Abowd, et al., Towards a better understanding of context and context-awareness, in: 1st International Symposium on Handheld and Ubiquitous Computing, 1999, pp. 304–307.
[64] G. Chen, D. Kotz, A survey of context-aware mobile computing research, in: Technical report, Dartmouth College, 2000.
[65] C. Perera, et al., Context aware computing for the internet of things: a survey, IEEE Commun. Surv. Tutor. 16 (1) (2014) 414–454.
[66] C. Chatfield, The Analysis of Time Series: An Introduction, Sixth ed., CRC Press, 2016.
[67] R. Rifkin, R. Lippert, Notes on regularized least square. Technical report, MIT-CSAIL-TR-(2007) 2007-025.
[68] T. Pahikkala, A. Airola, Rlscore: regularized least-squares learners, J. Mach. Learn. Res. 17 (221) (2016) 1–5.
[69] Q. Gui, et al., Exploring missing data prediction in medical monitoring: a performance analysis approach, in: Signal Processing in Medicine and Biology Symposium, 2014.
[70] C. Tudor-Locke, et al., Pedometer-determined step count guidelines for classifying walking intensity in a young ostensibly healthy population, Can. J. Appl. Physiol. 30 (6) (2005) 666–676.
[71] C. Tudor-Locke, et al., Patterns of adult stepping cadence in the 2005-2006 NHANES, Prev Med. 53 (3) (2011) 178–181.
[72] C. Vinader-Caerols, et al., Effects of alcohol, coffee, and tobacco, alone or in combination, on physiological parameters and anxiety in a young population, J. Caffeine Res. 2 (2) (2012) 70–76.
[73] S.K. Grove, et al., The Practice of Nursing Research: Appraisal, Synthesis, and Generation of Evidence, Elsevier Health Sciences, 2012.
[74] Garmin. Vivosmart HR | Activity Tracker, Retrieved on 2019. https://buy.garmin.com/en-US/US/p/531166.
[75] K. Grym, et al., Feasibility of smart wristbands for continuous monitoring during pregnancy and one month after birth, BMC Pregnancy Childbirth 19 (34) (2019).
[76] J. Allen, Photoplethysmography and its application in clinical physiological measurement, Physiol. Meas. 28 (3) (2007) R1–39.
[77] A. Bulling, et al., A tutorial on human activity recognition using body-worn inertial sensors, ACM Comput. Surv. 49 (3) (2014) 33:1–33:33.
[78] Linode. SSD Cloud Hosting & Linux Servers, Retrieved on 2019. https://www.linode.com/.
[79] Eric Jones, et al., SciPy: Open source scientific tools for Python, 2001, Retrieved on 2019. https://www.scipy.org/.
[80] F. Pedregosa, et al., Scikit-learn: machine learning in python, J. Mach. Learn. Res. 12 (2011) 2825–2830.
[81] M. Gönen, G. Heller, Concordance probability and discriminatory power in proportional hazards regression, Biometrika 92 (4) (2005) 965–970.
[82] I. Azimi, et al., Self-aware early warning score system for iot-based personalized healthcare, in: LNICST, volume 181, 2016.
[83] A. Anzanpour, et al., Self-awareness in remote health monitoring systems using wearable electronics, in: Design, Automation & Test in Europe Conference & Exhibition (DATE), 2017.

Iman Azimi received his bachelor's degree in biomedical engineering at the University of Isfahan, Iran, in 2010, and his master's degree in Artificial Intelligence and Robotics at the Sapienza University of Rome, Italy, in 2014. He is currently a Ph.D. candidate at the Department of Future Technologies, University of Turku, Finland. His current research interests focus on personalized health data analytics, remote health monitoring, Internet of Things, and embedded systems. He is the author of more than 15 peer-reviewed publications, both in medical and technological venues.

Tapio Pahikkala received his doctoral degree in 2008 from the University of Turku, Finland and he currently holds a tenure track associate professorship of machine learning with the University of Turku. He has authored more than 140 peer-reviewed scientific articles and participated in the winning teams of several international scientific competitions/challenges. He has led many research projects, supervised six doctoral theses, held several positions of trust in academia and served in the program committees of numerous international conferences. His current research interests include theory and algorithmics of machine learning, data analysis, and computational intelligence, as well as their applications on various different fields.

Amir M. Rahmani received his MSc from Department of ECE, University of Tehran, Iran, in 2009 and Ph.D. degree from Department of IT, University of Turku, Finland, in 2012. He also received his MBA jointly from Turku School of Economics and European Institute of Innovation & Technology (EIT) Digital, in 2014. He is currently Marie Curie Global Fellow at University of California Irvine (USA) and TU Wien (Austria). He is also an adjunct professor (Docent) in embedded parallel and distributed computing at the University of Turku, Finland. His work spans self-aware computing, runtime resource management for systems-on-chip and resource-constrained IoT devices, wearable sensor design, and Fog Computing. He is the author of more than 180 peer-reviewed publications. He is a senior member of the IEEE and the Associate Editor of ACM Transactions on Computing for Healthcare.

Hannakaisa Niela-Vilen works as postdoctoral researcher at the Department of Nursing Science, University of Turku, Finland. Her current research projects are about the possibilities of remote monitoring in maternity care, early contact between a mother and her newborn infant and breastfeeding. Before doctoral studies, she has worked seven years as a midwife in the labor and delivery unit in Turku university hospital. She was graduated as a midwife in 2002, Master of Nursing Science in 2010 and PhD in Nursing Science in 2016.

Anna Axelin is Associate Professor in the Department of Nursing Science at the University of Turku, Finland. She has conducted quantitative and qualitative research on maternity and neonatal care in multidisciplinary and international research groups. Dr. Axelin is leading the Health in Early Life and Parenthood (HELP) research group which aims to promote health and welfare in the early stages of life. Her special research interest is how to keep parents and sick newborns together throughout the infant hospital stay and strengthen their relationship already during pregnancy. One of her strategies to achieve this goal is to implement evidence-based practice in maternity and neonatal care with the help information technology.

Pasi Liljeberg received the MSc and PhD degrees in electronics and information technology from the University of Turku, Turku, Finland, in 1999 and 2005, respectively. He received Adjunct professorship in embedded computing architectures in 2010. Currently he is working as a professor in University of Turku in the field of Embedded Systems and Internet of Things. At the moment his research is focused on biomedical engineering and health technology. In that context he has established and leading the Internet-of-Things for Healthcare (IoT4Health) research group. Liljeberg is the author of around 300 peer-reviewed publications.