Journal of Universal Computer Science, vol. 23, no. 6 (2017), 539-559
submitted: 20/1/17, accepted: 19/5/17, appeared: 28/6/17 © J.UCS

Integrating Biomedical Sensor Data into a Simulation Learning Environment for Children Newly Diagnosed with Diabetes

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Abstract: Deploying Wireless Body Area Networks (WBANs) on/in human bodies has become an increasingly active area of research due to WBANs' capability to monitor human physiological signals, which is useful in a wide range of applications. However, there is a lack of e-learning applications taking advantage of the context-medical data coming from WBANs. This study is aimed at exploring the educational usefulness of integrating data captured by wearable biomedical sensors in a simulation learning environment. To this end, a system has been designed with the aim of introducing 8-12 year old children, newly diagnosed with type 1 diabetes mellitus, to the endocrine regulation of glucose metabolism processes. The system is evaluated in order to determine whether it is technically viable, and its suitability is validated for educational purposes. Technical viability is evaluated through a simulation, whereas educational usefulness is examined by a group of 13 health professionals in terms of fidelity, validity, interactivity and learning content. The results from this experience highlight the potential of the integration of biomedical sensor data in a simulation learning environment to foster the motivation of the target population and reflection about the health consequences of the patients' actual behaviors. The evaluators see potentials on this proposal and even recommended the incorporation of more biomedical sensors, and new functionalities to share the physiological state of the patients with healthcare stakeholders.

Keywords: eHealth, simulation learning environment, wearable computing
Categories: K.3.1, L.3.6, L.5.0

1 Introduction

Type1 diabetes mellitus (DM) is an important endocrine disorder and one of the most common chronic conditions in children. It is characterized by insulin deficiency as a result of the autoimmune destruction of pancreatic beta islet cells. Poor patient adherence to medical treatment (instructions to control the glucose levels by an endocrine) increases the risk of mortality and medical complications. Studies suggest that education is an effective way to enhance medication adherence, which, in turn, will benefit health outcomes and might improve the children's quality of life [IDF 2012].

A promising method for educating patients involves demonstrating the effect of various self-care actions on the disease control parameter through computerized simulations. Simulation learning environments (SLE) might be effective in teaching children with DM about the basic glucose metabolism processes for two main reasons. First, SLE might recreate medical situations to be practiced and managed with no risk to children' health. Second, children can be repeatedly exposed to unanticipated medical events to gain powerful insights into the consequences of their actions and the need to "get it right" [Makransky et al. 2016, Wehbe-Janek et al. 2015].

The effectiveness of SLEs could be enhanced by using contextualized information about patients. In this sense, the sustainable development of broadband and wireless Internet technologies, such as wearable and implantable biosensors, might have a positive impact on eHealth [Rahman et al. 2014]. In the diabetes arena, biomedical sensors are able to continuously monitor the vital signs that characterize the patient's actual physiological state. On the other hand, sensor data is being explored to support learning solutions that are 'effective, efficient, enjoyable, personal, and engaging' [Specht 2014].

This study is aimed at verifying the educational usefulness of integrating data captured by wearable biomedical sensors in a simulation learning environment. To this end, a WBAN (Wireless Body Area Network) [Chen et al. 2011] containing biomedical sensors to enable the sampling of vital signs of interest (e.g. glucose levels, blood pressure) is proposed. The data captured by the sensors is delivered to a simulation learning tool, called SLENDEr (Simulation Learning ENvironment for children with DiabEtes), which is deployed into the patient's smartphone. SLENDEr uses the collected data to provide context-based activities related to the endocrine regulation of the glucose metabolism processes of the patient.

The study involves two main steps. First, the system is evaluated in order to determine whether it is technically viable. To this end, simulations of the generation of sensor data at the rates used by commercial devices are used to determine the overhead of the wireless network and to adjust the amount of data that can be effectively processed by the learning tool. Second, since the simulation tool was a simplification of a real-world phenomenon and included context biomedical data, the resulting learning tool might affect its educational usefulness [Stainton et al. 2010]. Therefore, the educational usefulness of the learning environment proposed is explored in terms of fidelity, validity, interactivity and learning content [Feinstein and Cannon 2014, Zaharias and Poylymenakou 2009].

Due to the difficulties to get authorization to work with a vulnerable population in a medical study, this study do not include either children´s evaluation of the tool or real measures from the sensors.

In the following, we provide a brief overview of the use of wearable computing in education and how wearable devices can be integrated into WBANs to become part of context-aware biomedical learning applications (see Sections 2 and 3, respectively). Drawing on this background, we introduce the architecture and the learning simulation tool proposed in Section 4. After outlining our research approach in section 5, we present the technical viability results in Section 6 and educational usefulness results in Section 7. Finally, Section 8 summarize the conclusions of our research and outlines the future work.

2 Wearable Computing in e-Education

Today, sensors can be integrated into various accessories such as clothes, eyeglasses, wrist watches, headphones and smartphones. Some sensors, mostly medical-grade ones, are used on a stand-alone basis. As technology matures, we will increasingly witness the integration of sensors into wearable devices. The term wearable technology refers to electronic technologies or computers that are incorporated into items of clothing and accessories that can be worn comfortably on the body. Wearable devices include sensors and some form of communications that provide real-time information access. Their purpose is to offer readily accessible, portable and mostly hands-free access to electronic information and media [Tehrani and Michael 2014]. Educational researchers envisage that a broad use of wearable technology might have a high impact in education in future years [Specht 2014, Labus et al. 2015, Johnson et al. 2014]. Current applications include the use of biometric sensors for monitoring students' emotions, the use of Google Glass as a learning supporting device, and the use of wearable devices as training tools. Several e-Health platforms integrating biometric sensors for vital signals monitoring purposes are commercially available [Escolar et al., 2016].

Information on the learners' emotional state collected by means of biosensors measuring skin conductivity, heart rate, breathing and muscle activity has been used by pedagogical agents to guide the learning process according the students' emotions [Bosma and André 2004]. In the study, the researchers reported problems with the noise of the sensor signals and difficulties in correlating the emotional patterns detected with the biometric signals.

Google Glass has been explored as a teaching tool by several medical research groups, mainly to record students during standardized patient encounters and training sessions [Tully et al. 2015, Vallurupalli et al. 2013]. However, one of the stumbling blocks to the wider use of Google Glass has been concern over data security and patient privacy. The devices are not compliant with the Health Insurance Portability and Accountability Act of 1996 (HIPAA) because the data collected with Google Glass is accessible to Google and is not encrypted.

Additionally, wearable computing has been used as an effective learning environment for motor skill learning to assist learners in playing a musical instrument, handwriting, sports training, and learning sign language [Van der Linden et al. 2011] [Amma et al. 2014, James et al. 2011, Iwasako et al. 2014]. These training and

learning environments are based on the learning-by-doing approach and involve correcting the learner's movements until her optimal movements are achieved. In motor skill learning, the users' discomfort has been reported as the greatest barrier to adopting wearable devices.

Therefore, there is promising potential for the use of wearable technology in education. A recent research work [Bower and Sturman 2015] identified 14 affordances of wearable technologies, which include pedagogical uses such as simulation, feedback and in situ contextual information, aspects related to educational quality such as engagement, efficiency, and presence, and two potential logistical advantages, namely hands-free access and freeing up space. However, additional and clever educational applications will need to be developed using this technology to validate its affordances [Sultan 2015]. The new educational applications based on wearable technology must provide meaningful educational activities and must address the drawbacks stated earlier, namely, certifying that the amount and the quality of data provided by the sensors is useful in understanding the phenomena governing the educational process and avoiding the logistical and technical problems that may impede the adoption of the technology [Tehrani and Michael 2014].

3 Body Area Networks

The advances in lightweight, small-sized, ultra-low-power and intelligent monitoring wearable sensors are facilitating the development of Body Area Networks (BAN) [Chen et al. 2011], a class of Wireless Sensor Networks (WSN) [Akyildiz et al. 2002] devoted to the remote and continuous monitoring of people's health by means of several networked biomedical sensors, and eventually, actuators located strategically on the human body (e.g. ankle, waist, thigh) to enable the periodic sampling of one (or several) vital signs of interest, for instance, blood pressure, oxygen saturation or glucose level.

According to [Chen et al. 2011], the architecture of a BAN obeys a multi-layered design:

- Tier-1 or intra-BAN communication,
- Tier-2 or inter-BAN communication, and
- Tier-3 or beyond-BAN communication.

The design of Tier-1 includes the election of the monitoring devices (sensors and actuators) and the network technologies employed between them and/or with a nearby personal server device (receiver), typically in a star topology. Since these devices are usually battery-operated, a major challenge here is enlarging their lifespan, reducing the data rate and implementing more energy-efficient MAC (Medium Access Control) protocols. Another important issue is related to interconnecting both invasive and non-invasive sensors wirelessly, and the signalling techniques employed at the physical layer. Tier-2 covers the communication between the personal device and one or more access points to local networks (e.g. hospital, home, office). The communication technologies employed at this layer (e.g. Bluetooth, Zigbee, 3G) are more mature than the ones employed at Tier-1; the challenges at this layer include patient mobility, coverage, and network deployment. Finally, Tier-3 enables communication towards worldwide areas, provides the hardware components for permanently storing the data (data servers, also called base

stations) and services for the interested stakeholders, such as event notification, real-time diagnosis, prevention based on pattern analysis, and entertainment for the final users.

This three-tier architecture has been successfully deployed in several applications for diabetes monitoring [Gómez et al. 2002, Capozzi and Lanzola 2011]. In [Wang et al. 2013], a system is proposed to monitor the condition of a diabetic patient by using a BAN integrated by sensors with the capabilities of sensing, processing, and communication. E. Gomez et al. presented DIABTel, a telemedicine system for telemonitoring diabetic patients through telecare services that combines different ways of acquiring data [Gómez et al. 2002]. The data is evaluated in terms of a number of messages (sensor readings, therapy adjustment and patient requests), usability (user-friendliness, efficiency and guidance), and clinical state (number of hypoglycemias per week and median value of HbA1c). The results reveal a better control of the illness due to the number of therapy adjustments that doctors are able to perform, compared with conventional treatment. In [Capozzi and Lanzola 2011], the authors propose a multiagent software architecture that integrates both device and healthcare services to support home monitoring in diabetic patients in two different scenarios: remote monitoring of diabetes complications (long-term monitoring) and of an artificial pancreas device (short-term monitoring).

On the other hand, biomedical informatics is a rich domain for context-aware applications that get meaningful information about patients' physical conditions (e.g. blood glucose levels) from biomedical sensors [Bricon-Souf and Newman 2007]. These applications use the context to adapt their behavior and respond according to the context [Al-Bashayreh et al. 2013]. Examples of context-aware biomedical applications include systems that monitor patients with cardiovascular diseases, monitor the vital signs of the elderly, or monitor epilepsy patients. When developing context-aware biomedical applications, architecture techniques based on responsibility, frequency, context source and the acquisition process must be employed.

Pull and push techniques are used to determine the responsibility for acquiring sensor data. The responsibility can be taken by software components (pull) or by physical sensors (push). The frequency of events to acquire the data determines whether the context is generated instantly or periodically. Regarding the context source factor, the data might be acquired directly from the sensor hardware, through middleware architecture or from context servers. Finally, in [Perera et al. 2014], the researchers identify three means of acquiring context: sensed, derived and manually. The first acquiring technique occurs when the data is sensed through sensors, the second when information is generated by performing computational operations on the sensor data and the third when users provide context information manually.

4 Experimental Framework

Following the previous literature, we propose a basic architecture for a context-aware biomedical application that obeys a three-tier-based design and includes a Simulation Learning ENvironment for children with DiabEtes (SLENDEr), as shown in Fig. 1. Tier-1 is composed by wearable sensors; each one samples a vital sign at a suitable periodicity. After sampling, the sensors transmit raw data to a patient's wireless

personal device carried by the patient, e.g. a tablet or a smartphone, which represents Tier-2. The role of the personal device is twofold: On the one hand, it acts as the network gateway by receiving the samples originating from the wearable sensors and by forwarding them (via a WiFi connection) to a data server, which represents Tier-3. On the other hand, it embeds SLENDEr, a learning simulation environment that uses the context data collected by the sensors to change the parameters of the simulation. Tier-3 acts as a base station, a server located at the hospital that holds a database where the data corresponding to the patient is stored, processed and disseminated (when necessary) to the stakeholders that should be aware of the patient's medical situation to carry out adequate care and medical actuations.

For the purpose of this study, only glucose sensors used to measure the glycemia level will be considered, and only Tiers 1 and 2 will be considered in the simulated architecture.

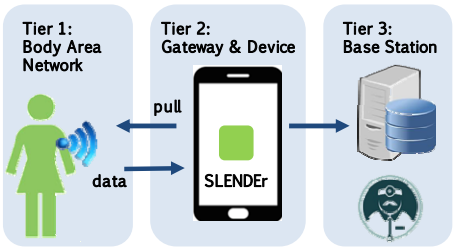

Figure 1: Architecture of the system

4.1 Integrating Biomedical Sensors into a Simulation Learning Environment

SLENDEr is a simulation learning environment that allows two types of interactions, namely, active and passive interactions. The former are actions that users perform to explore the learning content. The latter are the changes in the simulation parameters introduced by medical sensors worn by the patient. Therefore, the data collected by the sensors characterize the physical condition of the user, which, in turn, is relevant to the interaction between her and the simulation learning environment.

SLENDEr's learning materials have been framed around five core topics: eating, converting carbohydrates, proteins and lipids into glucose, and, removing waste. Each topic has a reading activity, an experimental activity and one or two multiple-choice questions (see Fig. 2). The SLENDEr simulation tool includes knowledge-based support and active and passive interactive capabilities to help learners discover the processes followed by the organism to get energy from protein, carbohydrates and fat in the absence of insulin. It supports:

- The structure of the discovery process, organized into several topics that require the completion of reading, experimental and assessment activities.
- Reading activities designed to provide the background information necessary to successfully accomplish the experimental activities for each topic, (Fig. 2, upper left corner).
- Experimental activities designed for the discovery of each learning concept, (Fig. 2, upper right corner).

- Context-based information to feed the experimental environment, (Fig. 2, lower left corner).
- Assessment activities to encourage students' reflection, (Fig. 2, lower right corner).

Figure 2: Learning activities associated with the topic: 'Convert carbohydrates into glucose'. Left to right, top to bottom: reading activity; experimental activity; demanded information; assessment activity.

When a learner decides to run the application with real biomedical data, SLENDEr pulls the latest glucose measure from the biomedical sensor and modifies the glucose level in the simulation according to the glucose value sent by the sensor. Then, the learner is ready to perform the contextual learning activities that are structured by the platform. The content necessary to understand the main processes involved in the simulation activities is provided by reading activities. Concrete experiences are possible due to the contextual data and the experimental activities. Finally, reflection is fostered by assessment activities that provide students with the necessary feedback.

The simulation learning environment designed has potential learning benefits for children who are newly diagnosed with diabetes that combine the benefits associated with SLEs with those associated with contextualized learning. First, its activities, which are aligned with patients' medical situations, will provide learners with opportunities to take an active part in their instruction and might lead to increased motivation, engagement, and eventually, learned success [Keller 1979]. Second, SLENDEr helps the learner to acquire conceptual knowledge. In particular, it offers unique opportunities for dynamic, complex, and unanticipated medical situations to be practiced and managed with no risk to children's health [Makransky et al. 2016]. This potentially fosters deeper cognitive processing during learning, which, in turn, leads to better learning outcomes [Dean et al. 2010]. Third, the simplification of the

glucose metabolism processes will minimize the cognitive load for learners [Pillay et al. 2015]. Fourth, SLENDEr's interactive visualizations will potentially be easier to remember than textual information [Dean et al. 2010, Wu et al. 2014]. Finally, the context information, along with the simulations, will be potentially useful to foster the reflection of the patient about her need to adhere to her treatment [Wei 2014].

5 Method

This study consisted of two relatively autonomous parts that worked together to determine the technical viability and educational usefulness of SLENDEr. SLENDEr is meant to assist 8–12 year old children who are newly diagnosed with diabetes in understanding the endocrine regulation of the glucose metabolism processes followed by their bodies.

The first part of the study was a computer simulation of the behavior of three commercial wearable glucose sensors. The behaviors were compared, focusing on the sensors' capability of being integrated into a simulation learning environment. The second part of the study explored the educational usefulness of the learning environment in terms of two important constructs of the evaluation of simulation learning environments: fidelity and validity [Feinstein and Cannon 2014].

Since fidelity and validation involve the consensus of simulation designers and subject-matter experts, 13 health professionals participated in the study: eight doctors and five registered nurses from the "Centro de Salud Ciudad de los Periodistas" in Madrid. Health professionals were paediatricians and pediatric diabetes specialist nurses who work with children and young people affected by type 1 diabetes mellitus. The age of the professionals varied from 26 to 66 years old, with an average age of 51.2 years old (*SD* = 12,3).

The evaluators received the following scenario description:

Learner Profile: Sophie is 10 years old, and she has just been diagnosed with diabetes. She frequently uses her mobile phone to play, but she had never used any e-learning application.

Learner goal: Sophie must understand the endocrine regulation of the glucose metabolism processes followed by her body in the absence of insulin when she has just eaten.

Task to perform: The evaluators were asked to complete the following tasks using the SLENDEr application: (1) discover information; (2) navigate through the application; (3) perform a simulation with the system's data; and (4) perform a simulation using data from the wearable sensor. Finally, each evaluator answered the following open-ended questions:

Question 1: In your opinion, to what extent does the simulation model resemble reality?

Question 2: In your opinion, to what extent do the eventual disparities between the model and reality affect the learning process?

Question 3: In your opinion, to what extent do you think that the tool effectively measures learners' accomplishment of the learning objectives?

Question 4: In your opinion, to what extent are the data from biomedical sensors helpful to provide meaningful learning for patients?

Question 5: What do you think about the learning resources (e.g. text, simulations) used in the tool?

The first question was aimed at evaluating the fidelity of the system, which is the degree of similarity between the training and the operational situation in terms of the physical and functional characteristics of the system being simulated. Simulators do not need to be an exact representation of the real world in order to provide effective learning; what is more important is to show the general principles of the real object or processes along with the user's perception of the simulation's verisimilitude [Labus et al. 2015].

The second and third questions were intended to evaluate the validity of the simulation application following the definition of the American Psychological Association: "the degree to which evidence and theory supports the interpretations of [participants' performance] entailed by the proposed use of [the simulation]" [Stainton et al. 2010, Feinstein and Cannon 2014, AERA 2014]. Whereas many validity types have been described, validity research in medical education requires scrutiny of the simulation's content to determine whether the simulation accurately represents the desired phenomena, to judge the simulation tool's ability to measure the performance level of the participants, and finally, to determine the simulation's predictive ability: Does the simulation lead to the expected learning outcomes? [AERA 2014, Graafland et al. 2014].

The evaluators were helped by developers whenever they had problems understanding the SLENDEr interface. Problems occurred at the beginning of the intervention when three of the evaluators required help to open the application on their smartphones and to initiate the navigation through the application. In order to ensure independent and unbiased evaluations from each evaluator, they were not allowed to communicate with anybody during the intervention.

Using a qualitative method of content analysis [Hsieh and Shannon 2005], the written answers were inspected, highlighting all text that appeared to describe the initial coding categories: fidelity, validity, interactivity, learning resources and assessment. An analysis of the 45 written responses produced a total of 134 discrete observations across the data set. All of the highlighted text was coded using the predetermined categories whenever possible. After coding, the data from each category were examined to determine whether subcategories were needed.

To bring the system proposed in Fig. 1 into reality, we need to evaluate the connectivity between tiers and to evaluate the educational level of Tier-2 (SLENDEr). For this reason, the next two sections provide the evaluation of our approach from the technical (Section 6) and educational point of view (Section 7) that are apparently not related. However, we want to stress here the need of evaluation of our system from the two viewpoints, one to assess its feasibility by evaluating currently available sensors and network technologies, and the other one to assess its educational level.

6 Technical Viability Results

This section focuses on the performance exploration of the part of the system architecture that is integrated by a BAN composed of a single wearable glucose sensor. The sensor's data will be transmitted to the simulation learning environment. The evaluation is done through simulations aimed at determining the viability of a

real implementation of this subsystem, where the rates for data generation employed by real sensors are simulated. To this end, three Continuous Glucose Monitoring (CGM) sensors, certified for use with children, are evaluated: *ipro*, *abbot*, and G4/G5 Dexcom series. Table 1 shows a brief comparison of the main characteristics of the commercial sensors considered. The simulations are used to compare the following three metrics: 1) The traffic overhead in terms of the number of packets transmitted per unit of time; 2) the throughput of the wireless connection; and 3) the maximum number of packets that can be effectively processed by the simulation learning environment.

6.1 Traffic Overhead

With the purpose of avoiding glucose reading losses between fingersticks (it is estimated that nearly 78% are lost), Medtronic proposes its *ipro* kit, composed of a sensor implanted under the skin and an *ipro* recorder that receives and stores the readings from the sensor. A reading can be sent from the sensor to the receiver every five minutes, which represents a maximum of 288 daily readings. The *abbot* system comprises a continuous glucose monitoring (CGM) sensor and a reader device able to scan the sensor when located at distances from 1–4 cm. The sensor measures the glucose level every 15 minutes, which represents a maximum of 96 daily readings. Finally, the last sensor considered is the G4/G5 Dexcom series, which is able to transmit each reading via Bluetooth to a smartphone. We are interested in comparing the overhead when a BAN is integrated by only one of the three sensors (*ipro*, *abbot*, or Dexcom). Each BAN operates as follows: The sensor reads the glucose level of the patient at the interval given by its reading rate (see the fourth column in Table 1), transmits each reading to its receiver device and stores the reading in its memory. Figure 3 shows the number of readings taken by the three sensors according to its reading rate over time. Assuming that each reading taken is immediately transmitted to its receiver device (note that this is the typical behavior of WSN applications, which follows the pattern sense–store–transmit–sleep), the results also represent the traffic overhead in terms of the number of data packets that are delivered to the network or to the receiver device. Subsequently, the higher the reading rate, the bigger the traffic overhead. Note that ipro sensor does not currently support wireless communication and, therefore, it would not be adequate to be integrated with a smartphone.

Sensors	**Implantation mode**	**Autonomy (days)**	**Monitoring rate**	**Networking**
ipro	Under skin	6	5 minutes	No
abbot	Interstitial liquid	14	15 minutes	13.56 MHz Radio frequency
G4/G5 series	Under skin	7	5 minutes	Bluetooth

Table 1: Comparison between three wearable CGM sensors: ipro, abbot, Dexcom

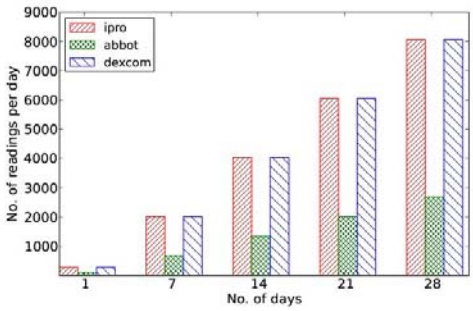

Figure 3: Maximum overhead due to the operation of ipro, abbot and dexcom sensors

6.2 Throughput

To be able to effectively measure the network throughput when data of variable sizes are sent, three wireless network technologies are considered: Bluetooth [Bluetooth 2004], WiFi 802.11n and ZigBee [ZigBee2005] with bandwidths of 3Mbps, 300Mbps and 250Kbps, respectively. Note that only the Dexcom sensor enables direct wireless communication with a smartphone via Bluetooth. The purpose of this experiment is to compare the throughput that is obtained by these three technologies regardless of the communication technology used by the sensor. We have computed the network throughput for Bluetooth, WiFi 802.11n and Zigbee for different data sizes ranging between 1 and 1024 bytes. Since WiFi has the larger bandwidth, and consequently obtains the best times, typically, this is not the preferred choice for communication inside a BAN and between a BAN and the gateway device, because of its high energy consumption. We have also computed the maximum number of data packets per second that can be transmitted using a Zigbee or Bluetooth connection when the data packet size ranges between 1 and 8192 bytes. For small packet sizes below 128 bytes (as usual for a BAN), Bluetooth can transmit more than 1500 packets, which would require a frequency of readings higher than the one that is actually used by the three sensors considered. Note that the maximum number of packets transferred on a WiFi connection would still be much larger than the one that is obtained with Bluetooth. We conclude that both Bluetooth and ZigBee are two technologies that fit well with the requirements of a BAN, since they support the transmission rate of the commercial sensors considered. WiFi, however, should be disregarded due to its high energy consumption. In fact, according to their specifications, both Bluetooth and ZigBee are designed for battery-operated devices transmitting at short distances small data sizes, while WiFi is normally intended for larger data sizes transfer at high speeds.

6.3 Maximum Number of Packets

Finally, we evaluate the number of data packets for each type (ipro, abbot, and dexcom) that have to be transmitted to exhaust the memory space at the receiver device that holds the simulation learning environment. To this end, different memory sizes ranging between 16 and 512 KB, and different data packet sizes ranging

between 1 and 2048 bytes are considered. Figures 4 and 5 show the number of days of uninterrupted operation of the three sensors to exhaust the memory space of the receiver, assuming that none of the packets are removed from the memory during that time. The number of days for packets sized 8 bytes and 128 bytes are shown in Figures 4 and 5 respectively. As observed, when the data packet size increases, the number of days required to fill the memory space decreases. Note that in some cases, for memory sizes below 32KB, the number of days is lower than the autonomy of the sensor, which would mean having to erase the memory in order to continue storing data; otherwise, the data will be lost or overwritten. Such a limitation on the memory space could impact the simulation learning environment and should be avoided; thus, a tradeoff is necessary between the autonomy of the sensors, the memory space and the data packet size to be transmitted. Subsequently, the optimal size of the message is the one that maximizes the number of uninterrupted days of operation of the sensor, let's say, λ, subject to the autonomy (in days) of the sensor being larger than λ. Otherwise, the memory of the device will be overwritten.

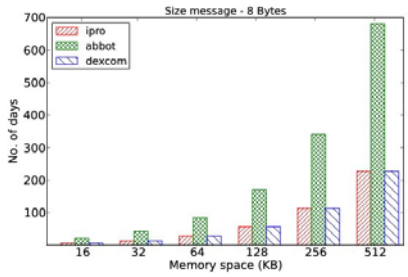

Figure 4: Number of days of uninterrupted operation of ipro, abbot, and dexcom to exhaust the memory size using messages of 8B

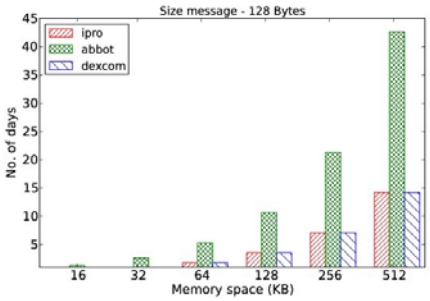

Figure 5: Number of days of uninterrupted operation of ipro, abbot, and dexcom to exhaust the memory size using messages of 128B

7 Educational Usefulness Results

In order to understand the diabetes pathology, it is necessary to have some knowledge of the physiological mechanisms that regulate the body's blood glucose. However, these mechanisms involve a series of chemical reactions occurring in the cells of complex organs such as the pancreas or the liver. For the purpose of this study, it was not necessary to have a full simulation of the processes involved in endocrine regulation of glucose, but the simulation needed to be correct and comprehensible for 8–12 year old children. The simplification that was made involved three aspects, namely the endocrine regulation processes, the graphical representation of the processes and background information. The results of the evaluation of the design decisions taken have been classified in terms of fidelity, validity and implementation of the experiential learning process, and they are presented below.

7.1 Fidelity

There were 12 comments in this category that reflect the participants' perception about the degree to which the SLENDEr simulator emulates the regulation mechanisms activated when blood glucose levels are high and the patient does not have enough insulin. Eight participants agreed that there were differences between the real glucose metabolism processes and how they were represented in the simulator. However, four participants remarked that there is a functional correspondence between the simulation and the applied context. All of the participants who answered this question stated that no relevant consideration was left out of the simulation; however, one of them pointed out that there are other regulation processes that were not considered. The following response summarizes the participants' general comments:

Diabetes is a very complex process and I think the model is far closer to reality, but the simulation adapts quite well to the basic level of pathophysiology of diabetes.

Therefore, according to the participants in the study, the SLENDEr simulator does not provide an accurate model of the regulation processes of glucose, but it is perceived as accurately reflecting the underlying basic concepts.

7.2 Validity

There were 15 comments comprising the participants' opinions about the potential benefits and drawbacks of the low-fidelity SLENDEr simulator for helping children who are newly diagnosed with diabetes to understand their illness. The participants also suggested some mechanisms to improve the validity of the simulator.

The low fidelity of the simulator was perceived as an advantage for the learning effectiveness of the SLENDEr simulator by eight of the participants. They claimed that the simplicity of the tool would allow patients to focus on the main aspects of the regulation process of diabetes:

[The simulator] strictly reflects what patients should learn about how the body works when ingesting food and there is not enough insulin.

The tool helps to reinforce concepts taught in the endocrinology service.

Three participants indicated that the abstraction chosen to represent the human organs might cause confusion to young children and suggested changing the graphical representation to one more familiar to children, closer to the representation of the human body in textbooks.

There were three comments about the convenience of not using the tool with newly diagnosed children, but with those who already have some initial training (two comments). Another comment suggested an improvement in the fidelity of the simulated processes in order to suggest parameters that would stabilize the patients' glucose levels.

Therefore, the evaluators perceived that despite the low fidelity of the processes simulated, the tool is potentially effective for helping patients to learn how their body reacts to a lack of insulin. However, it seems necessary to include some improvements in order to choose a better graphical representation of the human body. Further improvements in the representation would result in a more effective educational tool.

Regarding the ability of the tool to measure the participants' performance, the highest number of reported observations (10 out 20) was focused on the content of the multiple-choice questions. The participants described the questions as "*concise and clear*", "*directly related to the simulation*" and recognized the feedback provided as potentially educationally effective: "*I believe that the questions' feedback summarizes relevant information that patients must learn*". Eight comments highlighted the suitability of asking questions at the end of simulations as a mechanism of reflection and recognition of accomplishments. Two suggestions regarding the personalization of the tool were made:

I wonder if there is any possibility of adapting the questions to the child's age.

I suggest allowing patients a change of proficiency level according to her answers.

Therefore, the assessment included was perceived as useful in this learning tool. No comments were provided about the ability of the simulation tool to measure participants' performance.

Regarding the learning outcomes, it is expected that a diabetic learning tool will foster patients' adherence to treatment and will raise awareness about the need to control diabetes. Eight out of fourteen observations described the potential benefits of using the SLENDEr tool as a mechanism to reflect the risks involved when patients do not follow their treatment. A representative comment was provided by a physician:

I think that the use of the tool will allow children to understand the risks associated with non-adherence to treatment or a dietary transgression.

The rest of the observations remarked about the necessity to incorporate more simulations either to deal with more common risk situations or to allow practising daily control points. The risk situations mentioned included hypoglycemia, and the

control points identified as necessary to include were before meals and snacks, before and after exercise and before going to bed. Finally, the comments reported that SLENDEr is potentially useful for reflecting the risks of the disease, and there was a moderately high interest in including more learning material to simulate other risk situations associated with type 1 DM.

7.3 Interactivity

In this category, the evaluators reported 31 opinions about the potential educational effectiveness of the active and passive interactions. With regard to the potential benefits of the active interactions, there were eight comments highlighting the simulator's potential to increase patients' knowledge about their illness. There were four opinions about the potential of the simulator as an engagement tool. Three of the evaluators said that the simulator has potential as an engagement tool, whereas another stated that children would be more motivated to engage with an educational game than with a simulator.

The incorporation in real time of blood glucose levels to the simulation learning tool was perceived by evaluators as useful for learning purposes in three main ways. First, it was signalled as a potential motivating factor to look after them (four observations). Second, it was perceived as a useful reflecting mechanism about the consequences of poor disease control (three observations). Third, the educational relevance of having instant feedback about the effect of activities such as eating and exercise on blood glucose levels was highlighted (two observations).

There were three observations suggesting the incorporation of new context data into the system. They proposed the processing of data from biomedical sensors and from web-based services to provide physiological state indicators such as age, weight and size. One of the doctors suggested:

... for a more complete information about the actual situation of the patient, it would be necessary to include information about age, weight, size, heart rate, temperature, the amount of exercise that the patient intended to do, the amount of ingested calories the patient expected to consume.

There were another seven observations suggesting the convenience of using context information for four different purposes: 1) to reflect about actual, previous and recurrent patient physiological states (two observations); 2) to provide personalized assistance to patients considering their actual physical condition (one observation); 3) to anticipate what is likely to happen next (two observations); and 4) to involve the patients' families and physicians in the patient education and training (two observations). Three of the most representative comments follow:

I think it would be useful for the patient, her family and her doctor to have some of their simulations recorded. Such a capability would allow patients to resume simulations with previous physiological states and help us to analyze more deeply recurring situations for this particular patient.

With information about the actual glucose level, the actual physical activity level and the calorie intake, the patient might observe the immediate effects of her

treatment adherence and hopefully she will understand the benefits of controlling her glucose levels.

I wonder if it is possible to include capabilities to suggest what to do when there is a blood sugar imbalance and to notify the family and the doctor when a dangerous situation is detected.

Therefore, the active interactions included were perceived as potentially effective in terms of knowledge acquisition and motivation, both to learn about the diabetes and the risks of the illness.

On the other hand, the evaluators highlighted the capabilities of passive interactions to customize simulations in such a way that they reflect patients' risks in a timely manner. They envisaged that these capabilities would be helpful for the personalization of the consequences of poor adherence to treatment. The evaluators also suggested the incorporation of more real-time data from patients and the extension of the learning tool to incorporate patients' families and physicians.

7.4 Learning Resources

SLENDEr has two types of learning resources, namely text and simulation activities. The text is aimed at providing the basic knowledge to understand simulations, whereas the simulation activities have been designed to explore distinguishable metabolic processes in a maximum of five steps.

From a total of 42 observations about the learning resources, 11 were related to vocabulary, nine were opinions about the volume of the information provided, 9 reflected the participants' judgments about the accuracy of the information and 13 described the participants' perceptions about the educational quality of the simulations.

The highest number of observations about the vocabulary (9 out of 11) reported that some words employed were too technical to be used in this learning context. However, two comments remarked that the information attached to different elements of the simulation was useful and easy to understand.

The volume of information was considered too high in seven out of nine comments about this subject; the evaluators who reported this drawback suggested two solutions to solve this problem. One solution proposed was to give less information (three observations), and the other was to include images with the text (four observations).

Regarding the quality of the information, there were nine observations recognizing that the information was complete and correct. There were no negative comments about this topic.

The concepts behind the simulations were perceived as being presented in a simple and direct way (seven observations). However, there were four observations stating that the simulations were not suitable for 8–12 year old children; all these observations also referred to the vocabulary used. The following observations are examples of both types of opinions.

The simulations are easily comprehensible.

Including terms such as "ketones" in the simulation will confuse more than help children.

Therefore, the participants perceived that the quality of the information provided was, in general, inadequate for young children and suggested several ways to address this drawback. The quality of the simulations was generally perceived as adequate for learning purposes; the negative comments were probably due to the terminology used in the simulations

8 Discussion and Conclusions

The present study was designed to determine whether a learning simulation tool with capabilities to use real physiological states provided by biomedical wearable sensors can be educationally effective to teach 8–12 year old children the diabetes regulation processes occurring in their bodies. To this end, a prototype of the WBAN architecture, in which raw biomedical data was integrated into the simulation learning tool, was evaluated by a group of healthcare professionals who used the tool and gave their opinions in an open-ended questionnaire.

The communication between the sensors and SLENDEr was evaluated by the simulation in terms of the traffic overhead, throughput and maximum number of packets to transmit. We evaluate the feasibility of integrating sensors into our system by emulating the data rates generated by real glucose sensors used in children, ipro, abbot, and dexcom. The results demonstrated that such data rates can be effectively processed by SLENDEr. The network technologies WiFi, Bluetooth, and Zigbee were compared. These technologies provide transmission rates sufficient for the sensors; however, the high energy consumption of WiFi impacts the autonomy of the sensors, and therefore, this makes it an inadequate choice. Finally, the amount of packets that have to be transferred from the sensors to the receiver device to completely deplete its memory was considered. The optimal packet size is the one that maximizes the number of uninterrupted days the sensor can operate without overwriting the memory of the receiver, which is a function of the sensor autonomy, sampling rate, and memory capacity.

In a broad sense, the purpose of any computer simulation is to gain understanding of the original object by studying the behavior of the simulation in a cost-effective way. A difficulty to overcome in this study was to simplify the glucose metabolism to be understood by 8-12 year old children. The results of the educational evaluation are promising that a simplified process model might be an effective method for introducing 8-12 year old children to the endocrine regulation of glucose metabolism processes. This result has promising implications in the educational arena. The reduction and abstraction of a real-world phenomenon might create less cognitive load for the learner [Stainton et al. 2010]. The participants' main concern was about the text included to support the simulation activities: It was perceived as too technical for 8–12 year old children. This drawback must be addressed prior to full scale development.

The participants in this study perceived that the simulation processes might help patients to gain a better understanding of their illness in a potentially motivating learning environment and also to reflect on the risks associated with type 1 DM. This

is an encouraging result in the educational and medical fields. On the one hand, educational researchers agree that students who are motivated to learn are more likely to engage, persist, and expend effort for task completion than those who are unmotivated [Csikszentmihalyi 1991, Keller 1979]. On the other hand, a good understanding of the consequences of chronic illness such as diabetes is associated with good treatment adherence [Dean et al. 2010]. However, caution must be applied, as some authors claim that knowledge alone is not enough to promote behavior change in patients with diabetes [Pillay et al. 2015]. Therefore, further research should be oriented toward studying how the behavior may be changed by the knowledge provided by SLENDEr.

The use of raw data from wearable sensors as input to SLENDEr was also perceived as useful for knowledge acquisition. The evaluators highlighted new educational potentialities of the learning environment mainly to motivate the target population to use a tool that reflects their medical condition, to foster reflection about the health consequences of patients' actual behaviors, and to provide personalized feedback about actions to take given their physiological state. Future research will explore whether the learning environment proposed is able to meet these expectations.

The evaluators suggested extending the functionality of the learning tool in two dimensions. They suggested including more biomedical sensors in the platform (e.g. blood pressure, temperature) and providing selected information to patients' families, physicians and caregivers. These two dimensions encompass elements for Tier-1 and Tier-3 of the full architecture envisaged and seem to be aligned with the current trends in wearable computing in eHealth [Wu et al. 2014, Wei 2014] and eLearning [Labus et al. 2015], whereby several actors (e.g. patients, doctors, students, professors) provide and use data from external sensors.

A strength of this study is the multidisciplinary nature of the research team and the diverse sample of evaluators who participated were paediatricians and pediatric diabetes specialist nurses who work with children and young people affected by type 1 diabetes mellitus. However, this study has some limitations. The evaluators' views may or may not accurately represent the views of the broader population of health professionals, because all of them were recruited from the same health center. Due to resource constraints and the time limitations of health professionals, the evaluation has been performed in one case study.

Our findings agree with a recent study about the educational affordances of wearable technologies [Bower and Sturman 2015] including a pedagogical use that our results also suggest is relevant, namely simulation, and particularly, the simulation of physiological processes using biomedical context data. The learning environment was perceived as potentially motivating and useful for providing real-time feedback. It was also found useful for promoting reflection. These two findings have been identified as educational affordances of wearable and sensor technologies in previous works [Bower and Sturman 2015, Specht 2014].

Future work will address the limitations of SLENDEr's current design, increase the graphical content and incorporate more biomedical sensors into the learning tool, as well as new functionalities to share relevant information with healthcare stakeholders. With a consolidated version of the platform, SLENDEr will be evaluated by 8-12 year old children who are newly diagnosed with type 1 DM.

Acknowledgements

The authors would like to thank to the many busy professionals who generously gave their time to examine the tool and complete the questionnaire. We are also especially thankful to Dr. Estefanía Ballesteros who helped us to understand the diabetes disorder and to Eng. Diego Villarán who helped us with the interface's design.

This work was supported in part by the Spanish projects EEE CICYT (TIN2011-28308-C03-01), RESET-UC3M: Reformulando Ecosistemas Escalables Educativos under the grant CICYT (TIN2014-53199-C3-1-R), eMadrid under the grant S2013/ICE-2715 and by the Programme for Research and Innovation of University of Castilla-La Mancha, co-financed by the European Social Fund (Resolution of 25 August 2014). On the other hand, this work has been also funded by the Programme for Research and Innovation of University of Castilla-La Mancha, co-financed by the European Social Fund (Resolution of 25 August 2014) and by the Spanish Ministry of Economy and Competitiveness under project REBECCA (TEC2014-58036-C4-1-R) and the Regional Government of Castilla-La Mancha under project SAND (PEII_2014_046_P).

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