EDMON - A Wireless Communication Platform for a Real-Time Infectious Disease Outbreak Detection System Using Self-Recorded Data from People with Type 1 Diabetes

Ashenafi Zebene Woldaregay [1], Eirik Årsand [2], Alain Giordanengo [1, 2], David Albers [3], Lena Mamykina [3], Taxiarchis Botsis [1] and Gunnar Hartvigsen [1, 2]

[1] Department of Computer Science, University of Tromsø – The Arctic University of Norway, Tromsø, Norway, ashenafi.z.woldaregay@uit.no

[2] Norwegian Centre for E-health Research, University Hospital of North Norway, Tromsø, Norway

[3] Columbia University, N.Y., USA

Abstract

The relation between an infection incident and elevated blood glucose (BG) levels has been known for long time. People with diabetes often experience variable episodes of elevated BG levels up on infections incident. Hence, we proposed an Electronic Disease Surveillance Monitoring Network (EDMON) that uses BG pattern and other relevant parameters to detect infected diabetes individuals during the incubation period. The project is an extension of the results achieved in the mobile diabetes (mDiabetes) field within our research team for the last 15 years. The proposed EDMON system is a kind of public health surveillance, which uses events analysis at individual levels (called micro events) to reach on a conclusion for uncovering events on the general populations (called macro events) based on spatio-temporal cluster detection. It incorporates self-management mobile apps, sensors, wearables, and point of care (POC) devices to collect real-time health information from individuals with Type 1 diabetes. In this paper, we will present the proposed EDMON system architecture along with the design requirements, system components, communication protocols and challenges involved herein.

Keywords

Type 1 Diabetes, Wireless Communication, BG Pattern Detection, Infection Detection.

1 INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder, which is mostly caused by either failure of pancreas β-beta cells to produce insulin secretion (Type 1) or lack of body response to insulin action (Type 2)(IDF, 2015). According to recent reports, there are approximately 450 million adults with diabetes worldwide and is projected to raise to 642 million by 2040 (IDF, 2015). Currently, there is no cure for diabetes; however, it can be prevented from creating further complication with one's proper self-management of the disease. The advent of information and communication technology (ICT) has much revolutionized self-management and made treatment of the disease a lot easier than before, which is mostly connected with the introduction of mobile apps (mHealth), wearables and sensors, and POC devices that can provide individually tailored information for a better informed decision making (patient empowerment) (Walseth et al., 2005; Li et al., 2017; Issom et al., 2015; Botsis et al., 2009). These advancements in turn have also created huge accumulation of the individual patient health data gathered on a daily basis, which creates opportunities for further analysis of these data to capture relevant information for better self-management and treatments (Béranger et al., 2016; Mohammadi, 2015). The introduction of big data, data mining and advanced analytic concepts have made the detection of aberrant pattern, an outbreak signal, a way more relevant and easier than before (Vayena et al., 2015). In this regard, use of patient self-gathered data for public health surveillance purpose has now become more apparent than ever; given the ubiquitous nature and widespread use of mHealth apps, wearables and sensors for self-management purpose (Walseth et al., 2005; Issom et al., 2015).

Likewise, the introduction of cloud computing technologies since the millennium has brought a significant improvement in various healthcare delivery settings, of which public health surveillance is not an exception (Swan et al., 2013; Council 2017).

Currently, most of the existing electronic disease surveillance systems rely on data sources (surveillance indicators and events) that span from the incident of the first symptoms till physicians or laboratory confirmation, such as web based (i.e. google search engine) (Choi et al., 2016), Over-the-counter (OTC) pharmacy drugs sell (Pivette et al., 2014), school absenteeism (Lawpoolsri, et al., 2014) or work absenteeism (Paterson, Caddis, and Durrheim, 2011), and others leaving the incubation period out of their systems. According to the Centres for Disease Control and Prevention report (Holt et al., 2013) on indictors for chronic disease surveillance, more than 20 individual diabetes indicator measures are given while the use of BG patterns as surveillance indicators are not indicated, which shows the complexity and uniqueness of the proposed approach. Botsis et al. (Botsis et al., 2012) presented the most notable proof of concept study that empirically supports the use of blood glucose pattern of diabetes individuals as surveillance event indicator. Moreover, blood glucose pattern has also been described as event indicators for surveillance purpose in other related literatures (Botsis et al., 2012; Botsis et al., 2010; Lauritzen et al., 2011).

Paper from the 15th Scandinavian Conference on Health Informatics SHI2017, Kristiansand, Norway, 29 - 30 August.
Conference Proceedings published by Linköping University Electronic Press.

The proposed EDMON system is a real-time early disease outbreak detection system that uses self-recorded health data from people with Type 1 diabetes. It is a kind of public health surveillance, which uses micro events analysis (detecting infection induced elevated BG pattern on an individual level) to reach on a conclusion for uncovering macro events on the general populations based on spatio-temporal cluster detection. The system will analyse the individual's blood glucose levels in real time, an online context**,** to look for aberrant patterns; variable episode of elevated blood glucose levels as a result of metabolic instability due to infection incident (Woldaregay et al., 2016; Årsand et al., 2005; Rayfield et al., 1982). Therefore, the surveillance case definition encompasses the infection induced deviated pattern of the individual's BG dynamics. In addition, patterns of other supporting parameters such as insulin injections, physical activity, and dietary information along with physiological parameters like body temperature, blood pressure, and others will also be included. Of course, it is not only infections that could cause variable episode of elevated blood glucose levels, and factors such as stress could also result in somehow similar pattern. As a result, the plan is to incorporate all contributing variables known to the patients in the surveillance case definition and analysis so as to suppress the effects of these confronting variables. Moreover, the spatio-temporal nature of the EDMON's system is supposed to alleviate these challenges; given that the probability of having sufficient number of people to be stressed at a specific location and specific time interval is probably low to trigger the necessary threshold as compared to an infection incident. This characteristic is highly dependent on the contagious nature and its progressive prevalence of an infection after any initial incident. EDMON will use techniques from big data analytics, social media, mobile computing and a novel health monitoring systems. If successful, EDMON will pave the way for the next generation disease surveillance approaches. In this paper, we will present the proposed EDMON's system architecture along with the design requirements, system components, communication protocols and the challenge involved herein.

2 BACKGROUND AND RELATED WORKS

2.1 Wireless communication platforms

Currently, the rapid development of information communication and technology (ICT) and Internet of Things (IoT) have created opportunities for a quantified-self, which aims to empower patient's decision making based on documenting their own health condition. This in turn has created a rapid pace on the integration, communication and use of wearables, sensors, POC devices and other body area network for physiological monitoring and other health related purposes (Swan, 2013; Béranger, 2016). Diabetes is not an exception in this case, experiencing a rapid advancement in its field. In this regard, different communication systems, protocols and standards for various purpose such as intelligent diabetes monitoring, remote diabetes surveillance, remote diabetes management, tele-management and tele-monitoring, follow-up systems, data analysis, personalized and customized feedback and decision making have increasingly been studied and presented in the literatures, e.g. (Huzooree, Khedo, and Joonas, 2017; Liao et al., 2004; Mougiakakou et al., 2010; Mougiakakou et al., 2005; Martinez et al., 2011; Al-Taee et al., 2015; Chang et al., 2016), but none of the recent studies have considered detection of infection incidents in diabetes people as the underlying purposes.

For example, Huzooree et al. (Huzooree, Khedo, and Joonas, 2017) developed a communication platform for a wireless body area network for remote diabetes patient monitoring and analysis. The system integrates physiological data from the body area network into a standalone mobile app, which sends these data into a remote server for further analysis and monitoring (Huzooree, Khedo, and Joonas, 2017). Moreover, Mougiakakou et al. (Mougiakakou et al., 2010) developed a communication platform for an intelligent remote diabetes monitoring, management, follow up and treatments for Type 1 diabetes patients. The system uses state of the art technologies and standards and consisted of two units; a patient unit and patient management unit (Mougiakakou et al., 2010). Mougiakakou et al. (Mougiakakou et al., 2005) also developed a telemedicine system that provides tele-monitoring and tele-management services for type 1 diabetes individuals. Besides, Liao et al. (Liao et al., 2004) developed a communication platform for remote diabetes surveillance, where the diabetes individual is monitored from home by remote healthcare givers. The system promotes the individual with diabetes to measure and update his/her status at home, which is communicated to their healthcare givers. In addition, Martinez et al. (Martinez et al., 2011) developed a system that provides a remote monitoring of the individual diabetes patient's metabolic profiles through Application Hosting Device (AHD), which manages the sensor platform and allows sending IHE-PDC messages compliant with Continua Health Alliance at a WAN level along with a mobile application. The system incorporates three modules;1073 adaptation, Data Access API and Sensor Management module. The patient is able to register physical activity, food intake (menu and CHO quantities), blood pressure, weight and glycaemia measurement manually, medication intake (i.e. insulin and other drugs), and special events (i.e. stress at work, holiday and birthday party), which are integrated into a diary application (Martinez et al., 2011). Furthermore, Al-Taee et al. (Al-Taee et al., 2015) presented a platform to support self-management through remote collection and monitoring of self-gathered data and provision of personalized feedback on the smartphone based on Internet of Things (IoT). Based on the current and historical self-gathered data, the system enables real-time clinical interaction and tailored feedback to the individual needs (Al-Taee et al., 2015). Likewise, Chang et al. (Chang et al., 2016) developed a context aware, interactive cloud based mHealth system that can provide a real time, two way communication between diabetes patients and caregivers by using Internet of Things technology.

2.2 State of the art

For the past 15 years, our research team has been working on the patient unit and created and developed the Diabetes Diary, which is now available in both google play (Android) and app store (Apple) (Nse, 2017). Currently, our team is working towards a tailored version of the diabetes diary with more data integration, patterns analysis and monitoring options. The tailored version will include measurements like blood pressure, heart rate, body weight and temperature in addition to blood glucose, carbs intake, physical activity, and insulin injection. Moreover, a feasibility study towards the use of POC devices has been conducted (Botsis et al., 2009). The study concluded that devices like white blood cell count (XBC analyser) seems to be problematic due to usability issues and the coast is regarded as the main bottleneck (Botsis et al., 2009). Therefore, the plan is to request measurements from these POC devices only when it is necessary and appropriate.

There have been some research activities regarding the infection detection system using blood glucose levels as a potential indicator. For example, Årsand et al. (Årsand et al., 2005) presented an approach for developing an epidemic disease detection using blood glucose (EDDG) system based on blood glucose measurements. The paper describes the system components including the necessary equipment, data structures and data repository along with the proposed detection mechanisms. Furthermore, a number of studies regarding the outbreak detection computing algorithm have been conducted. For example, Woldaregay et al. (Woldaregay et al., 2016) have developed an infection detection algorithm based on the continuous glucose monitoring (CGM) readings. However, the study has considered only blood glucose patterns as the input to the system. Moreover, other similar studies like (Granberg et al., 2007) have tried to detect infection induced blood glucose deviation. Even though these studies have shown the proof of concept, they have certain limitations, i.e. the number of input parameters, real infection BG data and sample size. Therefore, the plan is to include more input parameters, a real infection BG data and larger sample size to develop a more robust approach for the computing algorithm.

3 EDMON DESIGN REQUIREMENTS

Diabetes self-management mobile applications (mHealth apps), sensors and wearables, including both invasive and non-invasive, and other POC devices should collect the patient's blood glucose level, insulin therapy, dietary intake (carbs), physical activity, and physiological information such as body temperature and blood pressure. Some other ideal and optional physiological parameters like white blood cell count, CRP test, heart rate, respiration, oxygen saturation, and stress level should be recorded and sent upon request from EDMON system. The measured parameters should be integrated into a standalone mobile app, i.e. personal health record application, which acts as a gateway for the data to be transferred to a private cloud (remote server) in a real-time scenario. Therefore, data quality is the determinant factor for successful processing, computation and interpretation of those health data (Huzooree, Khedo, and Joonas, 2017). As a result, all the recorded key diabetes and physiological parameters should be transferred securely and appropriately through either a mobile infrastructure or a private network and should be safely stored in the cloud (remote server) in a real-time environment. Any possible failure that may arise due to network coverage, sensors and wearables failure, lack of signal strength, transmission reliability, and delay, could lead to an unpredictable effect on the accuracy of the detection system, and also on the quality and reliability of patient tracking (Huzooree, Khedo, and Joonas, 2017; Sachidananda et al., 2010). Hence, ensuring the quality of information (QoI) attributes such as accuracy, timeliness, completeness, relevancy, and reliability (Sachidananda et al., 2010; Zahedi et al., 2008), along with system usability (ease of use) are key design requirements for the acceptance of the proposed EDMON system.

4 EDMON ARCHITECTURE

The EDMON architecture consists of a patient unit, computing unit, and end users, as shown in Figure 1 (Mougiakakou et al., 2010). The patient unit is responsible for collecting the necessary parameters into the user's smartphone. The computing unit will analyse the incoming data for aberrant patterns on the individual as well as on the cluster level. The end users (desktop, laptop or smartphone version of EDMON's application) could be physicians, patients, family and relatives, or the general public or any concerned hospitals or public health authority that should have access to the outbreak information from the system.

4.1 Communication architecture and protocols

EDMON is a three-tier architecture that incorporates; sensor and wearable tier, mobile computing tier, remote server (cloud) tier, as shown in Figure 2. This kind of architecture might be prone to a degraded data accuracy due to remote site computations as a result of transmission and other errors. However, we prefer to minimize the power consumption, and save the memory storage issues incurred in the participants' smartphones.

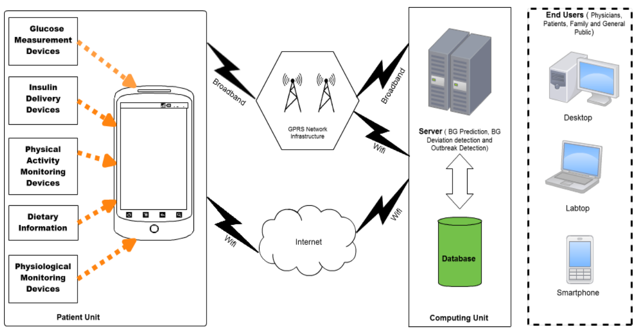

Figure 1. EDMON architecture.

In EDMON, the invasive and non-invasive sensors and wearables, and POC devices, record the data automatically and send these readings to the smartphone app (Diabetes Diary) using existing communication protocols that ensure security, robustness and privacy, i.e. Bluetooth and ZigBee (Huzooree, Khedo, and Joonas, 2017). In some cases, when there is no such automatic facility the user might be asked to record the data manually. The smartphone app acts as a gateway node, which integrates the data from the sensors and wearables nodes and forwards it to the access point. Secure communication protocols such as IEEE 802.11/Wi-Fi/GPRS could be used as a communication medium with the access point (Huzooree, Khedo, and Joonas, 2017; Rafe and Hajvali, 2014). The communication between the access point and the remote (server) could be implemented via a Protected Network, connected via an independent secure IP-network, i.e. the Norwegian Health Network, to enable secure electronic communication between the access points and the remote computing centre.

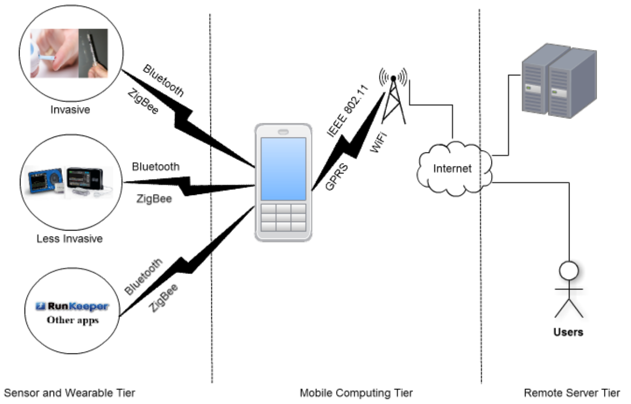

Figure 2. The three tire of EDMON Architecture.

4.2 Sensor and wearable tier

The first tier is a sensor and wearable tier that incorporates self-management apps, POC devices, wearables and sensors for collecting the diabetes key parameters and other necessary physiological parameters of the individual diabetes patients, as shown in Figure 2, where the data entry is either automatic or manual. The automatic data entry will use the device API, i.e. Bluetooth, whereas the manual data entry requires users to manually input like dietary information, i.e. menu and amount of CHO quantities and others. This node includes circadian cycle measurements of the individual's physiological parameters, diabetes key parameters and other point of care test devices. The diabetes key parameters include dietary intake, insulin injections, CGM readings, physical activity and other measurements. The physiological parameters group includes body temperature, blood pressure, oxygen saturation, respiration rate and stress level measurements. The POC measurements incorporates white blood cell count, CRP test and other necessary quantities. However, the frequency of these readings, physiological parameters and POC measurements, are determined by the EDMON system upon necessity except the key diabetes parameters, which are the default input to the system.

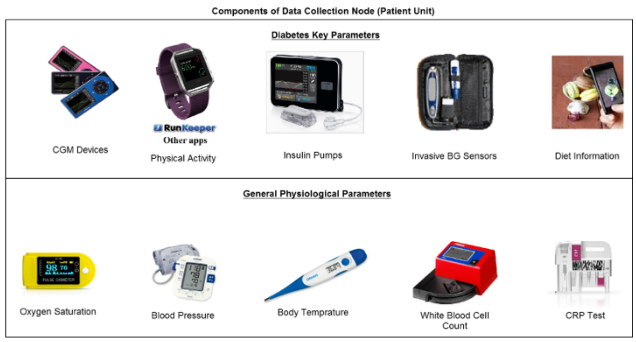

Figure 3. Components of EDMON data collector's node.

4.3 Mobile computing tier (Gateway Node)

The second tier is a mobile computing tier, which is a standalone mobile app that integrates the reading of the individual's key diabetes and physiological parameters. The mobile app acts as a sink for measurements that come from the diabetes individual's sensors, wearables and POC devices. It is built on the top of the existing diabetes mobile App-Diabetes Diary, which is developed by Norwegian scientists at the Norwegian Centre for E-health Research (NSE), as shown in Figure 4 (both English and Norwegian version). This tire also acts as a gateway that forwards the recorded parameters to the access point, as show in Figure 2. Currently, the tailored version of the diabetes diary supports measurements like blood glucose, insulin, physical activity, carbohydrate, calories, weight and medications (Årsand et al., 2016). Therefore, the plan is to add more monitoring option including more physiological parameters to enhance the accuracy of the infection detection capability based on the self-recorded data.

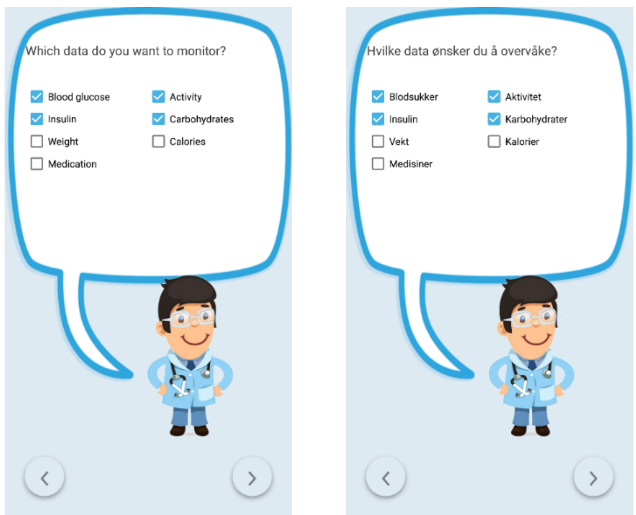

Figure 4. Diabetes Diary-Tailored Version.

4.4 Remote server (Cloud computing) tier

The third tier is a remote server (cloud computing) tier, which incorporates a repository and computing centres that will carry out the data storage and computation tasks respectively. This tier also fetches and provide the outbreak detection results for the responsible bodies, i.e., public health officials, physicians, patients, relatives and general public audiences.

Data Repository

The repository is used to store the incoming data from the participating Type 1 diabetes individuals. The user's data are stored in a data structure stamped with a user ID, time and geographical location containing the key diabetes and physiological parameters (Årsand et al., 2005). The size of the data repository will depend on the size of the area the system covers.

Computational Service

The computational server is the most crucial part (heart) of the EDMON system. The server carries out an intelligent data mining and advanced data analytics concepts to uncover both the micro and macro events. It performs various computation at individual and cluster levels including BG profiling, analysing, reporting and disseminating information. BG profiling involves modelling a personalized health model, which keeps track of the individual's blood glucose dynamics and predicts the upcoming blood glucose values depending on a set of input parameters, such as previous BG values, dietary intake, amount of physical activity, amount of insulin injection, and others. The analysis will carry out a comparison of the individual predicted BG and actual BG values so to look for any statistically significant aberrant patterns. Moreover, the aggregational analysis will look for a maximum number of micro events based on spatio-temporal cluster detection. The reporting and dissemination part of the computation respectively will organize the information in a user-friendly format (tables, graphs, and maps) and distribute this information, such as the spatial and temporal distribution of the disease outbreak on a map of the region, the degree of severity and others, to the audience via EDMON webpage or application.

5 DISCUSSION

Advanced systems and functionalities like EDMON could be a breakthrough in digital disease detection (DDD), and public health surveillance and might also have a significant improvement for diabetes self-management. The proposed wireless communication platform will use the state of the art communication standards and protocols, database and server technologies. However, given the sensitivity of health data there are challenges that need special attentions such as user privacy/security, quality of information and standardization issues, geographical location estimation and user mobility, and user acceptance.

Health related personal data are very sensitive and need to be treated confidentially throughout the system's data flow. In this regard, in addition to the recommended three tier architecture, it is necessary to look for robust approaches to ensure the user privacy and security during data collection and transmission as this is highly critical for successful design and acceptance of the proposed EDMON system. For example, privacy preserving mechanisms such as de-identification (Office for Civil Rigths, 2012; Uzuner, Luo, and Szolovits, 2007), which involves removal of user direct identifier, could be one possible options. For accurate data analysis, quality of data is the most determinant factor since corrupted, heterogeneous (due to multiple sensors, wearables and POC devices), missing, and delayed data could result in unpredictable performance degradation. Therefore, it is necessary to look for an advanced data quality control and pre-processing algorithm, which might pre-process the incurred heterogeneity, and check and request a retransmission upon corruption, delay, and missing data (Huzooree, Khedo, and Joonas, 2017). User acceptance is also an important factor that should be considered and tackled since people might not be willing to adopt a new system for multiple reasons such as lack of trust, lack of motivation, if the system hinders mobility, and lack of perceived usefulness and ease of use (Huzooree, Khedo, and Joonas, 2017). Therefore, it is necessary to look for approaches to buy users trust and enhance their motivation and perception. User mobility also could create challenges in terms of geographical location estimation and transmission power. However, a real time geographical location estimation techniques relying on the signal sent from the user through GPS or Wi-Fi positioning data and energy aware communication protocols could be an option (Niewiadomska-Szynkiewicz, 2013; Gautam and Gautam, 2009).

6 CONCLUSION

EDMON is a real-time early disease outbreak detection system that uses self-recorded health data from people with type 1 diabetes. It mainly exploits the presence of an elevated BG levels upon infection incidents. Therefore, the surveillance case definition will be formulated entirely based the individual's pattern of BG dynamics. However, patterns of other supporting parameters such as insulin, physical activity, and diet along with physiological parameters like body temperature, blood pressure and others will also be included. If successful, EDMON will pave the way for the next generation disease surveillance approaches. We presented the proposed EDMON architectures along with its persistent challenges that needs to be solved. We believe such kind of system might benefit other similar systems, i.e. diabetes patient monitoring, decision support and other patient empowerment system, and most importantly provoke further thought in the challenging field of real time electronic disease surveillance systems.

REFERENCES

[1] (Idf), I. D. F. 2015, *IDF diabetes atlas - 7th edition* [Online]. Available: http://www.diabetesatlas.org/.

[2] Walseth, O. A., Årsand, E., Sund, T. & Skipenes, E. 2005, Wireless Transfer of Sensor Data into Electronic Health Records. *Connecting Medical Informatics and Bio-Informatics.* IOS Press.

[3] Li, X., Dunn, J., Salins, D., Zhou, G., Zhou, W., Schussler-Fiorenza Rose, S. M., Perelman, D., Colbert, E., Runge, R., Rego, S., Sonecha, R., Datta, S., Mclaughlin, T. & Snyder, M. P. 2017 Digital Health: Tracking Physiomes and Activity Using

Wearable Biosensors Reveals Useful Health-Related Information. *PLoS Biol,* 15**,** e2001402.

[4] Issom, D.-Z., Woldaregay, A. Z., Chomutare, T., Bradway, M., Årsand, E. & Hartvigsen, G. 2015, Mobile applications for people with diabetes published between 2010 and 2015. *Diabetes Management,* 5**,** 539-550.

[5] Botsis, T., Walderhaug, S., Dias, A., Van Vuurden, K., Bellika, J. G. & Hartvigsen, G. 2009, Point-of-care devices for healthy consumers - a feasibility study. *J Telemed Telecare,* 15**,** 419-420.

[6] Béranger, J. 2016, Introduction. *Big Data and Ethics.* Elsevier, xi-xxxvi.

[7] Mohammadi, D. 2015, Turning big data into personalised diabetes care. *The Lancet Diabetes & Endocrinology,* 3**,** 935-936.

[8] Vayena, E., Salathe, M., Madoff, L. C. & Brownstein, J. S. 2015, Ethical challenges of big data in public health. *PLoS Comput Biol,* 11**,** e1003904.

[9] Swan, M. 2013, The Quantified Self: Fundamental Disruption in Big Data Science and Biological Discovery. *Big Data,* 1**,** 85-99.

[10] Council, C. S. C. 2017, Impact of Cloud Computing on Healthcare Version 2.0.

[11] Choi, J., Cho, Y., Shim, E. & Woo, H. 2016, Web-based infectious disease surveillance systems and public health perspectives: a systematic review. *BMC Public Health,* 16**,** 1238.

[12] Pivette, M., Mueller, J. E., Crepey, P. & Bar-Hen, A. 2014, Drug sales data analysis for outbreak detection of infectious diseases: a systematic literature review. *BMC Infect Dis,* 14**,** 604.

[13] Lawpoolsri, S., Khamsiriwatchara, A., Liulark, W., Taweeseneepitch, K., Sangvichean, A., Thongprarong, W., Kaewkungwal, J. & Singhasivanon, P. 2014, Real-time monitoring of school absenteeism to enhance disease surveillance: a pilot study of a mobile electronic reporting system. *JMIR mHealth uHealth,* 2**,** e22.

[14] Paterson, B., Caddis, R. & Durrheim, D. 2011, Use of workplace absenteeism surveillance data for outbreak detection. *Emerg Infect Dis,* 17**,** 1963-1964.

[15] Holt, J. B., Huston, S. L., Heidari, K., Schwartz, R., Gollmar, C. W., Tran, A., Bryan, L., Liu, Y. & Croft, J. B. 2015, Indicators for Chronic Disease Surveillance — United States, 2013. CDC.

[16] Botsis, T., Lai, A. M., Palmas, W., Starren, J. B., Hartvigsen, G. & Hripcsak, G. 2012, Proof of concept for the role of glycemic control in the early detection of infections in diabetics. *Health Informatics Journal,* 18**,** 26-35.

[17] T.Botsis, O.Hejlesen, J.G.Bellika & G.Hartvigsen 2007, Blood glucose levels as an indicator for the early detection of infections in type-1 diabetics. *Advances in Disease Surveillance.*

[18] Botsis, T. & Hartvigsen, G. 2010, Exploring new directions in disease surveillance for people with diabetes: lessons learned and future plans. *Stud Health Technol Inform,* 160**,** 466-470.

[19] Lauritzen, J. N., Arsand, E., Van Vuurden, K., Bellika, J. G., Hejlesen, O. K. & Hartvig-Sen, G. 2011, Towards a mobile solution for predicting illness in Type 1 Diabetes Mellitus: Development of a prediction model for detecting risk of illness in Type 1 Diabetes prior to symptom onset. 1-5.

[20] 20. Woldaregay, A. Z., Van Vuurden, K., Årsand, E., Botsis, T. & Hartvigsen, G. Electronic Disease Surveillance System Based on Input from People with Diabetes: An Early Outbreak Detection Mechanism. Proceedings from The 14th Scandinavian Conference on Health Informatics 2016, Gothenburg, Sweden, April 6-7 2016, 2016. Linköping University Electronic Press, 23-27.

[21] 21. Årsand, E., Walseth, O., Andersson, N., Fernando, R., Granberg, O., Bellika, J. & Hartvigsen, G. 2005, Using blood glucose data as an indicator for epidemic disease outbreaks. *Studies in Health Technology and Informatics,* 116**,** 217-222.

[22] 22. Rayfield, E. J., Ault, M. J., Keusch, G. T., Brothers, M. J., Nechemias, C. & Smith, H. 1982, Infection and diabetes: the case for glucose control. *Am J Med,* 72**,** 439-450.

[23] 23. Béranger, J. 2016, 1 - The Shift towards a Connected, Assessed and Personalized Medicine Centered Upon Medical Datasphere Processing. *Big Data and Ethics.* Elsevier, 1-95.

[24] 24. Huzooree, G., Khedo, K. K. & Joonas, N. 2017, Wireless Body Area Network System Architecture for Real-Time Diabetes Monitoring. *In:* Fleming, P., Vyas, N., Sanei, S. & Deb, K. (eds.) *Emerging Trends in Electrical, Electronic and Communications Engineering: Proceedings of the First International Conference on Electrical, Electronic and Communications Engineering (ELECOM 2016), Bagatelle, Mauritius, November 25 -27, 2016.* Cham: Springer International Publishing, 262-271.

[25] Liao, Y. T., Tang, S. T., Chen, T. C., Tsao, C. H., Lee, T. C., Huang, Y. F. & Young, S. T. 2004, A communication platform for diabetes surveillance. *Conf Proc IEEE Eng Med Biol Soc,* 5**,** 3313-3315.

[26] Mougiakakou, S. G., Bartsocas, C. S., Bozas, E., Chaniotakis, N., Iliopoulou, D., Kouris, I., Pavlopoulos, S., Prountzou, A., Skevofilakas, M., Tsoukalis, A., Varotsis, K., Vazeou, A., Zarkogianni, K. & Nikita, K. S. 2010, SMARTDIAB: a communication and information technology approach for the intelligent monitoring, management and follow-up of type 1 diabetes patients. *IEEE Trans Inf Technol Biomed,* 14**,** 622-633.

[27] Mougiakakou, S., Stoitsis, J., Iliopoulou, D., Prentza, A., Nikita, K. & Koutsouris, D. 2005, A Communication Platform for Tele-monitoring and

Tele-management of Type 1 Diabetes. *Conf Proc IEEE Eng Med Biol Soc,* 3**,** 2207-2210.

[28] Martinez, A., Ruba, W., Sánchez, A. B., Meneu, M. T. & Traver, V. 2011, Architecture for Lifestyle Monitoring Platform in Diabetes Management. 55**,** 194-200.

[29] Al-Taee, M. A., Al-Nuaimy, W., Al-Ataby, A., Muhsin, Z. J. & Abood, S. N. 2015, Mobile health platform for diabetes management based on the Internet-of-Things. 1-5.

[30] Chang, S.-H., Chiang, R.-D., Wu, S.-J. & Chang, W.-T. 2016, A Context-Aware, Interactive M-Health System for Diabetics. *IT Professional,* 18**,** 14-22.

[31] (Nse), N. C. F. E.-H. R. *Diabetes Diary* [Online]. Available: http://www.diabetesdagboka.no/en/.

[32] Granberg, O., Bellika, J. G., Arsand, E. & Hartvigsen, G. 2007, Automatic infection detection system. *Stud Health Technol Inform,* 129**,** 566-570.

[33] Sachidananda, V., Khelil, A. & Suri, N. 2010, Quality of information in wireless sensor networks: A survey. *ICIQ (to appear)*.

[34] Zahedi, S., Srivastava, M. B. & Bisdikian, C. 2008, A computational framework for quality of information analysis for detection-oriented sensor networks. 1-7.

[35] Rafe, V. & Hajvali, M. 2014, A reliable architectural style for designing pervasive healthcare systems. *J Med Syst,* 38**,** 86.

[36] Årsand, E., Bradway, M., Giordanengo, A., Mužný, M. & Wangberg, S. C. 2016, The need to tailor mobile phone-based diabetes self-management tools. *The 9th International Conference on Advanced Technologies & Treatments for Diabetes (ATTD 2016)* Milan, Italy.

[37] Office for Civil Rights, O. 2012, Guidance Regarding Methods for De-identification of Protected Health Information in Accordance with the Health Insurance Portability and Accountability Act (HIPAA) Privacy Rule [Online]. Available: https://www.hhs.gov/hipaa/forprofessionals/privacy/special-topics/de-identification/.

[38] Uzuner, O., Luo, Y. & Szolovits, P. 2007, Evaluating the state-of-the-art in automatic de-identification. *J Am Med Inform Assoc,* 14**,** 550-563.

[39] Niewiadomska-Szynkiewicz, E. 2013, Energy Aware Communication Protocols for Wireless Sensor Networks. 7776**,** 135-149.

[40] Gautam, A. K. & Gautam, A. K. 2009, A Protocol for Energy Efficient, Location Aware, Uniform and Grid Based Hierarchical Organization of Wireless Sensor Networks. 40**,** 273-283.