From Smart Health to Smart Hospitals

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Abstract. Prolonged life expectancy along with the increasing complexity of medicine and health services raises health costs worldwide dramatically. Advancements in ubiquitous computing applications in combination with the use of sophisticated intelligent sensor networks may provide a basis for help. Whilst the *smart health* concept has much potential to support the concept of the emerging P4-medicine (preventive, participatory, predictive, and personalized), such high-tech medicine produces large amounts of high-dimensional, weakly-structured data sets and massive amounts of unstructured information. All these technological approaches along with "big data" are turning the medical sciences into a data-intensive science. To keep pace with the growing amounts of complex data, *smart hospital* approaches are a commandment of the future, necessitating context aware computing along with advanced interaction paradigms in new physical-digital ecosystems. In such a system the medical doctors are supported by their smart mobile medical assistants on managing their floods of data semi-automatically by following the human-in-the-loop concept. At the same time patients are supported by their health assistants to facilitate a healthier life, wellness and wellbeing.

Keywords: Smart health · Smart hospital · Ubiquitous computing · Pervasive health · P4 medicine · Context awareness · Computational intelligence

1 Introduction and Motivation

Life expectancy on our planet is still increasing [1, 2]. The World Population Database of the United Nations Population Information Network, POPIN (http://www.un.org/popin) forecasts a further increase in life expectancy through 2050. This prolonged life expectancy along with an increasing survival of acute diseases poses a lot of challenges for health care systems worldwide, making the use of sophisticated technologies not an added value, but a requirement [3].

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Along with the worldwide increasing complexity of health care systems and the fact that modern medicine is turning into a data-intensive science, traditional approaches for handling this “big data” can no longer keep pace with demand, also increasing the risk of delivering unsatisfactory results. Consequently, to cope with this rising flood of data, *smart* approaches are vital [4–8].

Particularly, the advent of smart phones, powerful ubiquitous smart sensors and decreasing costs of data storage has led to an ongoing trend to record all sort of personal biomedical data over time [9, 10]. These recordings lead also to a growing amount of so-called longitudinal data, in the engineering domain better known as time series data [11, 12], being of much importance for predictive analytics – one of the cornerstones of P4-medicine (see Sect. 4.1).

The meanwhile “historic” vision by Mark Weiser of ubiquitous computing [13] and smart objects [14] is also true for healthcare: Moore’s law [15] is also applicable for biomedical sensors which will be embedded in more devices than we can imagine. The vision is that people will interact seamlessly in both cyberspace and physical space. The power of such cyber-physical systems [16], is in their “intelligence”, i.e. smartness, which lies in their adaptive behavior.

A major future trend is moving the human-in-the-loop [17], for a good reason, as both humans and computers have very different strengths, but both together can indeed be more powerful. At large scale this means to combine the best of two worlds: cognitive science with computer science [18, 19].

Recent technological advances in networked sensors, low-power integrated circuits, and wireless communications have enabled the design of low-cost, miniature, light-weight, and intelligent physiological sensor nodes [20]. All these developments leave enormous expectations to our future: Smart environments will be able to automatically track our health and will, to some extend, shift the point of care away from clinician’s offices – thus hopefully be of economic relieve of the much overstressed hospital systems and moving the preventive aspect into the foreground. There is a clear paradigm shift from explicit measuring your health vitals to sensors that fade in the background and track important measures. Second, consumers tend to increasingly like becoming their own health managers and actively participate in healthcare. This hypothesis is expressed through a booming movement called “Quantified Self” were consumer constantly track health vitals such as sleep patterns, blood pressure and body fat.

This paper provides a very brief overview about the concept of smart health, discusses the challenge of “big data” driven by the emerging P4-medicine, and debates some aspects of smart hospitals, with a focus on how to deal with the large amounts of data. Finally, we present some open questions and future challenges – only by touching some aspects on the surface just to stimulate the debate.

2 Glossary

Acceptance: A very important concept for the successful integration of any smart health concept, the term goes back to the work of [21].

Ambient Intelligence: This term was coined within the European research community [22], as a reaction to the terms Ubiquitous Computing [13] and Pervasive Computing [23], which were introduced and frequently used by American researchers. In contrast to the more technical terms of Ubiquitous and Pervasive Computing, Ambient Intelligence emphasizes aspects of Human–Computer Interaction and Artificial Intelligence. Hence, the emphasis of Ambient Intelligence is on better usability, more efficient and embedded services, user-empowerment and support for advanced human interactions [24].

Context Awareness: Involves knowledge about how individuals interact within a shared socio-technical environment and includes information about the participants' locations, their present and past actions, and their intentions and possible future actions [25, 26].

Context-aware computing: Integration of multiple diverse sensors for awareness of situational context that can not be inferred from location, and targeted at mobile device platforms that typically do not permit processing of visual context [26, 27].

E-Health: Describes the fusion of medicine and healthcare services through the use of information and communication technologies, with particular focus on everyday life and low cost devices [28].

E-Homecare: Similar to the E-Health, but with a strong focus on preventive care applications in the home domain [29]. E-Homecare services may include patient assessment, supervision of patient care, routine nursing care and health monitoring, medication administration and scheduled injections, management of dietary needs, daily exercise, and lifestyle changes [30].

P4-Medicine: Focusing on the four aspects: predictive, personalized, preventive and participatory, P4-medicine moves from a reactive to a proactive discipline supported by systems approaches to disease, emerging smart technologies and analytical tools [31]; actually "big data" is good for P4-medicine, as machine learning approaches may get better results by more training examples.

Privacy: A must in the health domain is to ensure privacy, data protection, safety and security; a particular necessity in smart health, as main security problems encompass protection Precautions, confidentiality, and integrity, which is a challenge as most of the smart devices are working in a wireless environment [32–34].

Smart: The word synonym for clever, socially elegant, sophisticated, shrewd, showing witty behaviour and ready mental capability, is a term which is intended to replace the overly stressed word "intelligent", mostly due to the fact that research in both human and artificial intelligence is lacking far behind the original expectations when the field of artificial intelligence was formed [35].

Smart Health: A term, inherently integrating ideas from ubiquitous computing and ambient intelligence applied to the future P4-medicine concept, thus tightly connected to concepts of wellness and wellbeing [3, 36], and including big data, collected by large amounts of biomedical sensors (e.g., temperature, heart rate, blood pressure, blood and urine chemical levels, breathing rate and volume, activity levels etc.) and actuators, to monitor, predict and improve patients' physical and mental conditions.

Smart Hospital: An old dream of a highly interactive environment saturated with high-end ubiquitous devices [37], and closely related to the context aware health paradigm [38]; this topic is in the strategic focus of large companies including IBM, Siemens, Google, etc., as it is highly business relevant, as it might help to overcome the worldwide cost problems of health systems.

Smart Multi-agents: consist of n interacting smart agents within an given environment and are used to solve difficult problems, impossible solvable by an individual agent. The goal of an agent based model is to search for explanatory insight into the collective behavior of the agents, which can be software agents, robots, humans or collective human teams. Smart agents are usually active software agents with simple goals (e.g. birds in flocking or wolf-sheep in the prey-predator model), or they can be complex cognitive agents. Such approaches have enormous capacity for solving biomedical problems.

Ubiquitous Computing (UbiComp): A vision by Weiser (1991) [39], who argued, that computers should be integrated into the physical environment, and hence be effectively invisible to the user, rather than distinct objects on the desktop. Making many computers available throughout the physical environment enables people to move around and interact with computers, more naturally than they currently do, leading to the disappearing computer concept [40].

Wellness Technology: A term mainly introduced to correct the negative connotations of 'technology for disability' and associated with technical devices for the prevention of deterioration, the support of changes in lifestyle, and the improvement of social contacts [41], becoming now more important [42].

3 From Ubiquitous Computing to Smart Health Environments

Ubiquitous computing provides enormous possibilities for establishing smart health services as integral parts of future care concepts [43], which are challenged by our ageing society. In this context, in particular smart homecare environments are often propagated as a promising solution for taking care of elderly or disabled people. Sensors and new interaction technologies seamlessly integrated in such environments offer various forms of personalized and context-adapted medial support, including assistance to carry out everyday activities, monitoring personal health conditions, enhancing patient safety, as well as getting access to social, medical and emergency systems. By providing a wide variety of services, smart healthcare applications bear the potential of bringing medical, social and economical benefits to different stakeholders. The goals are from enhancing comfort, supporting autonomy enhancement up to emergency assistance, including detection, prevention, and prediction (Fig. 1).

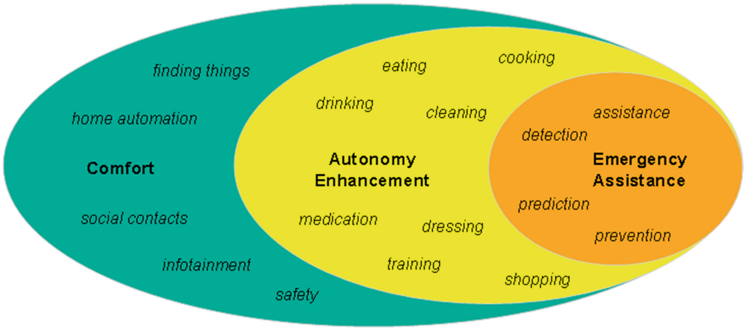

Fig. 1. From emergency assistance (right) to autonomy enhancement and comfort [44].

Technological challenges include mobility, invisibility (smart devices embedded in our daily objects, e.g. clothes as in wearable computing [45], watches [46], glasses [47], etc.), natural communication including voice and gestures instead of keyboard or mouse [48], and most of all adaptivity and context-awareness, as those two important issues "adaptive behavior in context" are key for "intelligence" i.e., capable of reacting to all abnormal and exceptional situations in a flexible way.

3.1 Emergency Support

The majority of existing systems for detecting and preventing medical emergencies focus on falls and congestive heart failures as their main application areas. In particular fall detection becomes more and more important as recent statistics show that over 30 % of the people over 65 years and 50 % of the people over 80 years fall at least once a year [49]. In approximately one fourth of these cases, people suffer serious injuries with sustaining effects on their mobility and independence [50]. As many of these falls happen when people are alone at home, several projects started to develop mobile emergency systems, which should enable users to call for help in an emergency situation [51]. While mobile solutions seem to be a promising approach at first sight, empirical evidence shows that patients often do not carry those devices with them or are simply not able to operate them when medical problems have occurred. Consequently, several research projects developed prototypes of pressure sensitive floor elements allowing the detection of falls without additional technology being worn by the patient. While early systems distributed pressure sensitive floor tiles at specific locations within the environment (e.g. [52, 53]), more recent approaches use distributed sensors to cover an entire room and thereby enable fine-grained location detection [54], see Fig. 2.

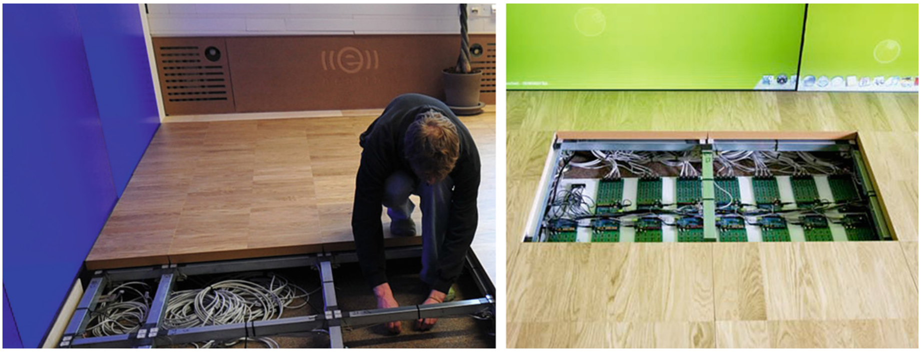

Fig. 2. Smart Floor consisting of an array of pressure sensitive floor tiles for unobtrusively monitoring patients in home environments [54, 55].

3.2 Monitoring of Patients with Chronic Diseases

Long-term treatment of chronic conditions does not only increase the quality of life for patients, it is also expected to bring significant economical benefits compared to traditional care concepts. Hence, it is not surprising that a broad variety of smart health services have been developed for various kinds of chronic diseases. For example, Klack et al. (2011) [56] developed an assistive home monitoring system for patients suffering from end-stage heart failure, which incorporates medical data captured via different biosensors embedded into the patient's physical surrounding. The system focuses particularly on patients with implanted mechanical circulatory support devices, including ventricular assist devices and total artificial hearts and provides an easy and unobtrusive way for monitoring crucial vital parameters over extended periods of time. Figure 3 shows the monitoring system in a home environment. An infrared camera is integrated behind a translucent interactive display, weight sensors are installed under the entire floor and blood pressure and coagulation monitoring devices are implemented in a coffee table next to the sofa.

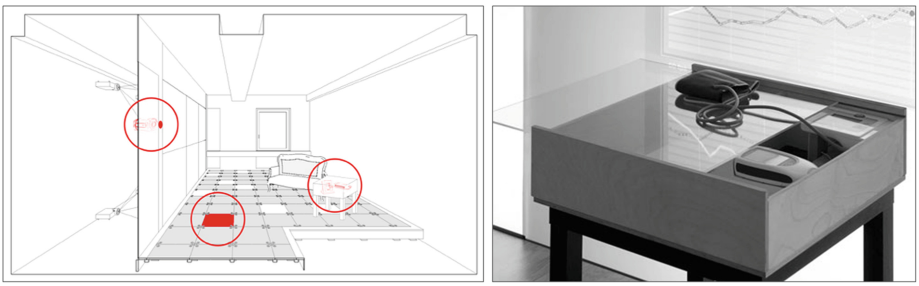

Fig. 3. Medical sensors integrated in a smart home environment (left), blood pressure and coagulation-monitoring device embedded in a coffee table (right), from the RWTH Living Lab

Similar research prototypes have been developed for patients with diabetes [57], (for the importance of diabetes refer to [58]), pulmonary diseases [59], memory loss [60–62], physical impairments [63–65], for the aurally disabled [66, 67] for the elderly [68, 69], or for wellness of the young [42].

An interesting pioneering sample work has been presented by Park et al. (2003) [61]: in their smart home project they devised a set of intelligent home appliances that provided awareness of the end users needs and to improve day-to-day home life with various smart technologies, including smart memories (the smart home learns favourite ambient settings), smart pen (translates and offers additional help on vocabularies during reading of text), gate reminder (reminds you before you leave your house on important issues), smart photo album (see here also [70]), smart wardrobe (looks up the weather forecast and recommends adequate clothing), smart dressing table, smart bed, smart pillow, smart mat, smart table (see here also [71]), smart picture frame, smart furniture (see here particularly [40]), smart refrigerator, smart sofa, smart greenhouse, smart wall, smart window, and smart bathroom.

3.3 Integrated Care Environments

Over the last years, several prototypes of integrated medical care environments have been developed, which incorporate different smart healthcare. For example, the Future Care Lab (Fig. 4) at RWTH Aachen University provides an intelligent care infrastructure, consisting of different mobile and integrated devices, for supporting elderly people in technology-enhanced home environments. The setup of the lab enables in situ evaluations of new care concepts and medical technologies by observing different target user populations in realistic usage situations. As the lab relies on a modular technical concept, it can be expanded with other technical products, systems and functionalities, in order to address different user groups as well as individuals with differences in their cognitive, health-related or cultural needs [43] (Röcker et al. 2010).

Fig. 4. An example of smart medical technologies integrated into a smart home environment, from the RWTH Living Lab

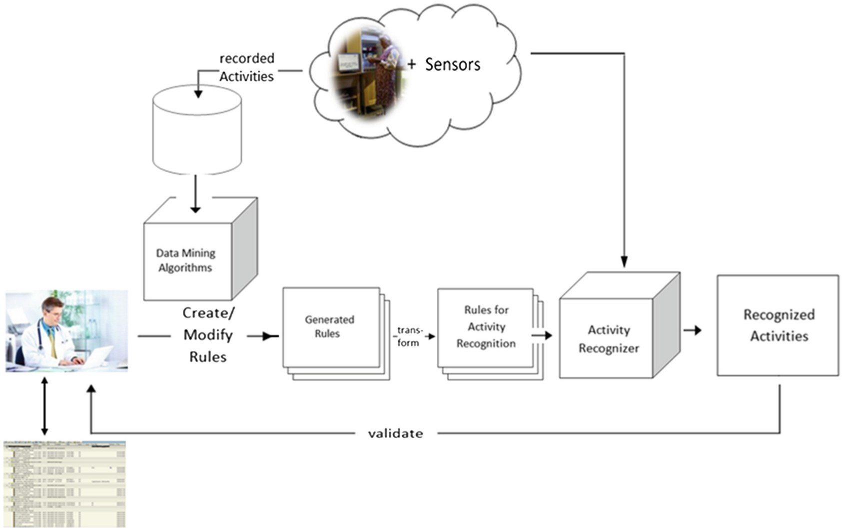

Fig. 5. Concept of Human-in-the-loop (Doctor-in-the-loop), similar to supervised learning. With massive sensor data only machine learning approaches can bring us further.

3.4 Machine Learning: Human-in-the-Loop

Whereas large amounts of data not good for humans, as they are difficult to handle manually, large data sets are good for machine learning algorithms, as the more training data are available the better results are achieved. However, a perfect match of both together is to include the human-in-the-loop. Figure 5 shows an example: a medical-doctor-in-the-loop crates and modifies rules on demand to train the algorithms, in the shown example for activity recognition.

There is not much related work on the human-in-the-loop approach yet, one of the most prominent ones to date is the work of Shyu et al. (1999) [72]: they implemented a human-in-the-loop (a physician-in-the-loop, more specifically) approach in which the medical doctor delineates the pathology bearing regions (regions of interest) and a set of anatomical landmarks in the image when the image is entered into the database. To the regions thus marked, their approach applies low-level computer vision and image processing algorithms to extract attributes related to the variations in gray scale, texture, shape, etc. Additionally their system recorded attributes which captured relational information such as the position of a region of interest with respect to certain anatomical landmarks and an overall multidimensional index is assigned to each image based on these attribute values.

4 From Smart Health to the Smart Hospital

4.1 Future Medicine as a Data Science

Today the design of a drug involves more data science than biological or medical science. The life sciences are increasingly turning into a data intensive science [73–76]. In bioinformatics and computational biology we face not only increased volume and a heterogeneity and diversity of highly complex, multi-dimensional, multivariate and weakly-structured, noisy and dirty data [6, 7, 77–79], but also the growing need for integrative analysis and modeling [80–85]. Due to the increasing trend towards P4-medicine: Predictive, Preventive, Participatory, Personalized [76, 86], even more amounts of large and complex data sets, particularly omics-data [87], including data from genomics, epi-genomics, meta-genomics, proteomics, metabolomics, lipidomics, transcriptomics, epigenetics, microbiomics, fluxomics, phenomics, etc., are becoming available. A recent article on "HCI for Personal Genomics" by [88] gets straight to the point: Recent advances in -omics along with Web technologies have led to a dramatic increase in the amount of available complex data sets to both expert and non-expert users. They emphasize that the HCI community is challenged with designing and developing tools and practices that can help make such data more accessible and understandable. However, the problem is, that despite the fact that humans are excellent at pattern recognition in dimensions of lower than three [89], most of our current data is in dimensions much higher than three, making manual analysis difficult, yet often impossible [90]. Today, biomedical experts both in daily routine and science are no longer capable of dealing with such increasingly large, complex, high-dimensional and weakly-structured data sets. Consequently, efficient, useable computational methods, algorithms and tools to interactively gain insight into such data are a commandment of the time [91].

Consequently, a synergistic combination of methodologies and approaches of two areas offer ideal conditions towards unraveling these problems: Human-Computer Interaction (HCI) and Knowledge Discovery/Data Mining (KDD), with the goal of supporting human intelligence with machine learning – human-in-the-loop – to discover novel, previously unknown insights into the data [18]. Big Data is bad for humans, but good for machines, as machine learning algorithms improve their precision with the amount of training samples, however, what we really need is not more data – but *better* data.

4.2 Mobile Medical Doctors Assistants

The vision of a "mobile medical doctor's assistant" is an example of a cognitive computing project (see Sect. 5) that shall enable a more natural interaction between medical professionals and biomedical data and would be a cornerstone in the development of a smart hospital, and can contribute to enhanced patient safety [92]. One step to reach such a goal is in the application of sophisticated modern technologies such as the Watson Content Analytics. Technologically, "Watson" consists of diverse algorithms, created in the context of cognitive computing research to demonstrate the capability of the DeepQA technology [93]. The challenge to date is, that Watson has "no eyes and no ears", so Watson needs sophisticated user interfaces, to date Watson the current algorithms – sophisticated as they are – are far from being usable for the non-expert end user [5].

A future vision is to make the Watson technology useable from a smart phone – so that a medical professional can ask questions to the data, e.g. "Show me the similarities, differences, anomalies … between patients with symptom X and patients with symptom Y". Why mobility? Medical professionals work in an environment which requires high mobility; within their daily routine their sphere of activity alters frequently between wards, outpatient clinics, diagnostic and therapeutic departments and operating theatres – they rarely sit in an office. Although access to stationary clinical workstations is provided in the hospital, their locations do not always coincide with the user's current workplace. In order to fulfill a high health service standard, the medical staff has an extensive demand for information at a number of locations – which actually only mobile computers can supply [94]. For example: Up-to-the-minute electronic patient record information is not always available at the bedside [95, 96]. New orders or diagnostic results noted during rounds must be transcribed to the electronic patient records via a clinical workstation at a later time – whereas a mobile computer enables direct access [97–100].

4.3 Smart Hospital

Mark Weiser (1991) expressed his vision of invisible computing by his famous sentence: "… the most profound technologies are those that disappear [39]". We interpret this and develop it further: "The best technology is those who is in the direct workflow", and practically not perceived as such. A smart hospital would integrate all aforementioned approaches with the aim to support both professionals and patients.

Approaches to a smart hospital are rare to date, a search in the Web of Science as of December, 30, 2014 returned only 22 hits (title = "smart hospital"). The most prominent example is a project on Activity recognition for the smart hospital, by the group around Jesus Favela [37]: they developed an approach for automatically estimating hospital-staff activities, where they trained a discrete hidden Markov model (HMM) to map contextual information to a user activity. The vision of the authors is called iHospital and includes a highly interactive smart environment saturated with heterogeneous computing devices. At the core of this approach is context aware computing (see Sect. 5).

5 Future Challenges

5.1 Challenge 1: Context Aware Computing

Context is *key* in the development of the smart hospital in the sense that it is any *information* that can be used to characterize the situation of entities (people, places, objects), considered to be relevant to the *interaction* between an end user and an ubiquitous computing application [101]. A classical paper [102] provides a good overview of context in the field of artificial intelligence. If context is redefined continually and ubiquitously, then how can users form an accurate model of a constantly evolving digital world? If system adaptation is negotiated, then how do we avoid disruption in human activities? A clear architecture and a well-founded, explicit relationship between environment and adaptation are the critical factors; indeed, they are the key that will unlock context-aware computing at a global scale [103]. Such approaches require the integration of concepts in User Experience and Context-aware computing in the sense of [26], and [27] and to see our surrounding environment as a Physical-Digital Ecosystem [104–106]. Context aware computing is not only key for the smart hospital, but for the overall smart health principle: Situational awareness can be used to reduce the amount of explicit input a person is required to provide a computer. Contextual information of what and where the user task is, what the user knows, and what the system capabilities are, can simplify the user scenario [107]. Improving the user experience *is not enough;* we need concepts, frameworks, and methods that will enable it to consider humans and computers as part of our complex world full of limitations and opportunities (see also challenge 4).

5.2 Challenge 2: Cognitive Computing

Cognitive computing (cc) is suited to solve medical problems: because it is on how to deal with complex situations and information uncertainty, and dealing with probable information is the key challenge in biomedical informatics [108]. The quest towards a smart hospital requires new breakthroughs in the overlapping area of cognitive science and computer science: Whilst high-dimensionality of our data is often regarded as a curse [109], it is also possible that very high dimensionality actually facilitates processing: for example, numbers (i.e., scalars) can be seen as one-dimensional data, but in a computer they can be represented by strings of bits, i.e. by high-dimensional vectors, so a 32-bit integer can be seen as a binary vector in $\mathbb{R}^{32}$. Such a high-dimensional representation makes simple algorithms and circuits for high-precision arithmetic possible. We can contrast this with one-dimensional representation of numbers. The slide rule represents them one-dimensionally and makes calculating awkward and imprecise. Thus, the dimensionality of an entity (a number) and the dimensionality of its representation for computing purposes (a bit vector) are separate issues – the first with the existence in our world, the other with the manipulation by algorithms in abstract spaces – which is more suitable for computing. Pentti Kanerva (2009) [110] shows a nice example of the advantages of such a hyper-dimensional approach, which we cannot discuss here due to the limited space but we can summarize: A grand challenge of cognitive computing is to explore both hyper-dimensional representation of data and **randomness.** This brings us further beyond Von-Neumann machines and is a core topic of brain informatics [111–113] – which may bring us to both smart health and smart hospitals.

5.3 Challenge 3: Stochastic Computation

Closely related to cognitive computing by emphasizing the aspect of randomness is the concept of stochastic computation [114]. Stochastic computing (sc) was proposed in the 1960s as a low-cost alternative to conventional binary computing. It is unique in that it represents and processes information in the form of digitized probabilities and employs low-complexity arithmetic units which was a primary design concern in the past – due to the limited computing power and inaccurate results [115]. Meanwhile, Bayesian computational techniques such as Markov chain Monte Carlo (MCMC), Sequential Monte Carlo (SMC), and Approximate Bayesian Computation (ABC) methods are well established and have revolutionized the practice of Bayesian statistics, however new grand opportunities have appeared with the emergence of massive, high-dimensional and complex data sets [116, 117]. Stochastic computation is an approach for the design of robust and energy-efficient systems-on-chip (SOC) in nanoscale process technologies [118], which will be vital for smart hospital environments. The reduction of size along with massive parallelization is one step towards implementing stochastic computation approaches, hence to overcome classical von Neumann machines to perform meaningful and accurate computations in neural circuits. Much work is needed here in the future, but there are promising ideas for the realization of smart health and smart hospital particularly in programmable and autonomous stochastic molecular automata, which have been shown to perform direct analysis of disease-related molecular indicators in vitro and may have the potential to provide in situ medical diagnosis and cure [119].

5.4 Challenge 4: Smart Multi-agent Collectives with Experts-in-the-Loop

Multi-agent systems are an extremely interesting research area [120–123] and are becoming continually important for solving medical problems (e.g. [124]). Human–Agent collectives (HAC) are an upcoming class of socio-technical hybrid systems in which both humans and smart agents may develop a flexible relationship to achieve both their individual and collective goals. It is increasingly accepted that it is both necessary and beneficial to involve human experts, working as active information processors, in a concerted effort together with smart agents [125, 126]. Such approaches are completely in line with the goal of combining cognitive science with computer science [19], following the HCI-KDD approach [18]. The challenge in Human-Agent collectives is, that despite relevant work in the AI, HCI and Ubicomp communities a comprehensive scientific foundation is lacking, hence is of urgent need for fundamental research; in particular the challenges are in flexible autonomy (balance control between human experts and smart agents), agile teaming, incentive engineering and most of all on how to provide a necessary infrastructure, and the application of machine learning to network metrics and the human labelling of graphs provide a lot of interesting research challenges [127]. There are several best practice examples from disaster management [128, 129].

5.5 Challenge 5: Beyond Data Mining

As Yvonne Rogers pointed out in the Foreword to this volume: Being smart about health data is not straightforward: Smart health has the potential to enable more people to manage their own health, and in doing so become more aware and better informed. But it also raises many moral questions. Who owns the health data being collected? Who is willing to share their health data? Where do the new streams of health data end up? All these questions must be considered when realizing a smart hospital. These are grand challenges and not easy to tackle and can be summarized as "What comes beyond data mining?", to close with the words of Tim Menzies "Prediction is all well and good – but what about decision making?" [130].

References

1. Oeppen, J., Vaupel, J.W.: Demography - broken limits to life expectancy. Science **296**(5570), 1029 (2002)
2. Mathers, C.D., Stevens, G.A., Boerma, T., White, R.A., Tobias, M.I.: Causes of international increases in older age life expectancy. Lancet **385**(9967), 540–548 (2015)
3. Röcker, C., Ziefle, M., Holzinger, A.: From computer innovation to human integration: current trends and challenges for pervasive HealthTechnologies. In: Holzinger, A., Ziefle, M., Röcker, C. (eds.) Pervasive Health, pp. 1–17. Springer, London (2014)
4. Holzinger, A., Dehmer, M., Jurisica, I.: Knowledge discovery and interactive data mining in bioinformatics - state-of-the-art, future challenges and research directions. BMC Bioinform. **15**(Suppl 6), I1 (2014)
5. Holzinger, A., Stocker, C., Ofner, B., Prohaska, G., Brabenetz, A., Hofmann-Wellenhof, R.: Combining HCI, natural language processing, and knowledge discovery - potential of IBM content analytics as an assistive technology in the biomedical field. In: Holzinger, A., Pasi, G. (eds.) HCI-KDD 2013. LNCS, vol. 7947, pp. 13–24. Springer, Heidelberg (2013)
6. Holzinger, A.: On knowledge discovery and interactive intelligent visualization of biomedical data - challenges in human–computer interaction and biomedical informatics. In: DATA 2012, pp. 9–20 (2012)
7. Holzinger, A.: Weakly structured data in health-informatics: the challenge for human-computer interaction. In: Proceedings of INTERACT 2011 Workshop: Promoting and Supporting Healthy Living by Design, pp. 5–7. IFIP (2011)
8. Duerr-Specht, M., Goebel, R., Holzinger, A.: Medicine and health care as a data problem: will computers become better medical doctors? In: Holzinger, A., Roecker, C., Ziefle, M. (eds.) Smart Health. LNCS, vol. 8700, pp. 21-39. Springer, Heidelberg (2015)
9. Culler, D.E., Mulder, H.: Smart sensors to network the world. Sci. Am. **290**(6), 84–91 (2004)
10. Ghrist, R., de Silva, V.: Homological sensor networks. Notic. Amer. Math. Soc. **54**(1), 10–17 (2007)
11. Esling, P., Agon, C.: Time-series data mining. ACM Comput. Surv. (CSUR) **45**(1), 12 (2012)
12. Holzinger, A., Schwarz, M., Ofner, B., Jeanquartier, F., Calero-Valdez, A., Roecker, C., Ziefle, M.: Towards interactive visualization of longitudinal data to support knowledge discovery on multi-touch tablet computers. In: Teufel, S., Min, T.A., You, I., Weippl, E. (eds.) CD-ARES 2014. LNCS, vol. 8708, pp. 124–137. Springer, Heidelberg (2014)
13. Weiser, M.: Some computer science issues in ubiquitous computing. Commun. ACM **36**(7), 75–84 (1993)
14. Weiser, M., Gold, R., Brown, J.S.: The origins of ubiquitous computing research at PARC in the late 1980s. IBM Syst. J. **38**, 693–696 (1999)
15. Moore, G.E.: Cramming more components onto integrated circuits. Electronics **38**(8), 114–117 (1965)
16. Wu, F.J., Kao, Y.F., Tseng, Y.C.: From wireless sensor networks towards cyber physical systems. Pervasive Mob. Comput. **7**(4), 397–413 (2011)
17. Schirner, G., Erdogmus, D., Chowdhury, K., Padir, T.: The future of human-in-the-loop cyber-physical systems. Computer **46**(1), 36–45 (2013)

18. Holzinger, A.: Human-computer interaction and knowledge discovery (HCI-KDD): what is the benefit of bringing those two fields to work together? In: Cuzzocrea, A., Kittl, C., Simos, D.E., Weippl, E., Xu, L. (eds.) CD-ARES 2013. LNCS, vol. 8127, pp. 319–328. Springer, Heidelberg (2013)
19. Holzinger, A.: Trends in interactive knowledge discovery for personalized medicine: cognitive science meets machine learning. Intell. Inform. Bull. **15**(1), 6–14 (2014)
20. Milenkovic, A., Otto, C., Jovanov, E.: Wireless sensor networks for personal health monitoring: issues and an implementation. Comput. Commun. **29**(13–14), 2521–2533 (2006)
21. Davis, F.D.: Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. **13**(3), 319–339 (1989)
22. Aarts, E., Harwig, E., Schuurmans, M.: Ambient intelligence. In: Denning, J. (ed.) The Invisible Future, pp. 235–250. McGraw-Hill, New York (2001)
23. Satyanarayanan, M.: Pervasive computing: vision and challenges. IEEE Pers. Commun. **8**(4), 10–17 (2001)
24. Ramos, C., Augusto, J.C., Shapiro, D.: Ambient intelligence - the next step for artificial intelligence. IEEE Intell. Syst. **23**(2), 15–18 (2008)
25. Abowd, G.D., Dey, A.K.: Towards a better understanding of context and context-awareness. In: Gellersen, H.-W. (ed.) HUC 1999. LNCS, vol. 1707, pp. 304–307. Springer, Heidelberg (1999)
26. Gellersen, H.W., Schmidt, A., Beigl, M.: Multi-sensor context-awareness in mobile devices and smart artifacts. Mob. Netw. Appl. **7**(5), 341–351 (2002)
27. Bardram, J.E., Hansen, T.R., Mogensen, M., Soegaard, M.: Experiences from real-world deployment of context-aware technologies in a hospital environment. In: Dourish, P., Friday, A. (eds.) UbiComp 2006. LNCS, vol. 4206, pp. 369–386. Springer, Heidelberg (2006)
28. Yan, H.R., Huo, H.W., Xu, Y.Z., Gidlund, M.: Wireless sensor network based e-health system - implementation and experimental results. IEEE Trans. Consum. Electron. **56**(4), 2288–2295 (2010)
29. Demiris, G., Rantz, M.J., Aud, M.A., Marek, K.D., Tyrer, H.W., Skubic, M., Hussam, A.A.: Older adults' attitudes towards and perceptions of 'smart home' technologies: a pilot study. Med. Inform. Internet Med. **29**(2), 87–94 (2004)
30. Demiris, G., Tan, J.: Rejuvenating home health care and tele-home care. In: Tan, J. (ed.) E-Health Care Information Systems: An Introduction for Students and Professionals, pp. 267–290. Jossey-Bass, San Francisco (2005)
31. Hood, L., Friend, S.H.: Predictive, personalized, preventive, participatory (P4) cancer medicine. Nat. Rev. Clin. Oncol. **8**(3), 184–187 (2011)
32. Weippl, E., Holzinger, A., Tjoa, A.M.: Security aspects of ubiquitous computing in health care. Springer Elektrotechnik und Informationstechnik, e & i **123**(4), 156–162 (2006)
33. Holzinger, A., Nischelwitzer, A., Friedl, S., Hu, B.: Towards life long learning: three models for ubiquitous applications. Wirel. Commun. Mob. Comput. **10**(10), 1350–1365 (2010)
34. Kieseberg, P., Hobel, H., Schrittwieser, S., Weippl, E., Holzinger, A.: Protecting anonymity in data-driven biomedical science. In: Holzinger, A., Jurisica, I. (eds.) Interactive Knowledge Discovery and Data Mining in Biomedical Informatics. LNCS, vol. 8401, pp. 301–316. Springer, Heidelberg (2014)
35. Minsky, M.: Steps towards artificial intelligence. Proc. Inst. Radio Eng. **49**(1), 8–30 (1961)
36. Suryadevara, N.K., Mukhopadhyay, S.C.: Determining wellness through an ambient assisted living environment. IEEE Intell. Syst. **29**(3), 30–37 (2014)
37. Sanchez, D., Tentori, M., Favela, J.: Activity recognition for the smart hospital. IEEE Intell. Syst. **23**(2), 50–57 (2008)

38. Solanas, A., Patsakis, C., Conti, M., Vlachos, I.S., Ramos, V., Falcone, F., Postolache, O., Perez-Martinez, P.A., Di Pietro, R., Perrea, D.N., Martinez-Balleste, A.: Smart health: a context-aware health paradigm within smart cities. IEEE Commun. Mag. **52**(8), 74–81 (2014)
39. Weiser, M.: The computer for the twenty-first century. Sci. Am. **265**(3), 94–104 (1991)
40. Streitz, N., Magerkurth, C., Prante, T., Röcker, C.: From information design to experience design: smart artefacts and the disappearing computer. Interactions **12**(4), 21–25 (2005)
41. Cowan, D., Turner-Smith, A.: The role of assistive technology in alternative models of care for older people. In: Sutherland, I. (ed.) With Respect To Old Age: The Royal Commission for the Long Term Care of the Elderly, Appendix 4, vol. 2, pp. 325–346. The Stationery Office, London (1999)
42. Holzinger, A., Dorner, S., Födinger, M., Valdez, A.C., Ziefle, M.: Chances of increasing youth health awareness through mobile wellness applications. In: Leitner, G., Hitz, M., Holzinger, A. (eds.) USAB 2010. LNCS, vol. 6389, pp. 71–81. Springer, Heidelberg (2010)
43. Röcker, C., Wilkowska, W., Ziefle, M., Kasugai, K., Klack, L., Möllering, C., Beul, S.: Towards adaptive interfaces for supporting elderly users in technology-enhanced home environments. In: Proceedings of the 18th Biennial Conference of the International Communications Society (2010)
44. Kleinberger, T., Becker, M., Ras, E., Holzinger, A., Müller, P.: Ambient intelligence in assisted living: enable elderly people to handle future interfaces. In: Stephanidis, C. (ed.) UAHCI 2007 (Part II). LNCS, vol. 4555, pp. 103–112. Springer, Heidelberg (2007)
45. Kern, N., Schiele, B., Schmidt, A.: Multi-sensor activity context detection for wearable computing. In: Aarts, E., Collier, R.W., van Loenen, E., de Ruyter, B. (eds.) EUSAI 2003. LNCS, vol. 2875, pp. 220–232. Springer, Heidelberg (2003)
46. Holzinger, A., Searle, G., Prückner, S., Steinbach-Nordmann, S., Kleinberger, T., Hirt, E., Temnitzer, J.: Perceived usefulness among elderly people: experiences and lessons learned during the evaluation of a wrist device. In: International Conference on Pervasive Computing Technologies for Healthcare (Pervasive Health 2010), pp. 1–5. IEEE (2010)
47. Muensterer, O.J., Lacher, M., Zoeller, C., Bronstein, M., Kubler, J.: Google glass in pediatric surgery: an exploratory study. Int. J. Surg. **12**(4), 281–289 (2014)
48. Holzinger, A.: Finger instead of mouse: touch screens as a means of enhancing universal access. In: Carbonell, N., Stephanidis, C. (eds.) UI4ALL 2002. LNCS, vol. 2615, pp. 387–397. Springer, Heidelberg (2003)
49. Overstall, P.W., Nikolaus, T.: Gait, balance, and falls. In: Pathy, M.S.J., Sinclair, A.J., Morley, J.E. (eds.) Principles and Practice of Geriatric Medicine, vol. 2, 4th edn, pp. 1299–1309. Wiley, Chichester (2006)
50. Ruyter, B.D., Pelgrim, E.: Ambient assisted-living research in carelab. Interactions **14**(4), 30–33 (2007)
51. Noury, N., Fleury, A., Rumeau, P., Bourke, A., Laighin, G., Rialle, V., Lundy, J.: Fall detection-principles and methods. In: 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2007, EMBS 2007, pp. 1663–1666. IEEE (2007)
52. Addlesee, M.D., Jones, A., Livesey, F., Samaria, F.: The ORL active floor. IEEE Pers. Commun. **4**, 35–41 (1997)
53. Orr, R.J., Abowd, G.D.: The smart floor: a mechanism for natural user identification and tracking. In: CHI 2000 Extended Abstracts on Human Factors in Computing Systems, pp. 275–276. ACM (2000)

54. Leusmann, P., Mollering, C., Klack, L., Kasugai, K., Ziefle, M., Rumpe, B.: Your floor knows where you are: sensing and acquisition of movement data. In: 2011 12th IEEE International Conference on Mobile Data Management (MDM), pp. 61–66. IEEE (2011)
55. Ziefle, M., Röcker, C., Wilkowska, W., Kasugai, K., Klack, L., Möllering, C., Beul, S.: A multi-disciplinary approach to ambient assisted living. In: Röcker, C., Ziefle, M. (eds.) E-Health, Assistive Technologies and Applications for Assisted Living: Challenges and Solutions. IGI Global, Hershey (2010)
56. Klack, L., Möllering, C., Ziefle, M., Schmitz-Rode, T.: Future care floor: a sensitive floor for movement monitoring and fall detection in home environments. In: Lin, J. (ed.) MobiHealth 2010. LNICST, vol. 55, pp. 211–218. Springer, Heidelberg (2011)
57. Baker, A.M., Lafata, J.E., Ward, R.E., Whitehouse, F., Divine, G.: A web-based diabetes care management support system. Jt. Comm. J. Qual. Patient Saf. **27**(4), 179–190 (2001)
58. Donsa, K., Spat, S., Beck, P., Pieber, T.R., Holzinger, A.: Towards personalization of diabetes therapy using computerized decision support and machine learning: some open problems and challenges. In: Holzinger, A., Roecker, C., Ziefle, M. (eds.) Smart Health. Lecture Notes in Computer Science LNCS, vol. 8700, pp. 235–260. Springer, Heidelberg, Berlin (2015)
59. Morlion, B., Knoop, C., Paiva, M., Estenne, M.: Internet-based home monitoring of pulmonary function after lung transplantation. Am. J. Respir. Crit. Care Med. **165**(5), 694–697 (2002)
60. Ávila-Funes, J.A., Amieva, H., Barberger-Gateau, P., Le Goff, M., Raoux, N., Ritchie, K., Carriere, I., Tavernier, B., Tzourio, C., Gutiérrez-Robledo, L.M.: Cognitive impairment improves the predictive validity of the phenotype of frailty for adverse health outcomes: the three-city study. J. Am. Geriatr. Soc. **57**(3), 453–461 (2009)
61. Park, S.H., Won, S.H., Lee, J.B., Kim, S.W.: Smart home–digitally engineered domestic life. Pers. Ubiquit. Comput. **7**(3–4), 189–196 (2003)
62. Mynatt, E.D., Melenhorst, A.S., Fisk, A.D., Rogers, W.A.: Aware technologies for aging in place: understanding user needs and attitudes. IEEE Pervasive Comput. **3**(2), 36–41 (2004)
63. Holzinger, A., Nischelwitzer, A.K.: People with motor and mobility impairment: innovative multimodal interfaces to wheelchairs. In: Miesenberger, K., Klaus, J., Zagler, W.L., Karshmer, A.I. (eds.) ICCHP 2006. LNCS, vol. 4061, pp. 989–991. Springer, Heidelberg (2006)
64. Nischelwitzer, A.K., Sproger, B., Mahr, M., Holzinger, A.: MediaWheelie – a best practice example for research in multimodal user interfaces (MUIs). In: Miesenberger, K., Klaus, J., Zagler, W.L., Karshmer, A.I. (eds.) ICCHP 2006. LNCS, vol. 4061, pp. 999–1005. Springer, Heidelberg (2006)
65. Nischelwitzer, A., Sproger, B., Holzinger, A.: Assistive text input methods: 3D-space writing and other text input methods for powerwheelchair users: best practice examples on the MediaWheelie. In: Kempter, G., Hellberg, P.V. (eds.) Informationen Nutzbar Machen, pp. 75–80. Papst Science Publishers, Lengerich (2006)
66. Debevc, M., Kosec, P., Rotovnik, M., Holzinger, A.: Accessible multimodal web pages with sign language translations for deaf and hard of hearing users. In: 20th International Conference on Database and Expert Systems Application, DEXA 2009, pp. 279–283. IEEE (2009)
67. Debevc, M., Kožuh, I., Kosec, P., Rotovnik, M., Holzinger, A.: Sign language multimedia based interaction for aurally handicapped people. In: Miesenberger, K., Karshmer, A., Penaz, P., Zagler, W. (eds.) ICCHP 2012, Part II. LNCS, vol. 7383, pp. 213–220. Springer, Heidelberg (2012)

68. Holzinger, A., Searle, G., Nischelwitzer, A.K.: On some aspects of improving mobile applications for the elderly. In: Stephanidis, C. (ed.) HCI 2007. LNCS, vol. 4554, pp. 923–932. Springer, Heidelberg (2007)
69. Holzinger, A., Searle, G., Kleinberger, T., Seffah, A., Javahery, H.: Investigating usability metrics for the design and development of applications for the elderly. In: Miesenberger, K., Klaus, J., Zagler, W.L., Karshmer, A.I. (eds.) ICCHP 2008. LNCS, vol. 5105, pp. 98–105. Springer, Heidelberg (2008)
70. Nischelwitzer, A.K., Lenz, F.-J., Searle, G., Holzinger, A.: Some aspects of the development of low-cost augmented reality learning environments as examples for future interfaces in technology enhanced learning. In: Stephanidis, C. (ed.) HCI 2007. LNCS, vol. 4556, pp. 728–737. Springer, Heidelberg (2007)
71. Sproger, B., Nischelwitzer, A., Holzinger, A.: TeamTable: lowcost team-display hardware and tangible user interfaces facilitate interaction & learning. In: Kempter, G., Hellberg, P.V. (eds.) Informationen Nutzbar Machen, pp. 57–60. Papst Science Publishers, Lengerich (2006)
72. Shyu, C.R., Brodley, C.E., Kak, A.C., Kosaka, A., Aisen, A.M., Broderick, L.S.: ASSERT: a physician-in-the-loop content-based retrieval system for HRCT image databases. Comput. Vis. Image Underst. **75**(1–2), 111–132 (1999)
73. Ranganathan, S., Schonbach, C., Kelso, J., Rost, B., Nathan, S., Tan, T.: Towards big data science in the decade ahead from ten years of InCoB and the 1st ISCB-Asia Joint Conference. BMC Bioinform. **12**(Suppl 13), S1 (2011)
74. Dhar, V.: Data science and prediction. Commun. ACM **56**(12), 64–73 (2013)
75. Kolker, E., Özdemir, V., Martens, L., Hancock, W., Anderson, G., Anderson, N., Aynacioglu, S., Baranova, A., Campagna, S.R., Chen, R.: Toward more transparent and reproducible omics studies through a common metadata checklist and data publications. OMICS: A J. Integr. Biol. **18**(1), 10–14 (2014)
76. Holzinger, A., Dehmer, M., Jurisica, I.: Knowledge discovery and interactive data mining in bioinformatics - state-of-the-art, future challenges and research directions. BMC Bioinform. **15**(S6), I1 (2014)
77. Morik, K., Brockhausen, P., Joachims, T.: Combining statistical learning with a knowledge-based approach-a case study in intensive care monitoring. In: ICML 1999, pp. 268–277 (1999)
78. Sultan, M., Wigle, D.A., Cumbaa, C., Maziarz, M., Glasgow, J., Tsao, M., Jurisica, I.: Binary tree-structured vector quantization approach to clustering and visualizing microarray data. Bioinformatics **18**(Suppl 1), S111–S119 (2002)
79. Koch, I.: Analysis of Multivariate and High-Dimensional Data. Cambridge University Press, New York (2014)
80. Olshen, A.B., Hsieh, A.C., Stumpf, C.R., Olshen, R.A., Ruggero, D., Taylor, B.S.: Assessing gene-level translational control from ribosome profiling. Bioinformatics **29**(23), 2995–3002 (2013)
81. Li, W., Godzik, A.: CD-HIT: a fast program for clustering and comparing large sets of protein or nucleotide sequences. Bioinformatics **22**(13), 1658–1659 (2006)
82. Pržulj, N., Wigle, D., Jurisica, I.: Functional topology in a network of protein interactions. Bioinformatics **20**(3), 340–348 (2004)
83. Bullard, J.H., Purdom, E., Hansen, K.D., Dudoit, S.: Evaluation of statistical methods for normalization and differential expression in mRNA-Seq experiments. BMC Bioinform. **11**, 94 (2010)
84. Kiberstis, P.A.: All eyes on epigenetics. Science **335**(6069), 637 (2012)

85. Barrera, J., Cesar-Jr., R.M., Ferreira, J.E., Gubitoso, M.D.: An environment for knowledge discovery in biology. Comput. Biol. Med. **34**(5), 427–447 (2004)
86. Holzinger, A., Ziefle, M., Röcker, C.: Pervasive Health. Springer, London (2014)
87. Huppertz, B., Holzinger, A.: Biobanks – a source of large biological data sets: open problems and future challenges. In: Holzinger, A., Jurisica, I. (eds.) Interactive Knowledge Discovery and Data Mining in Biomedical Informatics. LNCS, vol. 8401, pp. 317–330. Springer, Heidelberg (2014)
88. Shaer, O., Nov, O.: HCI for personal genomics. Interactions **21**(5), 32–37 (2014)
89. Marr, D.: Vision: A Computational Investigation into the Human Representation and Processing of Visual Information. Henry Holt, New York (1982)
90. Donoho, D.L.: High-dimensional data analysis: the curses and blessings of dimensionality. In: AMS Math Challenges Lecture, pp. 1–32 (2000)
91. Holzinger, A.: Extravaganza tutorial on hot ideas for interactive knowledge discovery and data mining in biomedical informatics. In: Ślęzak, D., Tan, A.-H., Peters, J.F., Schwabe, L. (eds.) BIH 2014. LNCS, vol. 8609, pp. 502–515. Springer, Heidelberg (2014)
92. Stocker, C., Marzi, L.-M., Matula, C., Schantl, J., Prohaska, G., Brabenetz, A., Holzinger, A.: Enhancing patient safety through human-computer information retrieval on the example of german-speaking surgical reports. In: TIR 2014 - 11th International Workshop on Text-Based Information Retrieval, pp. 1–5. IEEE (2014)
93. Gondek, D.C., Lally, A., Kalyanpur, A., Murdock, J.W., Duboue, P.A., Zhang, L., Pan, Y., Qiu, Z.M., Welty, C.: A framework for merging and ranking of answers in DeepQA. IBM J. Res. Dev. **56**(3–4), 399–410 (2012)
94. Reuss, E., Menozzi, M., Buchi, M., Koller, J., Krueger, H.: Information access at the point of care: what can we learn for designing a mobile CPR system? Int. J. Med. Inform. **73**(4), 363–369 (2004)
95. Choi, J., Chun, J., Lee, K., Lee, S., Shin, D., Hyun, S., Kim, D., Kim, D.: MobileNurse: hand-held information system for point of nursing care. Comput. Methods Programs Biomed. **74**(3), 245–254 (2004)
96. Young, P.M.C., Leung, R.M.W., Ho, L.M., McGhee, S.M.: An evaluation of the use of hand-held computers for bedside nursing care. Int. J. Med. Inform. **62**(2–3), 189–193 (2001)
97. Moffett, S.E., Menon, A.S., Meites, E.M., Kush, S., Lin, E.Y., Grappone, T., Lowe, H.L.: Preparing doctors for bedside computing. Lancet **362**(9377), 86 (2003)
98. Konstantakos, A.K.: Personal computers versus patient care: at the desktop or at the bedside? Curr. Surg. **60**(4), 353–355 (2003)
99. Holzinger, A., Kosec, P., Schwantzer, G., Debevc, M., Hofmann-Wellenhof, R., Frühauf, J.: Design and development of a mobile computer application to reengineer workflows in the hospital and the methodology to evaluate its effectiveness. J. Biomed. Inform. **44**(6), 968–977 (2011)
100. Holzinger, A., Errath, M.: Mobile computer web-application design in medicine: some research based guidelines. Univ. Access Inf. Soc. Int. J. **6**(1), 31–41 (2007)
101. Dey, A.K., Abowd, G.D., Salber, D.: A conceptual framework and a toolkit for supporting the rapid prototyping of context-aware applications. Hum.-Comput. Inter. **16**(2–4), 97–166 (2001)
102. Brézillon, P.: Context in problem solving: a survey. Knowl. Eng. Rev. **14**(1), 47–80 (1999)
103. Coutaz, J., Crowley, J.L., Dobson, S., Garlan, D.: Context is key. Commun. ACM **48**(3), 49–53 (2005)
104. Harper, R., Rodden, T., Rogers, Y., Sellen, A.: Being Human: Human-Computer Interaction in the Year 2020. Microsoft Research, Cambridge (2008)

105. Sellen, A., Rogers, Y., Harper, R., Rodden, T.: Reflecting human values in the digital age. Commun. ACM **52**(3), 58–66 (2009)
106. Schmidt, A., Pfleging, B., Alt, F., Sahami, A., Fitzpatrick, G.: Interacting with 21st-century computers. IEEE Pervasive Comput. **11**(1), 22–31 (2012)
107. Selker, T., Burleson, W.: Context-aware design and interaction in computer systems. IBM Syst. J. **39**(3–4), 880–891 (2000)
108. Holzinger, A., Stocker, C., Dehmer, M.: Big complex biomedical data: towards a taxonomy of data. In: Obaidat, M.S., Filipe, J. (eds.) Communications in Computer and Information Science CCIS 455, pp. 3–18. Springer, Berlin Heidelberg (2014)
109. Catchpoole, D.R., Kennedy, P., Skillicorn, D.B., Simoff, S.: The curse of dimensionality: a blessing to personalized medicine. J. Clin. Oncol. **28**(34), E723–E724 (2010)
110. Kanerva, P.: Hyperdimensional computing: an introduction to computing in distributed representation with high-dimensional random vectors. Cogn. Comput. **1**(2), 139–159 (2009)
111. Ma, J.H., Wen, J., Huang, R.H., Huang, B.X.: Cyber-individual meets brain informatics. IEEE Intell. Syst. **26**(5), 30–37 (2011)
112. Zhong, N., Liu, J., Yao, Y., Wu, J., Lu, S., Qin, Y., Li, K., Wah, B.W.: Web intelligence meets brain informatics. In: Zhong, N., Liu, J., Yao, Y., Wu, J., Lu, S., Li, K. (eds.) Web Intelligence Meets Brain Informatics. LNCS (LNAI), vol. 4845, pp. 1–31. Springer, Heidelberg (2007)
113. Modha, D.S., Ananthanarayanan, R., Esser, S.K., Ndirango, A., Sherbondy, A.J., Singh, R.: Cognitive computing. Commun. ACM **54**(8), 62–71 (2011)
114. Jones, B., Carvalho, C., Dobra, A., Hans, C., Carter, C., West, M.: Experiments in stochastic computation for high-dimensional graphical models. Stat. Sci. **20**(4), 388–400 (2005)
115. Alaghi, A., Hayes, J.P.: Survey of stochastic computing. ACM Trans. Embed. Comput. Syst. (TECS) **12**(2s), 92 (2013)
116. Yoshida, R., Ueno, G., Doucet, A.: Special issue: bayesian inference and stochastic computation preface. Ann. Inst. Stat. Math. **66**(3), 441–442 (2014)
117. Tehrani, S.S., Mannor, S., Gross, W.J.: Survey of stochastic computation on factor graphs. In: 37th International Symposium on Multiple-valued Logic, 2007, ISMVL 2007, pp. 54–54. IEEE (2007)
118. Shanbhag, N.R., Abdallah, R.A., Kumar, R., Jones, D.L.: Stochastic computation. In: Proceedings of the 47th Design Automation Conference, pp. 859–864. ACM (2010)
119. Adar, R., Benenson, Y., Linshiz, G., Rosner, A., Tishby, N., Shapiro, E.: Stochastic computing with biomolecular automata. Proc. Natl. Acad. Sci. U.S.A. **101**(27), 9960–9965 (2004)
120. Olfati-Saber, R., Fax, J.A., Murray, R.M.: Consensus and cooperation in networked multi-agent systems. Proc. IEEE **95**(1), 215–233 (2007)
121. Wooldridge, M., Jennings, N.R.: Intelligent agents: theory and practice. Knowl. Eng. Rev. **10**(2), 115–152 (1995)
122. Costanza, E., Fischer, J.E., Colley, J.A., Rodden, T., Ramchurn, S.D., Jennings, N.R.: Doing the laundry with agents: a field trial of a future smart energy system in the home. In: Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems, pp. 813–822. ACM (2014)
123. Jennings, N.R., Corera, J.M., Laresgoiti, I.: Developing industrial multi-agent systems. In: ICMAS, pp. 423–430 (1995)
124. Roche, B., Guegan, J.F., Bousquet, F.: Multi-agent systems in epidemiology: a first step for computational biology in the study of vector-borne disease transmission. BMC Bioinform. **9**, 435 (2008)

125. Kamar, E., Gal, Y.K., Grosz, B.J.: Modeling information exchange opportunities for effective human–computer teamwork. Artif. Intell. **195**, 528–550 (2013)
126. Tambe, M., Bowring, E., Jung, H., Kaminka, G., Maheswaran, R., Marecki, J., Modi, P.J., Nair, R., Okamoto, S., Pearce, J.P.: Conflicts in teamwork: hybrids to the rescue. In: Proceedings of the Fourth International Joint Conference on Autonomous Agents and Multiagent Systems, pp. 3–10. ACM (2005)
127. Jennings, N.R., Moreau, L., Nicholson, D., Ramchurn, S.D., Roberts, S., Rodden, T., Rogers, A.: On human-agent collectives. Commun. ACM **57**, 80–88 (2014)
128. Gao, H., Barbier, G., Goolsby, R.: Harnessing the crowdsourcing power of social media for disaster relief. Intell. Syst. IEEE **26**(3), 10–14 (2011)
129. Takeuchi, I.: A massively multi-agent simulation system for disaster mitigation. In: Ishida, T., Gasser, L., Nakashima, H. (eds.) MMAS 2005. LNCS (LNAI), vol. 3446, pp. 269–282. Springer, Heidelberg (2005)
130. Menzies, T.: Beyond data mining. IEEE Softw. **30**(3), 92 (2013)