*e*Health Personalization in the Next Generation RPM Systems

Aleksandra Tesanovic[a] and Goran Manev[a,b]
[a]*Philips Research Laboratories*
High Tech Campus 37, 5656 AE Eindhoven, the Netherlands
aleksandra.tesanovic@philips.com
goran.manev@philips.com

Mykola Pechenizkiy[b] and Ekaterina Vasilyeva[b]
[b]*Eindhoven University of Technology*
Department of Computer Science
P.O. Box 513, 5600 MB Eindhoven, the Netherlands
{m.pechenizkiy, e.vasilyeva}@tue.nl

Abstract

Remote patient management (RPM) systems enable (i) monitoring of vital signs of patients at their home, and (ii) providing patients in their homes instructional, educational, or motivational feedback. As such, RPM systems collect a lot of (different types of) data about patients. Although richness of data provides an opportunity for tailoring and personalizing information services, there is a limited understanding of the necessary architecture, methodology, and tailoring criteria to facilitate personalization. In this paper we present (i) a possible next generation RPM system that enables personalization of educational content and its delivery to patients, (ii) introduce a generic methodology for personalization and emphasize the role of knowledge discovery (KDD) and (iii) outline the KDD process with a case study showing an example patient model and adaptation rules.

1 Introduction

Chronic diseases are the leading cause of death and healthcare costs in the developed countries. Chronic heart failure alone costs US economy over 33.7 billion dollars per year, of which 16 billion due to re-hospitalization[1]. EU healthcare system is experiencing similar cost expenditures[2]. 42% of re-hospitalizations are preventable by adequate patient monitoring, instruction, education and motivation (all of which can be done outside of the hospital). Hence, in order to maintain and improve quality of care without exploding costs, healthcare systems are undergoing a paradigm shift from patient care in the hospital to the patient care at home [8]. In that context, remote patient management (RPM) systems offer a great potential in reducing hospitalization costs and worsening of symptoms for patients with chronic diseases, e.g., coronary artery disease, heart failure, and diabetes.

An RPM system ideally should have both the ability to monitor vital signs and provide a feedback to the patient in terms of appropriate education and coaching. However, most of the educational and instructional material provided by RPM systems nowadays is generic and given to all patients regardless of their personality, current condition, physical, or mental state. Recent clinical studies show that education and coaching tailored toward the patient is a promising approach to increase adherence to the treatment and potentially improve clinical outcomes [6, 4].

Although the large volumes of data collected by RPM systems provide an opportunity for tailoring and personalizing information services, there is a limited understanding of the necessary architecture, methodology, and tailoring criteria to facilitate personalization of the content. In this paper we tackle these challenges by (1) presenting a possible architecture of the next generation personalized RPM systems (Section 3), (2) presenting a process of knowledge discovery (KDD) from RPM data (on an RPM database from a clinical trial [3]) that leads to identification of potentially useful features and patterns for patient modeling and construction of adaptation rules (Section 4). We conclude the paper (Section 5) with a summary of our efforts and the directions for further work.

2 Remote Patient Management Systems

In this section we review the state of the art in RPM systems, and discuss the adaptation challenge.

2.1 Current state of the art

Existing commercial RPM systems normally provide an end-to-end infrastructure (as shown in Figure 1) that con-

[1]http://www.ehnheart.org/
[2]http://www.americanheart.org/

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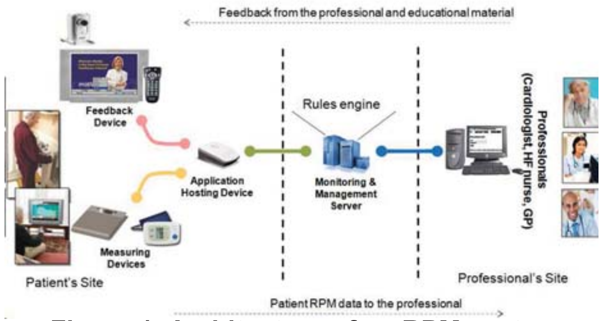

Figure 1. Architecture of an RPM system

nects patients at home with health professionals at their institution. The patients at home are equipped with a number of sensors measuring vital signs to obtain objective measurements about their physical condition. Patients are typically monitored on several vital signs depending on the chronic disease in question, e.g., weight and blood pressure for heart failure patients, glucose and weight for diabetes patients. The vital sign measurements are, via application hosting device, transferred to the monitoring and management server. Subjective measurements such as symptoms and quality of life (QoL) scores are also collected from the patients via questionnaires. The questionnaires can be presented to the patient directly via an application hosting device or feedback device such as a TV. Objective and subjective measurements (referred to as RPM data) are presented to the medical professional who, based on the indicated deviations from the normal values, adjusts the patient's treatment plan, including medications and lifestyle goals (nutrition and physical activity).

The majority of commercial RPM systems only have the link between the patient and professional that enables uploading patient data to the professional for review and treatment changes; these systems are typically referred to as remote patient monitoring systems as they provide only monitoring, but not the management part. The monitoring solutions, e.g., *HealthHero* (www.healthhero.com), *HomeMed* (www.hommed.com), do not have a separate feedback device but collect subjective data via an application hosting device. Patient coaching and education is found to be an influential factor for adherence to the treatment, both medications treatment and lifestyle adjustments [7]. The management solutions have a feedback to the patient that enables the professional to provide an appropriate education and counseling (coaching of the patients) via the feedback device. In this line, a number of RPM systems provide educational material for the patients to help them cope with their condition. Table 1 shows the comparison of the representative RPM systems that provide both measurements and education for managing chronic heart failure, namely solutions from *Health Hero Health TV*, *BL Healthcare TVx* (www.blhealthcare.com), *Card Guard* iTV (www.cardguard.com), and *Philips Motiva* (www.healthcare.philips.com). Table 2 gives an overview of different types of data (vitals, surveys, usage of the system) that are normally collected when the patient is using an RPM system.

Table 1. Comparison of RPM Systems

Comparison wrt: / RPM system		Health Hero Health TV	BL Health-care TVx	Card Guard iTV	Philips Motiva
Objective measurements	weight	●	●	●	●
	ECG		●	●	
	BP & Pulse	●	●	●	●
	SpO2	●	●	●	
	temperature		●		
	fluid status				
	glucose	●	●	●	●
	peak flow	●	●	●	
	PT/INR				
Subjective	questionaires	●	●	●	●
Education and counselling	nutrition	●	●	○	●
	physical activity	●	●	○	●
	smoking	●	○	○	●
	stress	●	○	○	●
	sleep disorders	●	○	○	
	weight reduct.	●	●	○	●
	worsening signs	●	●	○	●
	depression	●	○	○	●
	video conf.	●	●	●	

● – covered by RPM system, ○ – partly covered by the RPM system

RPM solutions can also be found in the research community. For example, the RPM system described in [2] also visualizes information for the patients on the TV, while presenting the information needed by the healthcare personnel on their PC. The system supports a Patient Health Diary with disease related questions, vital signs measurements such as heart rate, oxygen saturation, and blood glucose values and other senor data. Similarly, the system *C-Monitor* provides medical information and manages medical staffs and patients involved in the disease management [9]. The system supports two workspaces: for the doctors (to monitor patients' condition and adjust therapy) and for the patients (to post the symptoms, read documents regarding specific diseases and exchange information with the responding medical professional). The system allows the delivery of personalized documents to the patients such as diseases information, healthy lifestyle recommendations, suggestions

Table 2. An overview of different types of data

Data clases		Collected via	(Typical) Frequency
Medical history	**Causes**	Face to face meeting at a medical professional's institution	Once, when diagnosis for chronic condition is made
	Co-mobidities		
	Prior hospitaliz-s		
	Implanted devices		
Baseline data	**Vitals**	Face to face meeting at a medical professional's institution	Every few month, during regular follow-up
	Hight		
	Other diagnosis		
	Lab results		
Vital signs	**Weight**	An RPM system at a patient's home	Daily
	Blood pressure		
	Pulse		
Question -naires	**Symptoms**	Several alternatives: - An RPM system at a patient's home, but also can be collected: - Via a telephone contact by a medical professional - Via face to face meeting during regular checkups at medical professional institution	Varies depending on the protocol of care and can be collected: - Daily (RPM) - Weekly (RPM) - Montly (telephone) - Few months (face to face meetings)
	Depression		
	Anxiety		
	Overal health		
	Overal QoL		
	Stress		
	Sleep patterns		
	Fatique		
	Lonliness		
Bio-markers		Face to face meeting at a medical professional's institution	(Few) months
Medica-tions	**Disease related drugs**	- Via a telephone contact by a medical professional - Via face to face meeting during regular checkups	Few weeks to few months
	Non-disease related drugs		

on diet, etc.

2.2 Adaptation Challenge

In the TEHAF clinical study [4], nurses used Health Buddy system to deliver educational material to the chronic heart failure patients. During the study nurses observed their patients over a period of time, learning their behavioral characteristics, knowledge level and health state, and concluded that adjusting the content of the educational material based on symptoms, knowledge and behavior is beneficial for the patients. They have designed a simple manual adaptation scheme of the educational material (mostly in terms of quantity of education) and used that scheme to deliver the educational material to their patients, as illustrated in Table 3. Similarly a need for tailoring educational material has been identified in the recent COACH study [6].

Table 3. Four heart failure management programs tailored for four groups of patients [4]

Program #	Duration (days)	Symptoms	Knowledge & Behaviour change	Benefits
1	90	↑	↓	High monitoring High education
2	30	↑	↑	High monitoring Low education
3	90	↓	↓	Low monitoring High education
4	180	↓	↑	Low monitoring Low education

↑ (symptoms) patient is exhibiting increasing number of symptoms
↓ (symptoms) patient is stabilizing and has decreased number of symptoms
↑ (knowledge/behaviour) patient is showing knowledge of disease and behaviour in line with the treatment
↓ (knowledge/behaviour) patient is not showing knowledge and does not have behaviour in line with the treatment

As can be observed, commercial systems typically focus on raising alarms to the health professional based on patient's status of vital signs and their deviations from normal (baseline) values. These systems typically send the same content to all the patients, regardless of their current health condition, knowledge level, or a mental state. A step further are research RPM systems that to an extent provide aspects of personalization. However, this personalization is still limited and does not exploit available RPM data for adaptation of the educational content toward specific patient needs.

Research on personalization is ongoing in e-Learning and there are a number of successful implementation of adaptive hypermedia systems like AHA!, Interbook, etc. [1]. However, existing architectures are not adopted in eHealth applications such as RPM systems. Furthermore, in the mentioned systems, the adaptation and personalization is pre-authored and thus remains highly static and often subjective based on some domain expertise translated to the machine readable form. In the next section we suggest a general architecture of an personalized RPM system in which we follow general principles of personalization in e-Learning systems with KDD process as one of the key integrated components.

3 Next Generation Adaptive RPM Systems

A part of the architecture that provides a possible foundation for the next generation adaptive RPM systems (Figure 2).

The key components of the system that facilitate personalization and adaptation include: (1) patient (user) model, (2) domain model, (3) adaptation rules, (4) adaptation engine, and (5) KDD process. Further, there are authoring

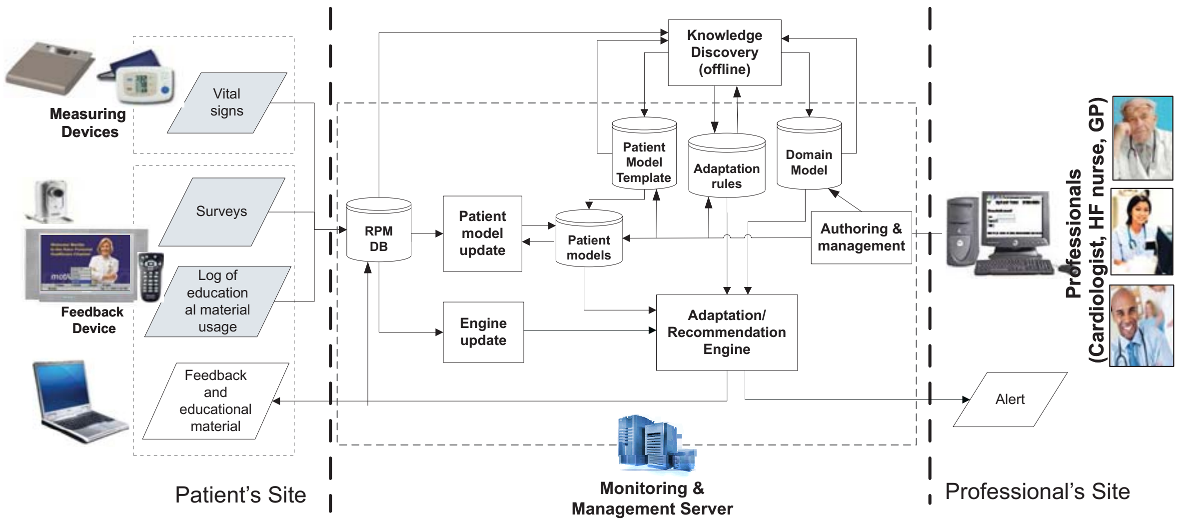

Figure 2. A high level view of the next generation RPM system

and management tools allowing medical experts and professionals to monitor, control and manage patient models, domain models and adaptation rules.

The *KDD process* is essential for discovering relevant actionable patterns that are the basis for creation of the patient model and the adaptation rules. This KDD process is (initially) done "off-line", using stable historical data available from an existing RPM database or from completed clinical trials relevant for the disease in question. Via this KDD process we obtain relevant patterns that are used to build a *patient model template*. The same patterns are utilized to build the *adaptation rules* and *domain model* of the available content material that is stored in corresponding databases. The KDD is highly iterative and interactive and involves considerable effort from domain and KDD experts. Moreover, this is by no means one-time activity. With accumulation of new evidence and possible contextual changes, models and rules might need a continuous update or extension. We discuss in detail KDD process and give examples of patient model and adaptation rules in Section 4.

Other processes, including actual adaptation of the content, are executed "on-line", during the use of the system. Namely, for each patient that uses the system, the patient model template is instantiated into a (personal) patient model which is stored in the *patient models* database and updated regularly, e.g., when relevant information becomes available in the *RPM database*. The *adaptation engine* takes the patient model and domain model, and generates personalized content, e.g., educational, instructional, motivational, or alerting. The content is then presented at the patient's feedback device, e.g., TV, a smart phone, or a computer and/or at the medical professional side (alerting). Based on patient usage of the system and his/her health behavior characteristics, the patient model will be updated. Potentially, adaptation strategies, or individual rules can be automatically revised (based on new evidence) or a corresponding alert can be sent to a human expert.

Developing personalized RPM systems or adaptation rules is possible only if we can learn key (potentially changing and dynamic) characteristics of the patients and track them continuously. Personalization can be organized using individual and group (or stereotype) user modeling. In a stereotype approach, the users are classified into several groups. In eHealth applications users can be classified according to their main disease, background in medicine (patients, nurses, and physicians), general education background (no degree, college degree, doctorate, etc), and their tasks (consultation, education, and emergency cases). Individual patient (user) models, besides the user's medical profile, could include also individual characteristics such as cognitive and psychological individual peculiarities, the interaction parameters – the last visited pages, used links, number of the particular pages visits, resource usages etc.

Table 4 gives an overview of possible features of various data classes that can play a role in the patient model of an RPM system. A feature can be *static*, e.g. gender, residence, language, or *relatively static*, e.g., age, cognitive impairment (which a patient can develop during the usage of RPM system) and *dynamic*, e.g., values of weight measurements or system usage. The example given is for heart failure, but can be generalized to any of chronic diseases given a specific set of relevant symptoms and vital signs for that chronic disease.

Table 4. Typical features included in a patient model template

Data class	Feature	Changes	
		Static	Dynamic
Demographic	Gender	x	
	Age	x	
	Country	x	
	Language	x	
Living status	Single/Family	x	
Baseline data	Weight		x
	Height	x	
	Body Mass Index		x
	Edema		x
	Biomarker values		x
Medical history	Cause of disease	x	
	Co-morbidities		x
	Implantables	x	x
Symptoms	Ankle swelling		x
	Breathlessness		x
	Depression		x
	Anxiety		x
Vital signs (Frequencies of values out of band)	weight		x
	heart rate		x
	blood pressure		x
	diastolic blood pressure		x
System usage (Frequency of measurements	weight		x
	blood pressure		x
	heart rate		x
Learning styles	Verbaliser/Imager	x	
	FD/FI	x	
Cognitive function	Reduced eyesight	x	
	Dementia	x	

Legend: *Frequency of vital sign measurements* - how often the patient has been using a sensor for a measurements (1 – every day, 0- not at all), *FD/FI* – field dependent/independent.

4 Knowledge discovery for patient modeling

The KDD process is shown in Figure 3. Here we consider different steps of this highly iterative and interactive process.

Relevant data selection is done using explorative statistical data analysis, outlier detection, and data cleaning approaches. With this, basic data preprocessing and selection of a subset of relevant data is performed. This process is particularly useful if using database from clinical trials as these normally have more elaborate data sets than ones present in RPM systems.

Feature extraction and construction using visual data exploration, namely event- and time-series analysis. The two analyzes are done in two iterative and interactive steps to get a better understanding of what features and relations between them may potentially describe patient current state and its short-term and long-term dynamics. As a result, different data views can be constructed, which serve as input for the next step of the process.

Pattern discovery (data mining) gives us a full set of patterns that potentially can be used for creating patient model and adaptation rules.

Actionable patterns selection is an effort of a domain expert to identify the relevant actionable patterns that should be a part of the model and rules.

In the rest of this section, we consider KDD process with a real RPM dataset (collected during a clinical study with heart failure patients [3]) and provide concrete examples of patterns and adaptation rules.

4.1 Feature extraction and construction

Before actual pattern mining or model learning takes place a number of data processing steps may be required to clean the data, find representative objects and features to present them in the best way. Here, we concentrate on the issues of feature extraction and construction for which we use event-pattern and time-series analysis.

Event-pattern analysis. We start with the analysis of dot charts[3], which are similar to a Gäntt chart as they show the spread of events over time by plotting a dot for each event in the log. The chart has a few (orthogonal) dimensions: one showing the time of the event, and the others showing (possibly different) components, e.g., patient ID and task ID, of the event. Time is shown along the horizontal axis. The first considered component is shown along the vertical axis, in boxes. The second component of the event is given by the color and/or shape of the dot.

The value of visual inspection of event patterns using dot chart is threefold, i.e. we get (1) an insight into *frequency* of and *precedence* of events starting from the beginning of the clinical study, from which we are able to decide what is the real start of the study and when it stopped (Figure 4 illustrates frequency of events on a timeline, starting from the patient enrolment in the program until the last recorded event), (2) clear *instances for data reduction*, e.g. it is easy to identify patients who used the system for a very short time period or had too few daily measurements (sparsely dotted lines in Figure 4) or events of a patient that also should not be taken into account in the further analysis, e.g. if a monthly contact via phone or measurement that took place while patient was in the hospital, and (3) *potentially interesting patterns* that further need to be confirmed and explored in the next steps of KDD process.

The true value of event-pattern analysis is in interesting pattern identification. We found e.g. that (see the top part of Figure 4): (i) a number of patients were measuring themselves during the working days, but not during weekends.

[3] We used DCA (Dot Chart Analysis) plug-in of ProM 5.0 open source process mining toolkit [5] available at www.processmining.org

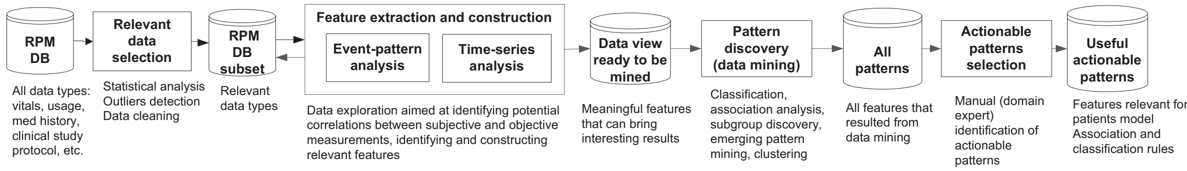

Figure 3. Knowledge discovery process

This points to the influential role of lifestyle habits to the use of system; (ii) patients start using the measurements devices more (or less) before or/and after contact with medical professionals, e.g. if a patient does not measure himself for some time, a clinical visit or a monthly contact event triggers the patient to re-start measuring. This implies possible strong correlation in the effect of communication to the motivation of patients to use the system; and (iii) patients may stop measuring themselves after clinical visits or monthly phone contacts, and then resume measuring after couple of days. This is a potential indicator of worsening of patients condition (not being able to measure) or improvement of their condition (they get reassurance by their care givers that they are doing well), or de-motivation by the contact.

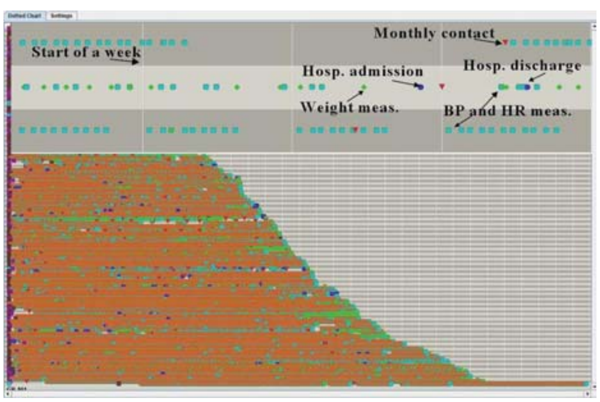

Figure 4. Dot chart analysis of usage data

Time series analysis. While event-pattern analysis provides us with patterns of events as discussed above, it does not provide information on how values of daily measurements or values of symptoms change during the time, or how these values are correlated.

We use time-series analysis for detailed visual exploration of changes and correlations in values of daily measurements or symptoms during the certain period. We visualized the daily measurements data, hospitalization events, and events from which we get information about symptoms for all patients. Weight timeseries for three patients are shown in Figure 5. Zoomed regions are shown in Figure 6 - 7, from which we can see e.g. correlation of weight with hospitalizations (Figure 6), and correlation of weight with symptom changes and hospitalizations (see Figure 7 for an example of weight correlations with a prominent symptom for heart failure, swelling of the ankles).

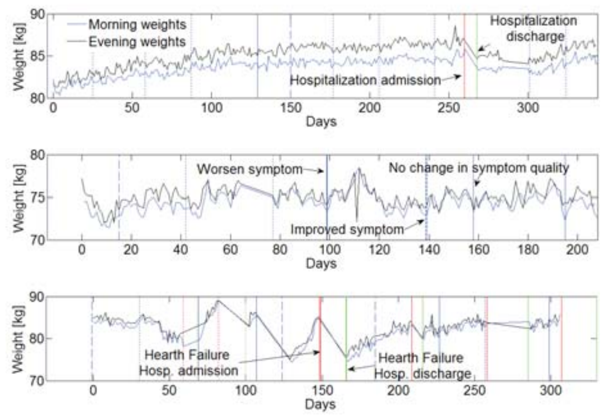

Figure 5. An example of weight time series of three different patients

In addition to well-known feature for heart failure (rapid weight increase before hospitalization) this rather simple approach helped us to additionally discover interesting symptom-related features that we then used in the next step of KDD, namely in searching for potentially actionable patterns, as we discuss in the following section.

4.2 Emerging pattern discovery

In general different types of approaches can be used for discovery of useful patterns, including association analysis, subgroup discovery, etc. In this study we search for discriminating patterns by defining corresponding classification tasks. For example, we searched for rules that would predict next symptom status and change in next symptom values. Recall that one of the key features of RPM systems is the ability to perform subjective assessment of the patient via questionnaires and thereby detect worsening of the symptoms and alert the care giver. Hence, it would be especially useful to be able to predict the changes in

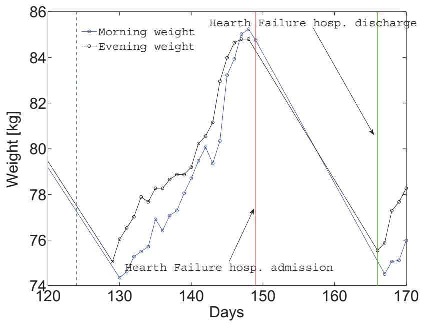

Figure 6. Hospitalization event (zoom-in of Figure 5)

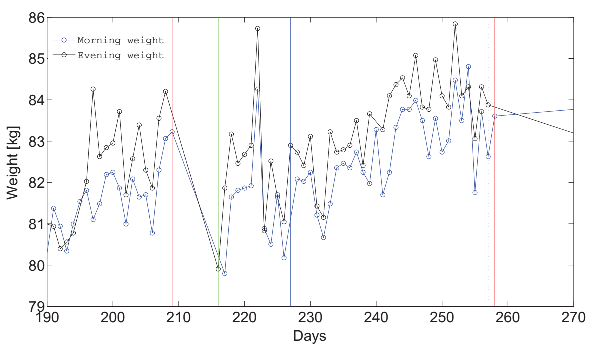

Figure 7. Swelling of ankles symptom change events (zoom-in of Figure 5)

the symptom values, especially detecting worsening, in advance in order to be able to intervene via education (coaching, lifestyle changes) or medications. We therefore focus the classification task on predicitng the next value of the symptoms. Available features from the clinical database, such as gender, age, and frequency of daily system usage, which are potentially impacting the status of the next value of symptoms are used in the classification task. In the clinical trial, the symptoms are evaluated every month (see also 2).

Table 5 illustrates example patterns found (with the help of popular J48 and JRIP classification techniques[4]) for two most prominent symptoms, breathlessness and swelling of ankles. We can observe that women in general are at higher risk to remain breathless (P1) and remain with swelling ankles if they do not use the system regularly (P4-P5). In general, patients are in risk if they are under-utilizing the system (P2-P3), while male patient population above 75 is at risk for worsening of their condition (P6).

Table 5. Examples of discovered patterns

	Patterns	Symptom
P1	(StartSymptom = 'B') & (Sex = F) => NextSymptom = B	Breath-lessness
P2	(StartSymptom = 'A') & (Age = '(37.5-81.5]') & (freqOfWeightUsage < 0.4) => NextSymptom = 'B'	
P3	(StartSymptom = 'A') & (Age = '(37.5-81.5]') & (freqOfPulseUsage < 0.4) => NextSymptom = 'B'	
P4	(StartSymptom = 'B') & (Sex = 'F') & (freqOfWeightUsage < 0.6) => NextSymptom = 'B'	Swelling of ankles
P5	(StartSymptom = 'S') & (Sex = 'F') & (freqOfWeightUsage < 0.6) & (Age < 74.5)=> NextSymptom = 'W'	
P6	(StartSymptom = 'S') & (Sex = 'M') & (Age >=74.5) => NextSymptom = 'B'	
Legend: Start/Next Symptom: G = good (no problem), S = small problems, A = average, B = bad (many problems), W = worse, I = improved		

In Table 6 we present possible adaptation rules based on previously discovered patterns P1-P6 from Table 5. As mentioned in Section 2, the current systems do not personalize the delivered content to the patient's condition, rather send the same content to all the patients. The care giver currently needs to, based on the current reported values of symptoms, do personalization over the phone or face to face consults, explaining to the patient why his certain behaviors and how influence the current breathlessness or similar.

With the rules presented in Table 6 the system would automatically identify patients at risk for worsening of their condition, notify the medical professional about risk, and send adequate content to the patient so that worsening can be prevented. Thereby, the actual workload of the care giver could be reduced as (part of) what is now done face to face or over the phone can be done automatically via the system.

Moreover, with the risk identification and adaptation of the content, the chances of improving clinical outcomes and thereby also reducing future workload associated with worsening are higher. E.g., the first rule based on pattern P1 would send content material to the patient to help her master her breathing, while at the same time notify the medical professional that this woman is at risk to remain breathless. Similarly the second rule based on patterns P2-P3 would identify patient at risk and send appropriate educational and instructional material to the patient and notification about risk to the professional. In this case a patient needs to be motivated to use the system, and properly instructed how to do so.

5 Conclusions and further work

Remote Patient Management (RPM) systems are expected to be increasingly used in the near future. The cur-

[4]We used WEKA 3.6 open source data mining toolkit [10] available from www.cs.waikato.ac.nz/ml/weka/

Table 6. Examples of adaptation rules

P#	Possible Rule	Desired effect	
		Patient	Medical professional
P1	If Sex=F and BreathlessSymptom=B then Send videos with breathing exercises	Regain control over the breathing	Notification for patient at risk
P2, P3	If BreathlessSymptom=A and Age=(37.5-81.5] and (feqOfWeightUsage <0.4 or freqOfPulseUsage < 0.4) then Send Motivational content	Motivation, instruction for using the system, education on breathlessness	Notification of patient at risk
P4	If SwellingSymptom = ‘B’ and Sex = ‘F’ and freqOfWeightUsage < 0.6 then Send Motivational video	Motivation, instruction for using the system, education on swelling ankles	Alert for additional action
P5	If StartSymptom = ‘S’ and Sex = ‘F’ and freqOfWeightUsage < 0.6 and Age < 74.5 then Send motivational content		Notification of patient at risk
P6	If SewllingSymptom = ‘S’ and Sex = ‘M’ and Age > 74.5 then Send educational content	Motivation, education on importance of managing condition	Notification of patient at risk

rent generation of RPM systems follows the one-size-fits-all approach despite of the wide acceptance of the benefits of personalization and adaptation of information services.

In this paper we presented an architecture of the next generation RPM systems that facilitates personalization of educational content and its delivery to patients. We introduced a generic approach for personalization of RPM and provided illustrative examples drawn from the analysis of data from a real clinical trial. With these examples we showed how patient profiling and tailoring of the educational material can be achieved. We considered only the off-line process of discovering useful actionable knowledge for adaptation. However, since some of the patterns are inherently changing over time, it is important to investigate the the potential of online learning, concept drift handling mechanisms, discovery and use of re-occurring contexts for the so-called second order adaptation. This is one of the directions of our further work.

RPM system are becoming also more interactive and therefore there is a natural need in development of other types of feedback personalization mechanisms in RPM systems. Other technologies including e.g. avatars, personalized information retrieval, and open corpus adaptation may become important add-ons to the future generation of RPMs. Integration of these technologies in the presented architecture is among the major directions of our further work.

It is worth mentioning that we considered several issues related to an RPM system design only from methodological and technological perspectives and did not discuss many open organizational (e.g., who is in charge of decision making with respect to adaptation and decision rules), legal, ethical, clinical, and other related issues.

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References

[1] P. Brusilovsky and E. Millán. User models for adaptive hypermedia and adaptive educational systems. *The Adaptive Web*, pages 3–53, 2007.

[2] T. Burkow, L. Vognild, T. Krogstad, N. Borch, G. Ostengen, A. Bratvold, and M. J. Risberg. An easy to use and affordable home-based personal ehealth system for chronic disease management based on free open source software. *Studies in health technology and informatics*, 136:83–88, 2008.

[3] J. Cleland, A. A. Louis, A. Rigby, U. Janssens, and A. Balk. Noninvasive home telemonitoring for patients with heart failure at high risk of recurrent admission and death. *Journal of American College of Cardiology*, 45(10):1654–1664, 2005.

[4] J. Janssen-Boyne. The healthbuddy system: a new way of telemonitoring. *European Heart Failure Congress 2008*.

[5] B. F. van Dongen, A. K. A. de Medeiros, H. M. W. Verbeek, A. J. M. M. Weijters, and W. M. P. van der Aalst. The prom framework: A new era in process mining tool support. In G. Ciardo and P. Darondeau, editors, *ICATPN*, volume 3536 of *Lecture Notes in Computer Science*, pages 444–454. Springer, 2005.

[6] M. Wal and T. Jaarsma. Adherence in heart failure in the elderly: Problem and possible solutions. *International Journal of Cardiology*, 125(2):203–208, 2008.

[7] M. Wal, T. Jaarsma, D. Moser, N. Veeger, W. Gilst, and D. Veldhuisen. Compliance in heart failure patients: the importance of knowledge and beliefs. *European Heart Journal*, 27:434–440, 2006.

[8] H. Wang. Disease management industry and high-tech adoption. *An Industry report from parks assiociates, Parks Associates*, 2008.

[9] X. Wang, R. Istepanian, T. Geake, J. Hayes, M. Desco, G. Kontaxakis, A. Santos, A. Prentza, and S. Pavlopoulos. A feasibility study of a personalized, internet-based compliance system for chronic disease management. *Telemedicine and e-Health*, 11(5):559–566, 2005.

[10] I. H. Witten and E. Frank. *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann, 2nd edition, 2005.