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Integrated Visualisation of Wearable Sensor Data and Risk Models for Individualised Health Monitoring and Risk Assessment to Promote Patient Empowerment

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	components of timeline for health monitoring and of node-link diagrams, chord diagrams and Sankey diagrams for risk analysis are presented to achieve ubiquitous and lifelong health and risk monitoring to promote people's wellbeing. It allows the patients not only to view existing risks but also to know the ways to change their lifestyles to reduce the risks. In addition it also allows people to selectively view and explore the risk paths in interest.

Integrated Visualisation of Wearable Sensor Data and Risk Models for Individualised Health Monitoring and Risk Assessment to Promote Patient Empowerment

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Abstract Patient empowerment delivers health and social care services to enable people to take more control of their health care needs. With the advance of sensor technologies, it is increasingly possible to monitor people's health with dedicated wearable sensors. The consistent measurements from a variety of wearable sensors implies that a huge amount of data may be exploited to monitor and predict people's health with proven models. In the process of health data representation and analysis, visualization can be used to promote data analysis and knowledge discovery via mature visual paradigms with well-designed user interactions. In this paper we introduce the role of visualisation for individualized health monitoring and risk management in the background of the European Commission funded project which aims to provide self-management of cardiorenal diseases with the assistance of wearable sensors. The visualisation components of timeline for health monitoring and of node-link diagrams, chord diagrams and Sankey diagrams for risk analysis are presented to achieve ubiquitous and lifelong health and risk monitoring to promote people's wellbeing. It allows the patients not only to view existing risks but also to know the ways to change their lifestyles to reduce the risks. In addition it also allows people to selectively view and explore the risk paths in interest.

Keywords: patient empowerment, visualisation, wearable sensor, health monitoring, risk management

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1. Introduction

Chronic diseases are seen as a sustainability challenge for people's health. With the trend of "predictive, preemptive, personalized and participative" healthcare (Shneiderman 2013), patient empowerment has become an important concern in heathcare to design and deliver health and social care services to enable people to take control of their health care needs. Patient empowerment is defined as "a process through which people increase their capacity to draw on their personal resources in order to live well with chronic conditions in their daily life" (EPF 2015). It requires a shift from disease-centred to patient-centred approach, combining self-awareness and self-management with well-integrated professional support.

On the other hand, personal health information has been increasingly collectible and accessible in the information era to serve more personalised health monitoring and predictive analysis in medical care (Pantelopoulos 2010). The widespread use of wearable monitoring devices and mobile apps will enable ubiquitous capture of personal health data. Effective collection of long-term health-status data, together with the clinical information that has long played the major role in health and medical decision making, can introduce more added value for health monitoring, risk management and medical decision making in a more ubiquitous, personalised and continuous manner.

The CARRE project (CARRE) – Personalized Patient Empowerment and Shared Decision Support for Cardiorenal Disease and Comorbidities – funded by the 7th Framework Programme of the European Commission, aims to provide innovative means for the management of cardiorenal diseases with the assistance of wearable sensors. The target of CARRE is to provide personalised empowerment and shared decision support for cardiorenal disease, which is the condition characterised by simultaneous kidney and heart disease while the primarily failing organ may be either the heart or the kidney. In CARRE, sources of proven medical knowledge will be semantically linked with sensor outputs to provide clinical information personalised to the individual patient, so as to be able to track the progression and interactions of comorbid conditions. The ultimate goal is to provide the means for patients with comorbidities to take an active role in care processes, including self-care and shared decision-making, and also to support medical professionals in understanding and treating comorbidities via an integrative approach. In addition to medical data, CARRE can not only directly access personal health and lifestyle data from devices such as Fibit (Fitbit), Withings (Withings) and iHealth (iHealth), but also access data from multiple heterogeneous data sources via Microsoft HealthVault (HealthVault) to collect personal health data such as steps, walking distance, calories, heart rate, sleep quality, blood pressure, weight, etc.

The consistent measurements from a variety of data sources implies that a huge amount of data needs to be collected, represented and analysed, which can hardly be achieved without proper visualization to promote data analysis and knowledge discovery via mature visual paradigms with well-designed user interactions. This paper presents the CARRE visualisation design: timelines are employed for measurement data monitoring, node-link diagrams, chord diagrams, Sankey diagrams etc. are chosen for risk factor visualisation and risk analysis. The risk paths can be selectively explored and visualised by risk element filtering in the search box. Personalised risk visualisation and interactive risk evaluation is demonstrated via the risk evaluation interface.

The paper is organised as follows: section 2 introduces related work in health data visualization; Section 3 introduces the CARRE risk model followed by section 4 which discusses the visualization tasks and major visualisation components in CARRE for health monitoring and risk assessment; section 5 presents the evaluation results of the visualisation and section 6 concludes with the summary and future work.

2. Related Work

Healthcare has been an important research and application field of data analysis and visualisation for several decades (Reddy 2015). Much of the focus is on the visualisation of electronic health records (EHRs). Rind et al. gives a detailed review of the related work (Rind 2011), categorising by individual patients or group of patients. In each category, the work is further divided by visual analytics of time series data or status at a certain time point. West et al. also presents a systematic review of innovative visual analytics approaches that have been proposed to illustrate EHR data (West 2015).

Lifelines (Plaisant 1998) is a pioneer work in visualisation of individual patient records, which provides a general visualisation environment for problems, diagnoses, test results or medications using timelines.

Lifelines2 (Wang 2009) provides visualisation of temporal categorical data across multiple records, which is better for a doctor to view to discover and explore patterns across these records to support hypothesis generation, and find cause-and-effect relationships in a population.

LifeFlow (Wongsuphasawat 2011) and EventFlow (Monroe 2013) are tools for event sequence analytics for a group of patients. They extract and highlight the common event sequence from patient records.

Outflow (Wongsuphasawat 2012) and DecisionFlow (Gotz 2014) uses Sankey diagram (Riehmann 2005) style visualization to help visualise and analyse the causal relationships of events in complex event sequences.

VISITORS (Klimov 2010), which is based on KNAVE (Shahar 1999) and KNAVE II (Shahar 2006), uses aggregation to extract meaningful interpretations from multiple patients' raw time-oriented data. PatternFinder (Fails2006) provides tools for the user to query patterns by specifying the attributes of events and time spans.

The existing work has made detailed visualisation research mostly on EHRs and event analysis. While the work on predictive visual analysis of healthcare data is highly valuable (Groves 2013), it is still rare due to its complexity. CARRE aims to provide personalised risk management and analysis with proven risk models (Kaldoudi 2015) extracted from medical literatures, which is a key difference from the existing healthcare visual analytics systems.

3. The Risk Model

In CARRE the risk model is a large semantic graph structure data consisting of interlinked entities, such as risk elements and risk evidence, that are either related to ground knowledge in cardio-renal disease and comorbidities (symptoms, diseases, risk factors, treatments, medical evidence source data, educational content, etc.) or personalised to each patient (patient demographics, medical history, sensor data, lifestyle data, etc.) (Kaldoudi 2015). The data structure of the risk factor repository is shown in Figure 1.

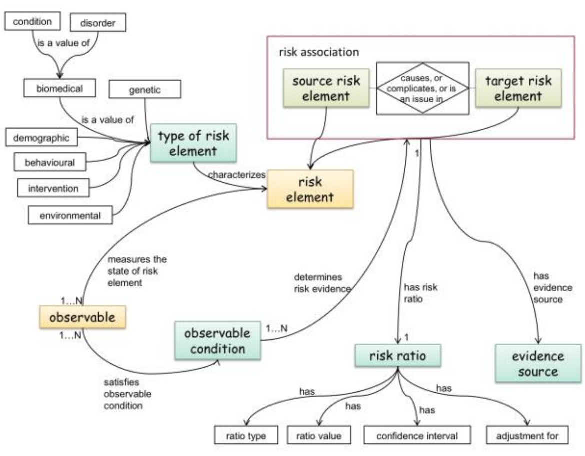


Figure 1 The risk model structure in CARRE risk repository

The key concepts in CARRE risk factor network are defined as follows:

Risk Element: Risk elements include all the conditions/disorders/diseases involved in the comorbidity as well as any other risk causing agent, e.g. demographic (e.g. age, sex, race), genetic (gene polymorphisms), behavioural (e.g. smoking, physical exercise), etc.
Risk Factor: The association of one risk element as the risk source with another risk element as the negative outcome under certain conditions, is a risk factor. A source risk element can be associated to a target risk element with more than one conditions.
Risk Observable: Risk observables are physical variables that can be measured or otherwise ascertained (e.g. biomarkers, biometric variables, biological, etc.).
Risk Evidence: A risk evidence is a criteria controlled one observable condition to invoke a risk association. For example, diabetes will cause heart failure with a risk ratio of 1.39 when diabetes diagnosis is true and glycated haemoglobin is between 9.0 and 10.0. A risk association can be activated by multiple risk evidences with different risk ratios.

The risk data are input and stored in the CARRE repository (Third 2015) by medical professionals via the web-based risk factor entry system, as shown in Figure 2.

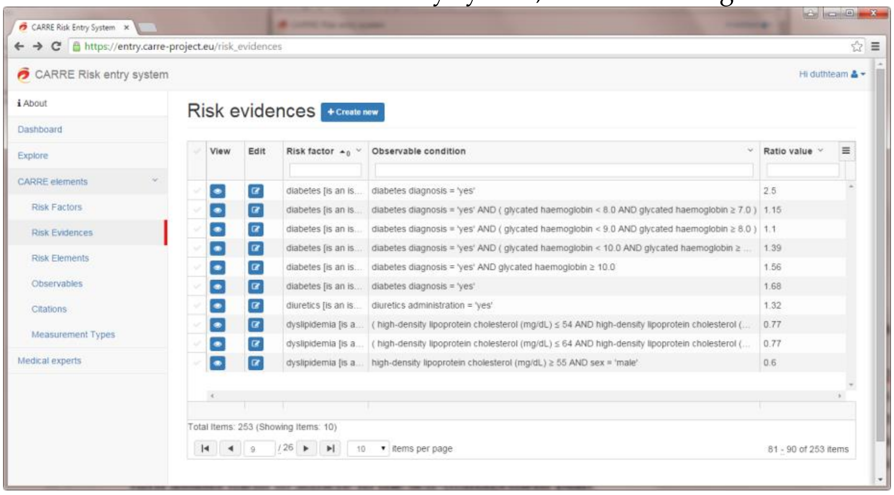


Figure 2 The CARRE risk entry system

Currently there are 98 risk factors (associations), 53 risk elements, 253 risk evidences and 63 observables in the CARRE risk data repository.

To gain intuitive knowledge of the health status data and the risk data, visualisation is indispensable in CARRE to provide patients and clinicians the ability to view, understand and interact with this linked knowledge and also take advantage of personalised empowerment services. The aim is to help patients to understand their own health status and risks, which in turn empower them to take more active control of their health self-management and disease treatment.

4. Visualisation

Visualisation and visual analytics combines automated analysis techniques with interactive visualisations for an effective understanding, reasoning and decision-making on the basis of very large and complex datasets (Keim 2010). It is designed to promote knowledge discovery and utilisation of large datasets via effective visual paradigms and well-designed user interactions. Visualisation becomes the medium of an interactive analytical process, where humans and computers cooperate using their respective distinct capabilities for data processing and visual recognition for the most effective results. Visualisation is an indispensable technology for healthcare information representation and analysis.
In CARRE the data can be generally categorised into fitness measurement data collected from sensors, medical biomarker measurements from personal electronic health records (PHR) and risk factor data extracted from medical literatures. The role of visualisation is to visualise health

data, risk factor data and provide integrated visual analysis of health data and risk factor data.

Based on the risk model and the personal health data, the visualization tasks of CARRE include:

- Visualisation of the risk models to help medical professionals to explore the general disease progression model;
- Visualisation of the risk models to help patients to understand individual disease progression;
- Visualisation of individual measurement data using various graphic approaches to help users to understand the data;
- Visualisation of individual risks and allowing for analytical analysis of the impact of behaviour changes to the risks to help patient to understand the relations between the outcomes and their behaviours during the self-management.

CARRE provides web-based components for interactive health data visualization and risk analysis, including healthline for fitness and biomarker data, node-link diagram, chord diagram and sankey diagram for risk visualization, search box based risk filtering for risk exploration and interactive risk evaluator for risk monitoring and analysis.

4.1 Measurement data collection and visualisation

Fitness and medical measurement data are inherently time dependent. To visualise time-varying data, a linear form timeline is a natural choice and has been used by the previous work. To visualise multiple varaibles, the CARRE Healthlines, a special form of timeline group, is used to visualise multiple variables of fitness sensors and biomedical markers. Data trends can be observed from the variable curves and data correlations may be discovered by comparison of the data curves of the multi-variables. As the data records may cover a long period, interactive techniques such as zooming and overview+details (Cockburn 2009) are employed in the healthline visualisation. The users can also select the variables they are interested from the variable list by drag-and-drop. Figure 3 shows multiple measurements visualised in the interactive healthline in CARRE.

Figure 3 The healthline visualises personal fitness and biomarker data

4.2 Visualisation techniques for the risk factors

As introduced in section 3, the risk factor data in the CARRE repository is essentially a graph whose nodes are risk elements with multiple attributes attached. Each directed link represents a risk association directed from the source to the target risk element. In CARRE node-link diagrams as well as other graph visualisation techniques, such as chord diagrams (Holten 2006), Sankey diagrams (Riehmann 2005), etc., are used to visualise the risk factors for professionals and patients to view the risks.

Node-link Diagram

Node-link diagram (Liu 2014) is one traditional technique to visualise graph data structure visually. Figure 4 is a force-directed node-link diagram visualisation of selected risk factors in the current CARRE repository. The node-link diagram clearly visualises risk associations and promotes studying and understanding of the risk factor data. By interactively viewing the graph, the user understands their risks in a more intuitive manner.

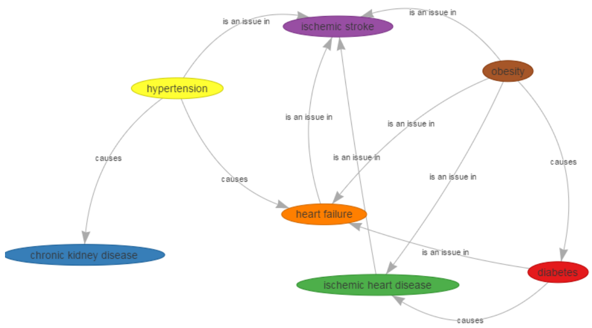


Figure 4 An example node-link diagram of risk elements and risk factors

Chord Diagram

The disadvantage of the node-link diagram is that without proper handling, when the number of nodes and links increase, the visualization becomes increasingly messy for effective recognition by human beings. Fortunately there are some network visualisation techniques to alleviate the problem, such as the chord diagram (Holten 2006).

The chord diagram is especially suitable for visualising risk association pairs. In a chord diagram all the nodes are arranged on a circle and the edges from one node are grouped and bundled, which reduces the hairball problems occurring in the node-link diagram. With mouse hover interactions all the edges from or to one node can be highlighted, thus making the observation of the connections from or to one node much easier, as shown in Figure 5.

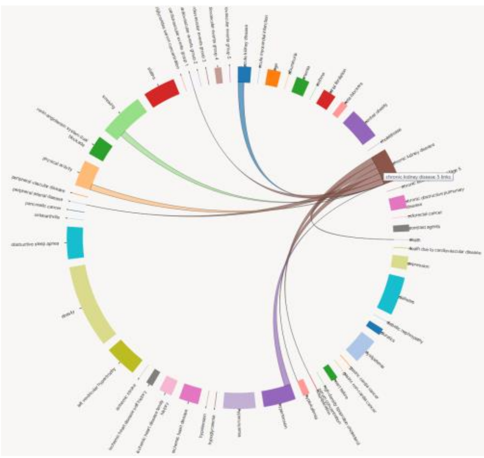


Figure 5 Mouse hovering on a certain risk element showing all the related risk associations

Sankey diagram

The disadvantage of the chord diagram is that it can only show the risk association pairs but cannot show the risk propagation paths. A Sankey diagram is a better choice for visualising causal flows. As introduced in the related work, OutFlow and DecisionFlow use Sankey diagram style visualisation to visually analyse the causal relationships of events. The advantage of the Sankey diagram is that it shows the multi-layer causal relationships of the elements in a much clearer and understandable way than the node-link diagram despite that it is not suitable for visualisation of general graph data. Figure. 6 shows a Sankey diagram in risk factor visualisation and exploration. It is fairly easy to identify the risks relating to a disease (risk element) and to recognise the routes of risk propagation from the visualisation.

4.3 Visual exploration of the risk factor repository

As introduced in section 3, the risk factor repository stores a number of risk factors. Instead of viewing all the risk factors in a single view, medical professionals and patients are often interested in risk factors related to some particular or individualized diseases such as diabetes, cardiovascular diseases, etc. Therefore it is often desired to provide interactive visual exploration of risk factors in interest. CARRE provides search box based filtering of the risk elements with the visualization to achieve selective visual exploration of the risk factor repository, as shown in Figure 6. The user inputs and edits interested risk elements in the search box. The visualization only shows those risk factors which contains the selected risk elements. Figure 6 is an example visualization in Sankey diagram, but other types of visualization suchas the node-link diagram and chord diagram can also be used.

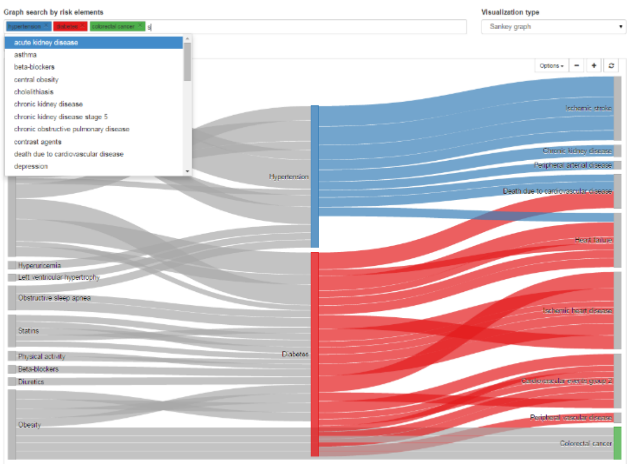


Figure 6. Sankey diagram exploration of risk factors based on risk element filtering

4.4 Individualised patient risk assessment

The ultimate goal of CARRE is to integrate the measurement data and the risk factor database to promote patient empowerment and individualized risk discovery, assessment and management. To achieve that goal an interactive risk evaluator is designed and implemented based on individual measurements and the user's inputs. The risk assessment is performed by the risk model parser which takes the risk evidence condition equations and the measurement values as input and evaluate if the conditions hold true. As shown in Figure 7, the risk associations are highlighted in the node-link diagram based on the patient's measurements, thus reducing the visual complexity.

To empower the patients to perform interactive risk analysis, the measurement slider panel is introduced to enable the user to understand potential risks and the ways to reduce existing risks. Risk predictions can be made by interactively adjusting the measurement values in the slider panel to reflect the risk changes with the patient's predicted conditions dynamically. Currently, the risk assessment is achieved by re-calculating the risks via the risk model parser with updated fitness and biomarker measurement data. For example, if the blood pressure drops to the normal range, the hypertension risk element may disappear. In another example if the user walks more, the obesity risk element and all risk factors related to obesity may disappear.

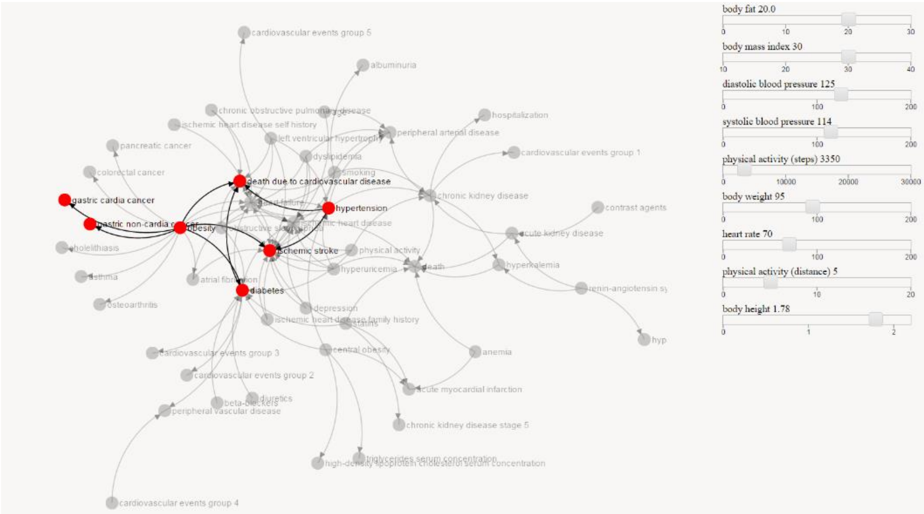


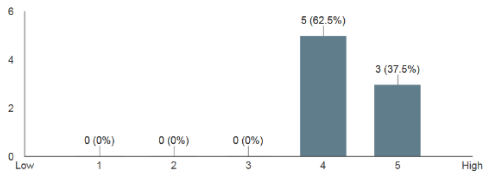
Figure 7 Interactive risk analysis: risks highlighted and changed according to individualized measurements

5. Evaluation

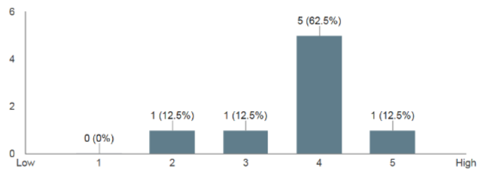
An evaluation of the web-based visualization modules has been undertaken by 8 users through a survey. The questions focus on the effectiveness of the visualization components.

For healthlines, we have the following questions and answers:

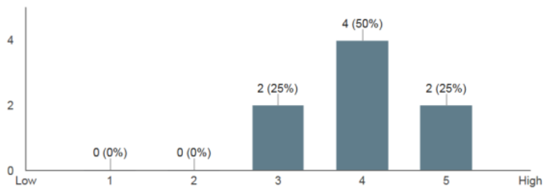
Can this function tell you the measurements collected over a time period?



Are graphs displayed with sufficient information?

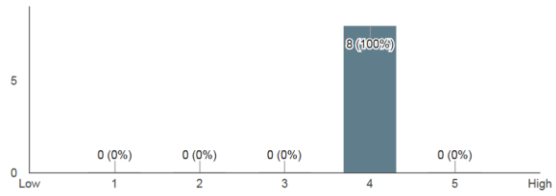


How smooth are the Healthline operations?

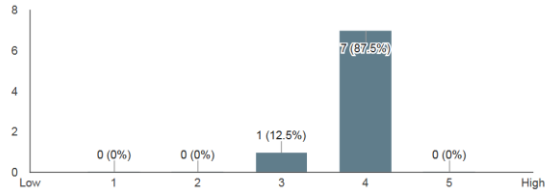


For the risk evaluation graph, we have the following questions and answers:

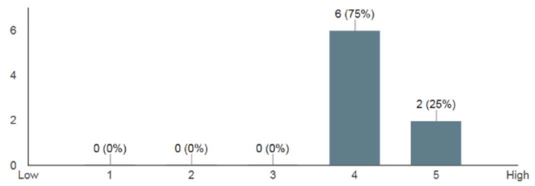
Can this function show clear information of risk?



Does the graph display sufficient information?



Are the diagrams easy to understand?



The evaluation results show that the visualization tools of the healthlines and risk graph are generally easy to understand and interact. They effectively visualise the time-varying measurement data and risk data with user interfaces providing most of the desired information. However, there is still room for improvements with the healthlines to meet the user's expectations to display more information.

6. Conclusions and Future Work

The increasing availability of personal health data in the internet era has promoted patient empowerment in the healthcare sector. Data collected from wearable sensors can be used with medical data to contribute to health monitoring, risk assessment and decision support with the support of professional clinicians. While there is large amount of data collected from a variety of data sources, without effective visualisation it is almost impossible to present the data and perform interactive data analysis. This paper introduces in particular the role of visualization for health monitoring and risk management based on patient measurements and proven risk models in CARRE.

Multiple variable time-dependant data visualised in linear healthlines helps to study and analyse fitness and biomarker measurements, especially when proper user interaction techniques are introduced. The network of risk elements and risk factors can be visualised with node-link diagrams, chord diagrams or Sankey diagrams.

Moreover, multiple risk elements can be input in the search box to selectively explore the risk factor repository, which is especially useful for patients or medical professionals interested in particular disease paths.

To empower the patients to view and assess their own risks, an interactive risk graph based on adjustable individual measurements is presented to support risk monitoring and assessment.

In conclusion, interactive visualisation is critical and effective in health risk management and analysis to promote patient empowerment. The future work will focus on integrating the risk model more closely with the individualised risk management as well as with visualization types of the Sankey diagram.

References

CARRE, CARRE Project. http://www.carre-project.eu/

Cockburn, A, Karlson A, Bederson BB (2009) A review of overview+detail, zooming, and focus+context interfaces. ACM Computing Surveys (CSUR) Surveys 41(1)

EPF (2015), EPF Background Brief: Patient Empowerment, http://www.eu-patient.eu/globalassets/campaign-patient-empowerment/briefing_paperpatient-empowerment_final_external.pdf

Fails, JA, Karlson AK, Shahamat L, et al. (2006) A visual interface for multivariate temporal data: Finding patterns of events across multiple histories, in Wong, P.C., Keim, D.A. (Eds.) 'IEEE VAST' (IEEE Computer Society, 2006) pp 167–174

Fitbit http://www.fitbit.com/

Gotz D, Stavropoulos H (2014) Decisionflow: Visual analytics for high-dimensional temporal event sequence data. IEEE Transactions on Visualization and Computer Graphics 20(12)

Groves P, Kayylai B, Knott D, Van Kuiken S (2013) The big-data revolution in us health care: Accelerating value and innovation

HealthVault. https://www.healthvault.com/

Holten D (2006) Hierarchical edge bundles: Visualization of adjacency relations in hierarchical data. IEEE Transactions on Visualization and Computer 12(5)

iHealth https://ihealthlabs.com/

Kaldoudi E, Third A, Gotsis G, Roumeliotis S, Karvelyte N, Rimseviciu L, Pafili K, Papazoglou D, Juozalenaite G, Semertzidou E, Visockiene Z, Zigeridou K (2015) CARRE Deliverable D.2.2: Functional Requirements & CARRE information model". https://www.carre-project.eu/project-info/deliverables/, CARRE: Personalized Patient Empowerment and Shared Decision Support for Cardiorenal Disease and Comorbidities, FP7-ICT-61140

Keim D, Kohlhammer J, Ellis G, et al. (2010) Mastering the Information Age – Solving Problems with Visual Analytics. Eurographics Association

Klimov D, Shahar Y, Taieb-Maimon M (2010) Intelligent visualization and exploration of time-oriented data of multiple patients, Artif. Intell. Med., 49, (1), pp. 11–31

Liu S, Cui W, Wu Y, Liu M (2014) A survey on information visualization: recent advances and challenges. The Visual Computer 30(12):1373–1393

Monroe M, Lan R, Lee H, Plaisant C, Shneiderman B (2013) Temporal event sequence simplification. IEEE Trans Vis Comput Graph. 19(12):2227-36.

Pantelopoulos A, Bourbakis NG (2010) A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis, IEEE Transactions on Systems, Man, and Cybernetics, 40(1):1-12

Plaisant C, Mushlin R, Snyder A, Li J, Heller D, Shneiderman B, Colorado KP (1998) Lifelines: Using visualization to enhance navigation and analysis of patient records. In: In Proceedings of the 1998 American Medical Informatic Association Annual Fall Symposium. pp 76–80

Riehmann P, Hanfler M, Froehlich B (2005) Interactive sankey diagrams. In: Proc. IEEE Symposium on Infomation Visualization, InfoVis 2005. pp 233–240. IEEE

Reddy CK, Aggarwal CC (2015): Healthcare Data Analytics. Chapman & Hall/CRC

Rind A, Wang TD, Aigner W, Miksch S, Wongsuphasawat K, Plaisant C, Shneiderman B (2011) Interactive information visualization to explore and query electronic health records. Foundations and Trends in HCI 5(3):207–298

Shneiderman B, Plaisant C, Hesse BW (2013) Improving health and healthcare with interactive visualization methods. IEEE Computer 46(1): 58–66

Shahar Y, Cheng C (1999) Intelligent visualization and exploration of time-oriented clinical data. Proc. 32nd Annual Hawaii Int. Conf. on Systems Sciences, Hawaii

Shahar Y, Goren-Bar D, Boaz D, et al (2006) Distributed, intelligent, interactive visualization and exploration of time-oriented clinical data and their abstractions, Artif. Intell. Med., 38(2):115–135

Third A, Kaldoudi E, Gotsis G, Roumeliotis S, Pafili K, Domingue J (2015): Capturing

scientific knowledge on medical risk factors. In: K-CAP2015: 8th International Conference on Knowledge Capture. ACM

Wang TD, Plaisant C, Shneiderman B, Spring N, Roseman D, Marchand G, Mukherjee V, Smith M (2009) Temporal summaries: Supporting temporal categorical searching, aggregation and comparison. IEEE Transactions on Visualization and Computer Graphics 15(6):1049–1056

West VL, Borland D, Hammond WE (2015) Innovative information visualization of electronic health record data: a systematic review. Journal of the American Medical Informatics Association 22(2)

Withings. http://www.withings.com/

Wongsuphasawat K, Guerra Gómez JA, Plaisant C, Wang TD, Taieb-Maimon M, Shneiderman B (2011) Lifeflow Visualizing an overview of event sequences. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. pp 1747–1756. CHI '11, ACM, New York, NY, USA

Wongsuphasawat K, Gotz D (2012) Exploring flow, factors, and outcomes of temporal event sequences with the outflow visualization. IEEE Transactions on Visualization and Computer Graphics 18(12):2659–2668, http://dx.doi.org/10.1109/TVCG.2012.225