

Chapter 4

Adopting Internet of things in health care: application of wearables for stress management

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Abstract

The aim of this chapter is to provide an overview of the concepts of electronic and mobile health and the application of the Internet of Things in healthcare. A model of mobile health which is based on wearable computing in the area of stress management and disease prevention has been proposed. Model consists of system that enables measurement of vital and environmental parameters in order to reduce stress and, thus, improve health. As a form of support to the wearable system, a mobile health application for well-being was developed, featuring relaxation content.

The aim of case study is to identify the psychophysiological signals indicating stress during students' term papers defending. Existence of differences between the measured values using the wearable system before, during and after the defense of student's term papers points to stress or arousal during test. Mobile health application for the purpose of

relaxation should minimize the excitement and impact on reducing stress during tests.

The results of the case study indicate that mobile health application for well-being with features for relaxation can reduce stress when defending term papers, as well as a decrease in anxiety over the duration of the test and during the relaxation period after the test.

Keywords: Internet of Things, Sensors, Wearables, eHealth, mHealth, Health, Multi-sensor Platforms, Stress management, Well-being, Mobile health application

INTRODUCTION

Subjective well-being is an emotional and cognitive evaluation that people have of their life, including happiness, satisfaction, peace, and life satisfaction. The quality of life is comprised not only of the standard of living, material wealth, income, employment, but also of the improvement of mental and physical health, spending time and learning about healthy environment, alongside physical activity and relaxation. Everyday activities which have a negative impact on health, including routine behavioral patterns, have a reflection on mental and physical health, and are predictors of future health issues. Traditional ways of monitoring health in humans consist of a periodical collection of certain vital parameters, most frequently after the onset of the signs or symptoms of a disease. Massive preventive health actions would be feasible if healthcare institutions were provided with correct and reliable diagnostic information in real time, independently of the patient's location and the distance from the treating institution (Thusu, 2011). Permanent monitoring of certain health factors is expensive and mostly unfeasible on a large number of people.

The promotion of healthy lifestyles and well-being, and their impact on health, has encouraged people to take part in managing their health. That has led to innovative solutions which have a key role in moving healthcare out of hospitals and doctors' offices and into users' homes. Technological and cultural changes have made it possible to collect high quality, objective data concerning an individual in all aspects of his or her life. One of the most popular components of well-being is stress management.

Many researches have been focused on identifying stress in different contexts.

The use of Internet of Things in different contexts is not a novelty, and the idea of constant monitoring of well-being is becoming more and more popular.

For years, experts have been predicting that the Internet of things – a system in which objects communicate between themselves or with other objects – would transform the way of life (Lopez Research, 2013). The ubiquity and availability of mobile and wearable devices allow for the collection of relevant vital health parameters the course of everyday human activities. Today, sensors which an individual can wear while performing everyday activities are available. In that way, devices connected to the Internet enable the monitoring of a person's condition or the observation of some vital parameters, e.g. heart rate, number of steps, electrocardiograms, measurements of temperature or measurements of blood glucose levels, which can sometimes be of vital importance for these users (Chouffani, 2015).

Internet of Things devices for stress management, which practically did not exist only a few years ago, are now available in all global markets. Wearables in the well-being sector enable the collection of data on the user's health status and lifestyles. People who, for personal or professional reasons, are involved in physical activity, running, swimming, fast walking, hiking, etc., whatever their age, also monitor vital parameters. Walkers and runners can carry devices on their wrist, upper arm, and head or in a pocket, measuring the speed of movement, counting the consumption of calories, measuring the heart rate, blood pressure, etc.

The entire data set collected by applications in the areas of promotion well-being and healthy lifestyles provides an insight into the status of a person's health, the monitoring of vital parameters, and provides motivation for achieving bigger and better results (following a diet, having better fitness results, keeping heart rate within the recommended limits etc.), an analysis of personal behaviour, stress management and numerous other activities in all areas of human life (Gross, et al., 2018).

By analyzing sensor data (Greco, Ritrovato, & Xhafa, 2019), we can determine which activities an individual is performing, the duration and intensity of effort, and many other relevant parameters. Through cross-referencing, comparison and analysis of data (Liu, Tamminen, Korhonen, & Röning, 2019), it is possible to determine a user's habits over a longer period of time and contribute to changing bad habits. The data collected for an individual can be used for the construction of a behavioral model which can be used to predict similar or same reactions in the future. Within health prevention activities, everyday sensor monitoring has the potential to detect early health conditions, prevent diseases, and make the treatment process more efficient and effective (Rabbi, Ali, Choudhury, & Berke, 2011).

The measurements of human behavior and external factors which affect behavior and the state of the body can be extremely valuable in identifying stressors. The presence of stress can be identified through the measurement of different vital parameters in a user's body, as well as by measuring environmental parameters which can have an impact on changing the values of the vital parameters (Jung & Yoon, 2017). In order to detect a change and behavior and to possibly identify stress, the following sensors are often used individually and in combination: GSR (Galvanic Skin Response) sensors (Bakker, Pechenizkiy, & Sidorova, 2011), microphone, heart rate and blood oxygen saturation sensor (Schobel, Schickler, Pryss, Nienhaus, & Reichert, 2013), respiration, ECG, EMG sensor (Healey & Picard, 2005), accelerometer (Kusserow, Amft, & Tröster, 2013), blood pressure (Lambiasea, Dorn, Chernegaa, McCarthy, & Roemmicha, 2012).

In order to detect stress, sensors and features of the mobile phone can also be used (calls, SMS, location services) (Sano & Picard, 2013).

There have been few researches dealing with the stressors and stress when controlling the results of studying, as well as introduction eHealth components in order to increase or eliminate the stress.

The research aims of this chapter are the concepts of the Internet of Things in the area of electronic health, wearable computing in different areas of well-being, as well as technical and technological setups necessary for the realization of Internet of Things solutions. This chapter

will present model of mobile health for stress management based on wearable computing which will enable the identification of the factors that cause changes in the values of individual vital parameters, and the factors that are stress predictors.

The aim of the research case study is to identify the use of wearables in detecting psychophysiological signals indicating stress in students. The stress measurement will be conducted during the oral defense of term papers. The mobile health application for well-being with contents for relaxing has been developed. Mobile application should enable relaxing students before term papers defense. The influences of mobile application for well-being with relaxation content in the presence of stress and anxiety levels, or change the behavior of students in certain contexts will be analyzed.

E-HEALTH

With the expansion of the Internet and the introduction of modern ICTs, a modernization of almost all aspects of business in society took place. The field of healthcare also saw a major change, with the application of modern ICTs aimed at improving people's health. Due to that, the prefix "e-" started to appear in front of the term "health".

Electronic health or e-health originated as the crossroads between health informatics, public health, and processes related to providing healthcare and to the information generated and transferred through the Internet and related technologies (Eysenbach, 2001).

According to the definition of the World Health Organization, electronic health (eHealth) denotes the use of information and communication technology in healthcare (World health organization, 2019).

According to the definition of the European Commission (European Commission, 2015), electronic health is defined as the application of information and communication technologies for fulfilling the needs of citizens, patients, healthcare professionals, healthcare providers and health policy creators. According to the same source, e-health denotes the use of information and communication technologies with the aim of:

advancing and improving prevention, diagnostics, treatment, monitoring and management;
improving the access to healthcare services and the quality of services owing to improved efficiency of the healthcare sector;
exchanging information between patients and healthcare providers, hospitals, healthcare professionals;
using telemedicine and portable devices for monitoring health status and for other types of information exchange.

There are different definitions of eHealth (Eysenbach, 2001), (Dzenowagis, 2005) (World health organization, 2019) (European Commission, 2015), but despite numerous derived definitions, there is a common state and consent that e-Health, in a wider sense, denotes not only technological development, but also a change in the way of thinking, the acquisition of positive habits. Electronic health has been created by forming a computer network of nearly all participants in the healthcare system, by using information-communication technologies, all with the aim of improving healthcare on the local, regional and global level.

The availability of healthcare services, the accessibility and the quality, and the price of healthcare services represent an issue in many countries around the globe (European Commission, 2012) (European Commission, 2012) (PricewaterhouseCoopers, 2012). There are different factors which because of which some individuals are unable to access healthcare institutions or education in order to maintain and improve health. It can be a lack of financial resources, patient's immobility, lack of knowledge or interest, inadequate weather conditions or long waiting lines (European Commission, 2012) (European Commission, 2012) (PricewaterhouseCoopers, 2012). Modern trends of e-health include mobile health and self-monitoring (Radenković, Despotović Zrakić, Bogdanović, Barać, & Labus, 2015).

MOBILE HEALTH

The term "mobile health" or "m-health" originated from the term "electronic health". Mobile health is a term which is used in providing health and medical care as well as in public health, with the support of mobile devices (World health organization, 2018), (World Health Organization, 2011). This term also covers healthy lifestyle applications

which, in a direct or indirect way, improve the health and quality of life of individuals. Such applications are often connected to medical devices or sensors (watches, bracelets etc.). Mobile health also covers personal health guides, applications providing health information and reminders using SMS and telemedicine through wireless communications (European Commission, 2014).

Mobile health, as an area of electronic health and a technology integrated within the healthcare sector, has an enormous potential for establishing better health communication, promoting healthy lifestyles, simplifying decision-making processes, both for professionals and for the patients, and finally for improving the quality of healthcare services by enabling easier access to medical and healthcare information in the places where the access to information is difficult or impossible. Smartphone applications, sensors, medical devices, and remote diagnostics offer numerous ways for providing healthcare. Advances in medicine have caused the extension of human lifespan, better healthcare, treating of chronic patients, which on the other hand makes healthcare more complicated and expensive. Mobile technologies help reduce the costs of providing healthcare and connect the individual to the healthcare provider (West, 2013).

The market of mobile phones and smartphones has seen such advances that even the cheapest mobile phone has some way of access to the Internet. Owing to a low price and accelerated expansion of the mobile network around the globe, tens of millions of people who did not use to have access to a landline or a computer are now using mobile devices as everyday tools for communication and transmission of information. Mobile communication provides new possibilities of spreading healthcare information amongst the populations of developing countries (World Health Organization, 2011) (Watkins, Goudge, Gómez-Olivé, & Griffiths, 2018). Their universal presence is the main reason for which they need to be taken into account in new technological solutions for providing healthcare and preventive services.

Mobile technologies have multiple key features which put them in a primary position in relation to other information-communication technologies, particularly when it comes to their use in the healthcare

sector (Free, et al., 2010). Many devices which are used in healthcare have wireless communication enabling continued monitoring and interaction, independently of the user's location. They also feature Internet access over WAP or broadband Internet. Mobile devices are personal, users always carry them with them, and they are available at all times. Their size is convenient, they are not too large, which makes them portable. Today's smart devices are light, with an improved battery life. The combination of all these features makes them irreplaceable at this time and their universal presence in the healthcare system keeps growing.

Mobile devices represent an ideal platform for many activities. Although they were originally used for communication and transmission of textual messages, over time they have become irreplaceable business assistants, and then even devices for quantitative monitoring of certain physiological parameters. With mobile phones, users are able to take part in their healthcare process, to monitor their health behaviour and habits on smartphones. They can access their medical records, monitor their vital parameters on portable devices (Salcedo & Espinosa, 2019), have access to lab test results from their homes, and monitor their health behaviour and habits through web applications on smartphones.

So the smart phones are often used for monitoring behaviour patterns that are indicative of the occurrence of symptoms of depression. In the study (Saeb, et al., 2015), existing built-in mobile phone sensors (GPS, location services) were used, as well as the mobile phones themselves (duration of use, frequency of use and way of use), and it was possible to identify a pattern which was closely related to depression symptoms in the general population.

A significant advance was also made in the way in which the data are acquired, so that the data are no longer only personal, but are also being shared with other users on social networks or with personal therapists.

Depending on the area of application, mobile health applications can be used to collect clinical and general health information and enable communication between individuals and the healthcare system (Costin & Rotariu, 2017). Moreover, the applications have the purpose of providing healthcare and preventive information, biofeedback, they perform monitoring and supervision, and they are also used for conducting

preventive programs, real-time monitoring of a patient's health status, and directly providing healthcare services (the area of mobile telemedicine).

Smartphone applications are rather popular among users and patients. Among them, there is a large number, over 160,000 (research2guidance, 2015) different commercial healthcare applications, which can be downloaded from online app stores. Health care applications which are downloaded in that way are generally not subject to standardisation or quality control, so their use for medical or healthcare purposes is often subject of debate. Mobile healthcare applications can be divided into nine categories (Heidi, et al., 2014) (UN Foundation-Vodafone Foundation Partnership, 2009) (Ventola Lee, 2014 May):

1. **Education and training.** Educational systems and systems for raising consciousness about health, which provide information on health promotion and disease prevention, educational programs, creation of virtual communities.
2. **Remote monitoring and access to data.** These are the applications for remote diagnostics and are most often used in primary healthcare, they provide access to remote databases and help healthcare professionals in decision-making.
3. **Patient monitoring.** Applications which provide treatment support in terms of controlling and conducting the treatment, rehabilitation, patient mobility, acquiring clinical data etc., as well as applications for reminders/scheduling of visits.
4. **Disease monitoring and epidemiologic supervision.** They enable the monitoring of infective diseases in real time.
5. **"Point-of-care" support.** They are used to provide physicians with permanent information for diagnostics, screening, treatment, access to healthcare information systems, as well as to the system for help in decision-making in diagnostics through mobile phones or tablets, instead of current static computers.
6. **eLearning.** It provides mobile platforms for support to educational systems in healthcare, communication, or continued education and training of healthcare professionals.
7. **Applications for improving quality of life.** Applications for the promotion of healthy lifestyles, fitness and well-being.

8. **Systems for medical emergencies.** They provide alerts for incidents, accidents or natural disasters.
9. **Applications for tracking finances.** They simplify the use of smart cards or vouchers in mobile payments.

INTERNET OF THINGS IN E-HEALTH

The Internet of Things represents a network of physical objects connected using wireless or wired Internet networks, which contain built-in sensor technology, allowing for interaction with the interior state of the smart device itself or with the external environment. Devices collect and exchange information directly between themselves, with other devices or through a cloud, where it is possible to collect, store and analyse data (Chouffani, 2015). For years, experts have been predicting that the Internet of Things – a system in which objects communicate between themselves or with other objects – would transform the way of life (Lopez Research, 2013).

According to Kevin Ashton, the first person to use the term IoT, people are limited by time and energy in collecting data about their environment and in using them in the right place and in the right time (Ashton, 2009). The devices which can store and analyse information, measure attributes and communicate between themselves can efficiently solve this problem, by producing a continuous flow of data which can be used for an adequate intervention (Prabhu & Iyappan, 2014). Internet of Things is a rapid innovation and a growing trend in expansion. Internet of Things technologies in business are most often used in mobile applications on users' phones, tablets or other digital devices, but also in production and distribution processes, where the product is monitored until the end user (TATA Consultancy Services, 2015). Forecasters say that by 2018 the total number of Internet of Things devices in use will have become equal to the number of smartphones, smart TVs, tablets (Adler, 2014).

Internet of Things is used to measure people's physical and psychological state in different life situations. For those measurements, different types of sensors, gateways, and cloud solutions are used in order for the measured data to be stored, analysed, and as such forwarded to the therapist, physician or to other locations.

Wearables are small electronic devices which are often composed of one or more sensors and have computing capabilities (Salah, MacIntosh, & Rajakulendran, 2014). They are a key component of items or objects which are worn on the body, e.g. on the head, foot, hands, wrists or waist, they can be built into clothes, or they can also be clothes themselves (Mann, 2014). They can take the shape of watches, sunglasses, clothes, contact lenses or even jewellery. Wearable devices are portable, which allows for the comfort and mobility of those wearing them. The measurements of certain parameters are possible during users' normal daily activities, whatever the location of the user, and the data will be transferred to a remote server or mobile device, where its further analysis and distribution will be performed.

Microcontrollers or microcomputers, i.e. processors, have the role of controlling the functioning of the sensors, processing the data and implementing network and routing protocols. Microcontrollers are small computers containing a processor, memory, and input/output peripherals. They contain limited memory, it is not possible to install an operating system on them, and they do not support multitasking. These are digital electronic devices in the form of integrated circuits which allow for devices and processes to be controlled. A microcontroller normally works in a control loop, namely it reads inputs and then sets up output according to the defined code. The loop is constantly repeated as long as the control of the process is taking place.

A microprocessor is a computer processor that incorporates the functions of a computer's central processing unit (CPU). The microprocessor is a multipurpose, clock-driven, register-based, programmable electronic device that accepts digital or binary data as input, processes it according to instructions stored in its memory, and provides results as output. The Arduino microcontroller and the RaspberryPi microcomputer are the most frequently used for testing and developing pilot projects. Actuators are devices which have the role of a switch. By using an actuator, it is possible to remotely control other devices. It is a mechanical device which moves or directs something, based on received instructions. Actuators can be electric, hydraulic, thermal, mechanical, pneumatic devices etc. or a combination thereof.

Wireless technologies constitute the basis of the Internet of Things system because they enable connecting the devices to other resources on the Internet. Sensors and smart devices connect to the Internet through an intermediary, most often through gateways. To do so, different types of wireless technologies and protocols are used to communicate with the gateways and transmit the collected information. A gateway integrates the information and forwards them onto the Internet.

Depending on the applied wireless technology, every sensor has its mark, which a gateways, as a more intelligent device, maps to a corresponding IP address, based on which the devices are identified on the Internet. Given the growing number of devices, as well as the introduction of the IPV6 address space, it is predicted that in the future IoT devices will directly connect to the Internet.

Internet of Things gateways have a key role in converting protocols, addresses and technologies. They enable wireless sensor networks and the Internet to be integrated, and provide the transfer of information from the sensor to the global Internet network, and the execution of applications hosted on Internet clouds. Cloud computing is based on virtualisation technologies and it is understood that information and services are stored on remote, scalable and shared resources (Radenković B. , Despotović Zrakić, Bogdanović, Barać, & Labus, 2015). Cloud computing has made it possible for computer resources to be stored and distributed to users according to their requirements, as well as for the resources to be processed simply and shared as needed.

Sensor networks are based on the following wireless technologies and protocols: RFID, WiFi, WiMax, 3G, 4G, LTE, IEEE 802.15.4/LoWPAN, etc. When it comes to wearable computing, the requirements of the modern business concern efficiency, optimisation, secure and permanent communication.

Over the last several years, we have been witnesses to an increased interest in wearable healthcare devices, both in research and in healthcare activities (fitness, wellness, devices for the disabled, dermatology etc.) (Ranck, 2012). The rapid development of new and different types of medical devices, including different sensors which are used alongside equipment, has been directed towards health status monitoring.

As nowadays many technologies are available (micro technologies, telecommunications, energy efficient devices which consume minimal amounts of energy, new fabrics and flexible sensors), it is possible to design new devices which are easy to use in order to increase the comfort and safety of patients. Sensors are also used in electronic medical devices, where their role is to convert different types of stimulants into an electric signal. In the area of healthcare, there are numerous devices such as devices for measuring blood pressure, blood glucose, devices for measuring body weight, thermometers, pulse oximeters, body composition analysers, home electrocardiograms, pedometers, bracelets and other devices, which help measure and monitor vital parameters. Internet of Things provides a simple network for these devices in order for information to flow constantly.

A large number of wearable healthcare devices (fitness, wellness, medical devices, well-being etc.) and mobile healthcare services have been implemented and successfully applied in the world (Salah, MacIntosh, & Rajakulendran, 2014).

Self-monitoring refers to collecting vital parameters and the parameters of a person's environment using sensors and other technologies for measuring and recording collected information. Quantified Self is a similar term which was defined in (Wikipedia, 2016) as the use of technological solutions for the collection of information concerning different aspects of a person's everyday life. Information that is most often recorded concerns food consumption and quality of breathing air, emotional states (mood, excitement, blood oxygen saturation etc.), behaviour and characteristics (mental and physical). This term, in combination with wearable sensors, is known as "lifelogging".

Apart from monitoring through self-report applications and social networks, a large number of mobile applications use sensors in order to enable passive monitoring of psychological responses, movement or the change of location. Sensors which monitor body posture in order to reduce back pain in people who spend a lot of time in a seated position are also significant and can be part of pain reduction interventions (Morris & Aguilera, 2012). Also an example is Jawbone UP, a necklace which monitors and feels activities, and a bracelet which monitors physical

condition, sending a result as a combination of exercise, diet and sleep. Systems like Sonamba, a wellbeing monitoring system (pomdevices, LLC, 2015), BreathResearch, Numera Libris and Libris+ use sensors to detect activities, analyse breathing or behaviour and monitor vital parameters. The research conducted among elderly adults shows that measurements inferred from mobile sensors highly correlate with traditional, well-established survey metrics (Rabbi, Ali, Choudhury, & Berke, 2011).

Psychological well-being through IoT and eHealth applications can provide significant support by using sensors which measure and analyse breathing patterns, such as Spire (Spire, 2015) and Muse (Interaxon Inc, 2015), a headband which uses a brain-sensing technology in order to measure brain activity during relaxation or different activities, and, based on the activity, it transforms signals into sounds.

Stress has been recognized as one of the leading problem in health care as well as its impact on people's health. Therefore, it's not surprising that stress is the subject of numerous researches, also in the field of Internet of Things in health. Stress activates the sympathetic nervous system, and its activation causes different reactions in the human body, such as the production of sweat, a heart rate increase and muscular activity. Long-term repetitions of such manifestations in any population are a frequent predictor of other health conditions and disorders, and even of mental illnesses which are hard to diagnose and treat.

The presence of stress can be identified through the measurement of different vital parameters on the user's body, as well as through the measurement of environmental parameters which can cause a change in the values of vital parameters. There are many researches dealing with stressor identification with the aid of different sensors and, more frequently, a combination of different sensors (heart rate sensor, GSR sensor, blood pressure sensor, accelerometer, etc.) (Rodic Trmcic, Labus, & Radenkovic, 2016) (Yang, et al., 2019).

Skin conductivity is one of the signals which are often used in lie detectors and also it has been included in many studies dealing with stress identification. In the study (Picard & Scheirer, 2001), a skin conductivity sensor was applied as a wearable device for the identification of a person's excitement in different activities, where a signal LED light simulated a

change in values. The same study cites an application in deaf people, where, through changes in the values of skin conductivity, it is possible to monitor excitement (happiness, joy) which cannot be expressed through words. The study (Zubair, Yoon, Kim, Kim, & Kim, 2015) also performed detection of mental stress in the course of everyday activities using skin conductivity sensors. In the case of a change in values, the user is sent an alert via mobile phone in order to manage the stressful situation or share information.

Using only a skin conductivity sensor for measuring stress onset, without monitoring the context in which the person is, can give a false impression of the presence of stress (Sykianaki, Leonidis, Antona, & Stephanidis, 2019). Every person reacts to stressful situations differently, therefore it is desirable to also implement other sensors or additional stress indicators, as well as observe changes in different contexts (Bakker, Pechenizkiy, & Sidorova, 2011).

In a following study, a skin conductivity sensor and existing mobile phone features (calls, SMS, location services) were used for stress detection, and the results were compared to the traditional research techniques for stress detection (respondent notes the changes in behavior in mobile phone) (Sano & Picard, 2013).

Heart rate is one of more certain indicators of the presence of a change in mood or stress, and it is useful to monitor it in actions of health prevention. Personal health monitors as a wireless body area network (BAN) have been used in soldiers. Individual monitoring systems were integrated with wireless systems and used as part of psychophysical evaluation of soldiers going through intensive training. Heart rate measurements were taken in order to quantify stress levels, and also as a predictor of resistance to stressful situations [168] (Rodic-Trmcic, Labus, Bogdanovic, Despotovic-Zrakic, & Radenkovic, 2018).

An electrocardiogram (ECG) measuring heart rate together with a respiration sensor, a skin conductivity sensor, has often been used in combination for stress detection in different life situations, e.g. when driving a car in different environments and situations (Singh & Banetjee,

2010) or for office stress management when performing everyday work-related activities (Wijsman, Grundlehner, & Hermens, 2013).

Among students, there is a frequent onset of stress whose sources lie in a change in habits, short deadlines, separation from home, social environment, long waiting in lines etc., all of which can significantly contribute to a reduction in academic performance (Sohail, 2013) (Rodic-Trmcic, Labus, Bogdanovic, Despotovic-Zrakic, & Radenkovic, 2018) (Can, Arnrich, & Ersoy, 2019).

A number of papers have looked into measuring the psychological state and physical reactions in students and their academic success, as well as calculating their correlation (Ping, Subramaniam, & Krishnaswamy, 2008), (Silvennoinen, et al., 2019), or the improvement of student's mental health (Millings, et al., 2015) (Rodic-Trmcic, Labus, Bogdanovic, Despotovic-Zrakic, & Radenkovic, 2018).

The research carried out by Shen, Wang & Shen (Shen, Wang, & Shen, 2009) by using psychological signals to predict emotions investigated the presence of different emotions in the studying process, and a proposal of a sensible e-learning model was presented. The data were acquired using three sensors: skin conductivity measuring electrodermal activity, photoplethysmograph measuring blood pressure, and sensor electroencephalograph measuring EEG brain activity. Measurements were taken over several weeks on one subject in natural environment, the closest possible to the everyday environment. In the study (Kusserow, Amft, & Tröster, 2013), a heart rate sensor was implemented together with a skin conductivity sensor, accelerometer and temperature sensor in a familiar natural context – public appearance of PhD students in front of an audience, where significant variations in the values of measured vital parameters were observed.

Also, study carried out by McGowan and others (McGowan, Hanna, Greer, & Busch, 2018) presents the design and results of students' heart rate activity during a series of university computer programming lectures. Finally, they find that there is a significant correlation between elevated heart rates and module scores.

Apart from the sensors worn on the body, which measure an individual's vital parameters, it is important to take measurements of certain properties of the environment which can cause or affect the onset of stress or a behavioral change (Birenboim, Dijst, Scheepers, Poelman, & Helbich, 2019). A research conducted in Minnesota, US, measured air quality in 85 classrooms, in 8 schools, using sensor packs mounted on classroom walls. The data were uploaded to a remote website via Internet. Unusual values of carbon monoxide and dangerous matters in illegal concentrations implied further investigations as soon as the results were obtained (Grimsrud, Bridges, & Schulte, 2006).

In the study (Lee & Chang, 1999), conducted in Hong Kong, in five classrooms, fitted with air conditioning or aired naturally, measurements were taken of temperature, relative humidity, carbon dioxide, sulphur dioxide, nitrogen oxide and nitrogen dioxide, particles with a diameter smaller than 10 μm , formaldehyde and total bacteria. Measurements were conducted inside and outside of the rooms. The results show that, in the majority of cases, particles with a diameter smaller than 10 μm were found to be most dangerous.

One study was performed in order to investigate the effect of smell on heart rate and short-term memory. Lemon and lavender were used as stimuli in order to increase or decrease heart rate, as well as to monitor the improvement or the deterioration of memory. The research was conducted in California, on 67 subjects, but it did not find statistical significance which would confirm the hypothesis concerning the influence of smell on heart rate. It was found that certain smells can alter the psychological response, as well as the mood and cognitive processes, but no significant link was found between smell, heart rate and short-term memory (Jackson, 2011).

Heart rate is one of more certain indicators of the presence of a change in mood or stress, and it is useful to monitor it in actions of health prevention. A heart rate measurement system is often implemented in devices related to sports (Polar Electro, 2019), fitness (BASIS Science, 2015), as part of health applications (Maiaa, et al., 2014), (Wu, et al., 2009), as part of remote diagnostics where data are forwarded to health institutions

(Kemis, et al., 2012) (Kakria, Tripathi, & Kitipawang, 2015), and in stress management (Millings, et al., 2015).

Apart from real-life situations, stress measurement can also be performed in a laboratory, which was successfully conducted in the paper (Kirschbaum, Pirke, & Hellhammer, 1993). Trier Social Stress Test (TSST) is a laboratory procedure which reliably causes stress in subjects, and it is composed of a combination of procedures which are known to have previously caused stress in people with certainty. TSST is nowadays used in numerous researches, and heart rate, cortisol, and prolactin are taken as stress indicators (Kirschbaum, Pirke, & Hellhammer, 1993), (Wijsman, Grundlehner, & Hermens, 2013).

The use of sensors and smartphones in monitoring health status usually implies: collecting data from the sensors; providing support to the user via a display with the measured values; providing Internet access for sharing the information; ensuring the low-power aspect, wearability, precision, longevity and reliability of devices.

MODEL OF MOBILE HEALTH FOR WELL-BEING BASED ON WEARABLE COMPUTING

In this chapter the model of mobile health for well-being based on wearable computing has been introduced. Wearable sensors which are worn on the body allow the vital parameters of the person wearing them to be measured. A smartphone acts as a gateway for transmitting the information to the server, and it also provides local processing of the information and reporting. The system for processing data from the environment and the vital parameters measured on the user's body is system based on the medical or health algorithms that operate actuators and health messages in a given context.

A model of mobile health for well-being based on wearable computing is illustrated on the Figure 1.

Different types of alarms and alerts can be sent in the form of SMS to the user's phone, depending on the measured information. The user has at his or her disposal a well-being app which helps him or her reduce stress if a

certain alarm sounds, suggesting that the values of certain vital parameters are high.

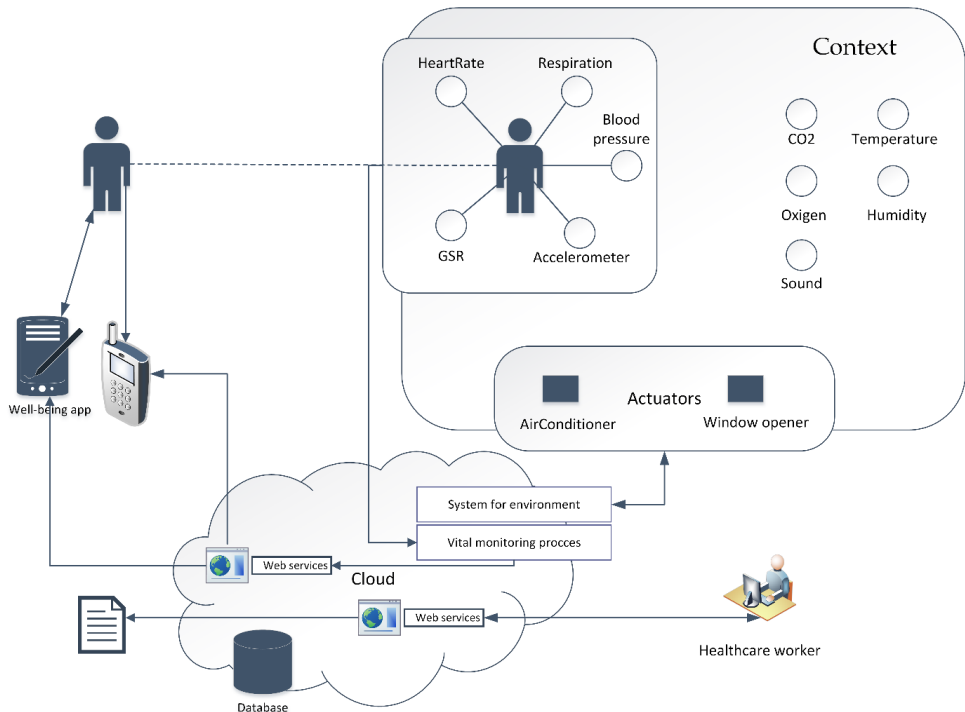


FIGURE 2. A model of mobile health for well-being based on wearable computing

Using wearable sensors, it is possible to measure respiration, heart rate, SPO2, blood pressure, skin conductivity (GSR), and intensity of movement using an accelerometer.

A smartphone, using an appropriate communication network (Wi-Fi, Bluetooth, GPRS, 3G), transmits the measured values to the server database. The values on the server are processed and are available to the therapist or to the user for further analysis or distribution. The healthcare professional or mentor who is registered on the user system is allowed to monitor and analyse information concerning the user and point out certain irregularities, as well as to organise preventive activities aimed at

improving and advancing health or to work on improving the stressful environment (Rodic-Trmcic, Labus, Mitrovic, Buha, & Stanojevic, 2017).

A well-being app provides a number of ways to eliminate stress, relaxation before the activity expected to be stressful for the user. Sensors are key elements of the well-being monitoring system. Body temperature is a basic physiological parameter and variations in its values can be a symptom of stress. The user's physical activity can be tracked through the smartphone and built-in sensors (pedometer, accelerometer etc.).

A heart rate sensor records the user's heartbeats and is an important parameter in evaluating the health status or the exposure to stress. The technology of measurement is usually based on two beams of light of different wavelength that are focused onto the human nail tip. The measured signal can then be obtained by a photosensitive element.

SpO₂ (peripheral capillary oxygen saturation) is an estimate of the amount of oxygen in the blood. The measured results are the percentage of oxygenated haemoglobin (haemoglobin containing oxygen) compared to the total amount of haemoglobin in the blood (oxygenated and non-oxygenated haemoglobin). SpO₂ can be measured indirectly, by pulse oximetry, which is a non-invasive method (it does not involve the introduction of instruments into the body). It works by emitting and then absorbing a light wave passing through blood vessels in the fingertip. Colour of the blood has variations depending of the oxygen saturation, and light wave passing through the finger will provide the value of the SpO₂ (Withings, 2015).

The Blood Pressure Sensor is a sensor designed to measure human blood pressure. It measures systolic, diastolic and mean arterial pressure by utilizing the oscillometric technique.

Galvanic Skin Response – skin conductivity sensor, GSR, is a method of measuring the electrical conductance of the skin. Strong emotion can cause stimuli to the sympathetic nervous system, resulting in more sweat being secreted by the sweat glands. GSR allows such strong emotions to be spotted by simply attaching two electrodes to two fingers on one hand (Seed Studio, 2015).

Humidity and temperature can affect the mood and state of the subject, so in the proposed model they are measured in the room using appropriate sensors. High humidity and temperature can result in the lowering of blood pressure, increased sweating and a feeling of unease, so they are connected to actuators which open the window or control the functioning of air conditioning.

Carbon-dioxide saturation in a room is measured using a carbon-dioxide sensor, and the obtained values help decide if the actuator which opens the window and airs out the room should be activated. An oxygen saturation sensor is in correlation with the CO2 sensor, and the measured value affects the decision of ventilation the room.

Since a high level of noise can cause concentration issues, the values are measured using a noise sensor, the obtained information is analysed, and appropriate action is taken according to the obtained parameters (e.g. the window is closed).

IMPLEMENTATION OF THE WEARABLE SYSTEM FOR WELL-BEING

Many students face different stressful situations when taking exams, which can have a negative impact on the very result of the exam or test. At the same time, bad results are not indicative of a student's poorer intelligence or knowledge (Ali & Mohsin, 2013), (Li, Xue, Zhao, Jia, & Feng, 2016). In this part, we put together in the case study, a wearable system for measuring vital parameters and environmental parameters and the mobile health application for well-being with relaxation features which was developed in order to monitor the changes in vital parameters among students in stressful situation for them. The data was stored on a local server (MySQL database). In that way, the information was able to be both monitored in real time and analysed by the mentor or the user.

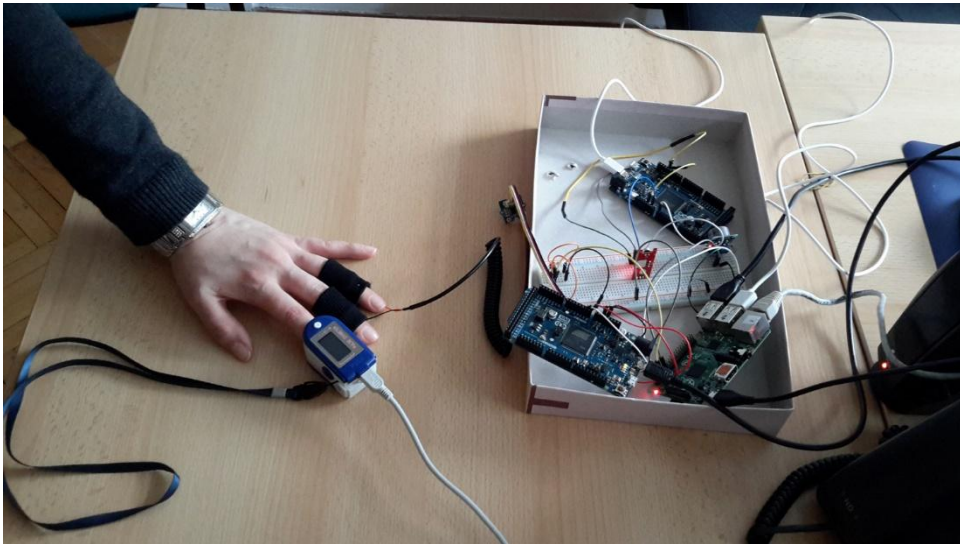


FIGURE 3 - System for monitoring vital parameters and environmental parameters

The implemented system is composed of a heart rate sensor and oximeter (Pulse Oximeter Contec CMS 50D+), a skin conductivity sensor (Grove – Galvanic Skin Response – GSR), sensors for measuring noise, temperature and humidity. The system was implemented using the *Arduino* microprocessor and the *Raspberry Pi* microcomputer. The implementation on these devices was carried out using the *Python* programming language and the *php* script language.

Figure 2 shows the cable connections between the microprocessor and different sensor.

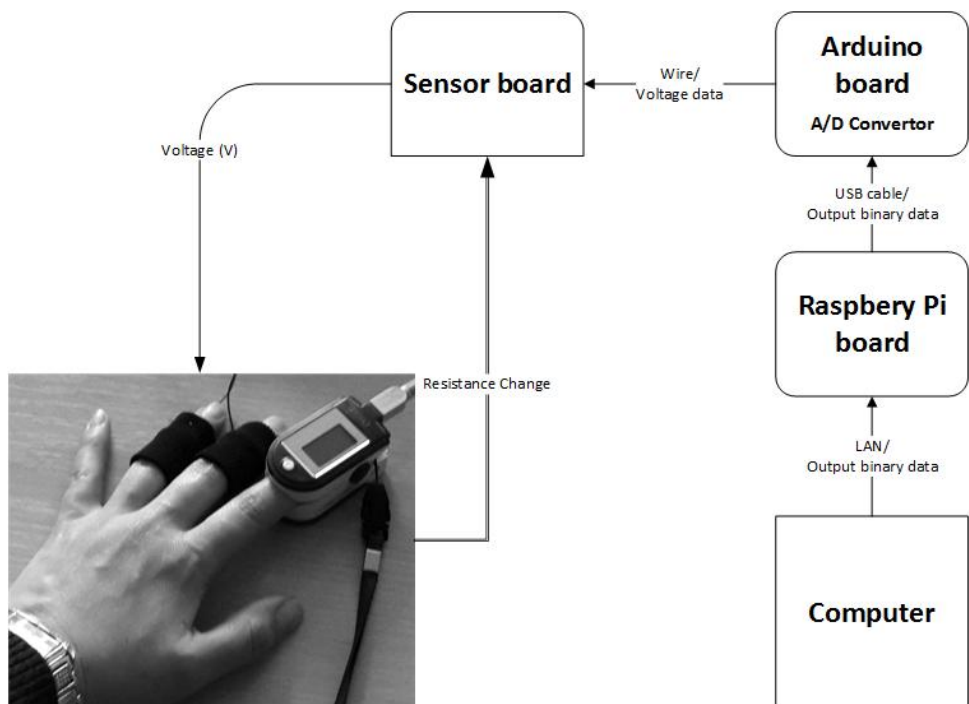


FIGURE 4. Path of the signal from GSR sensor to computer screen

A USB cable was used to connect Raspberry Pi and Arduino.

After receiving a piece of information from Arduino, Raspberry Pi has the role to read the information and, if no errors are recorded, to write that information into the MySQL database on the local server.

Values retrieved via sensors for skin conductivity have been converted through AD converter and as the output signal the voltage resistance change as binary data is presented.

Figure 3 shows a schematic of receiving signals through sensors GSR.

The data can be transferred via Bluetooth/GPRS/Wi-Fi/ZigBee communication modules. In the created module, we established communication via LAN.

It is possible to access to data with the values of environmental parameters and vital parameters through a web service which accesses the MySQL database on the server and looks up entries with recorded values. The values returned by the web service are in JSON format which is parsed and, based on the obtained values, a chart with heart rate values is drawn and shown on the screen.

The Android well-being application was created in the Android Studio 1.2.1 programming environment, using the Java programming language. Contents that students-assistants found to be relaxing were implemented in the app.



FIGURE 5. Android application for wellbeing with content for relaxing

METHODOLOGY

The application of the Internet of Things in vital sign monitoring and in different life situations aims to improve the quality of life, ensure well-being, and prevent diseases caused by repeated stressful situations.

The aim of case study is to identify the psychophysiological signals indicating stress during students' term papers defending. The difference between the measured values of GSR, oxygen saturation and heart rate, measured in students before and before, during and after the defence of the term papers using the created wearable system, will be established. Also, it will be examined and compared the results of respondent who had used the mobile health application for well-being for relaxation with respondent who hadn't used it.

The students were supposed to defend term papers in e-business, i.e. Internet of Things in e-health, and they were familiar with the concept of the wearable computing.

Sample

The testing of the implemented system took place in March 2016 at the E-business Laboratory of the Faculty of Organizational Sciences, University of Belgrade. The participants in the research were two female BA students at the Faculty of Organizational Sciences, University of Belgrade. The measurements were conducted over two days, one subject per day. The first student (respondent 1) constituted the experimental sample – she used the mobile health application for well-being with relaxation content, whereas the other student (respondent 2) served as the control sample – without the mobile health application for well-being with relaxation content.

Instrument

For this research, a general questionnaire was created, and it was filled out by the respondents in the first phase – pre-test. The general questionnaire consisted in demographic questions about the respondent. It was not anonymous.

In order to evaluate anxiety level before testing, after the test, and after relaxation following the completed test (Weenk, et al., 2018), Spielberger's (Spielberger, 1980) Text Anxiety Inventory (STAI) test and State-Trait Inventory for Cognitive and Somatic Anxiety (STICSA) test (Gros, Antony, Simms, & McCabe, 2007) were used. STAI is a self-report instrument for

measuring anxiety. It contains 20 questions and, according to the author, it was specifically designed to measure anxiety in high school and university students. The answers were provided in the form of a 4-point Likert scale, namely: 4 – very much so, 3 – moderately, 2 – a little, 1 – not at all. Respondents rated the extent to which each statement is true for them on a 4-point Likert scale. The instrument refers to the student’s state at the given time, independently of how the respondent felt in an earlier period. The questionnaire was in Serbian.

The STICSA State assesses how respondents “feel right now, at this very moment, even if this is not how you usually feel,” and the scale is composed of 21 self-report items. Respondents rate each item on a 4-point Likert scale, ranging from 1 (not at all) to 4 (very much so). The questionnaire was in English.

Table 1 shows the descriptive statistics of the sample.

TABLE 1. Descriptive statistics of the sample

	Respondent 1	Respondent 2
Sex	Female	Female
Age	23	22
Weight (kg)	79	65
Height (cm)	174	172
Smoker	No	Yes
Physical activity	Once a week, half an hour at least	A couple of times a week, half an hour at least
No. of years of study	5	4
Place of living during studies	Student dormitory	Rented apartment

Research design

As the basis for the test, the Trier Social Stress Test (TSST) method was used. Test protocols in certain researches can differ regarding the duration of the preparation of the test or the tests that are used (Birkett, 2011)

when compared to the original protocol (Kirschbaum, Pirke, & Hellhammer, 1993).

We opted for the following protocol, bearing in mind the population and the environment in which the test was conducted:

1. A comfortable room was provided for relaxing (in which the respondents wait for testing and relax after testing) and for testing (in which the TSST is conducted – preparing the presentation, the presentation itself, and the mathematics test).
2. The respondents were divided into two groups; one respondent was provided with the well-being Android smartphone app during the 15-minute wait for the test and after the test; the other respondent waited and relaxed in the room without a phone or any reading materials.
3. The students were assigned unique codes under which the tests and measurements were to be recorded.
4. The seating plan for the examiners and the respondent in the laboratory was determined and a camera was placed in front of the respondent.
5. The examiners were instructed to maintain eye contact with the respondent and avoid any facial expressions during the TSST.
6. In the room – laboratory in which the research was to take place a system for measuring vital parameters (heart rate, GSR, SPO2) and environmental parameters (humidity, temperature, and noise level) was installed, and pens and paper were provided (Figure 2).
7. The respondents were told not to take any food for 2 hours before the test, except for water.
8. At the very beginning of the test, the respondents were connected to the system for measuring vital parameters (heart rate, SPO2 and GSR were measured), and the general questionnaire, STAI and STICSA test were distributed.
9. Respondent 1 relaxed for 15 minutes using the well-being app with relaxation content. Respondent 2 waited for the test without any content.

10. TSST lasting 15 minutes was conducted. Heart rate and skin conductivity were measured during the test.
11. After the end of the test, the respondents were distributed STAI and STICSA anxiety measurement tests.
12. After filling out the questionnaires, the respondents were given a detailed explanation of the aim and the purpose of the research. The respondents relaxed for 15 minutes.
13. After rest and relaxation, anxiety tests (STAI and STICSA) were repeated.

Pre-test measurement

On arrival, respondent 1 was led to a comfortable room, sensors for measuring vital parameters (heart rate, SPO2 and GSR) were attached to her. Heart rate sensor was attached on forefinger, GSR sensor on middle and ring finger on the palm side of the left hand. She was then asked to fill out the general questionnaire, STAI and STICSA tests. After completing the tests, respondent 1 was given a tablet with a pre-installed Android relaxation application and short instructions on how to use it. The respondent was told that she had 15 minutes of relaxation during which she could relax using the application content. During the use of the mobile application, the duration of the use of the application and the content browsed by the user were tracked. The obtained values for the respondent were recorded. Respondent 2 relaxed for 15 minutes without the app or any other relaxation materials. During the pre-test, environmental parameters were measured (temperature, humidity and noise).

Test

The test began after the 15-minute rest and relaxation. Three examiners entered the room. The test consisted in three parts: the first part of the test, in which the respondent was asked to write preparatory notes for the presentation, lasting five minutes; the second part, in which the respondent was asked to present the term paper, lasting five minutes; the third part, in which an examiner asked the respondent five questions related to the paper and asked them to solve a mathematical problem. The

test began with one of the examiners reading the following text to the respondent: "You are expected to prepare notes for the presentation of your term paper within five minutes, and then to orally present your paper within exactly five minutes. Your presentation will be recorded. The time starts now!"

For the entire duration of the test, vital parameters (heart rate, SPO2 and GSR) were measured. The timer was set to five minutes. After the time was up, an examiner unexpectedly took the paper with preparatory notes from the respondent and asked her to move to the second part of the test – the defence of the term paper lasting five minutes.

If the respondent paused for more than 20 seconds, she was told that she could continue and the remaining time until the end of that part of the test was read out to her. After the 5-minute of the term paper defence, an examiner asked the respondent five questions related to the paper (approximately 2.5 minutes), and then the mathematical part of the exam started, lasting for approximately 2.5 minutes. The respondent was asked to count backwards, subtracting 13 from 1022. If the respondent made a mistake, they were asked to start from the beginning. They were informed of that by saying: "You are wrong! 1022." After the entire 15-minute test time was up, the respondent was told that TSST was completed and they were asked to repeat STAI and STICSA tests.

Post-test

After completing STAI and STICSA tests, the respondent was left to rest and relax for 15 minutes. Respondent 1 was given the well-being application, whilst respondent 2 was left in the room without a mobile phone or any relaxation material. At that point the respondent was informed that the goal of the test was to cause stress and to measure it. It was made clear to the respondent that the tasks they were given were unreasonably difficult and were in no way a reflection of their abilities, and also that the test and the presentation have no effect on their grade. After the period of rest, STAI and STICSA tests were repeated. During the entire

relaxation period, vital parameters (heart rate, SPO2 and GSR) were measured.

RESULTS

In this case study, we demonstrated the use of a wearable system and an Android mobile health application for well-being with relaxation content for performing Trier Social Stress Test on a sample composed of students. TSST is a standardised laboratory test, consisting in procedures which typically cause stress in people. TSST is a useful alternative to physical stressors, such as a treadmill or cold surface, and it produces much more realistic psychological stress, considering the circumstances and the environment (Birkett, 2011).

Figures 5 and 6 show the results of the two conducted tests: STICSA and STAI in respondents 1 and 2.

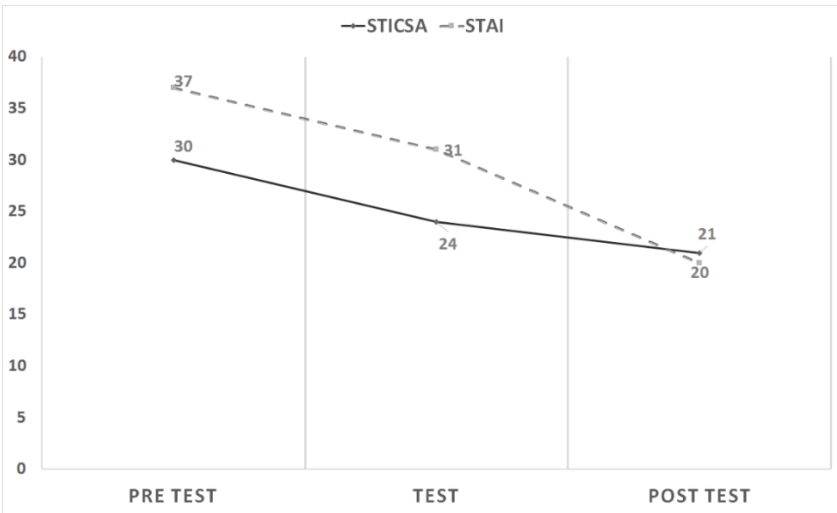


FIGURE 6. The results of two tests: STICSA and STAI for respondent 1 (with app for relaxing)

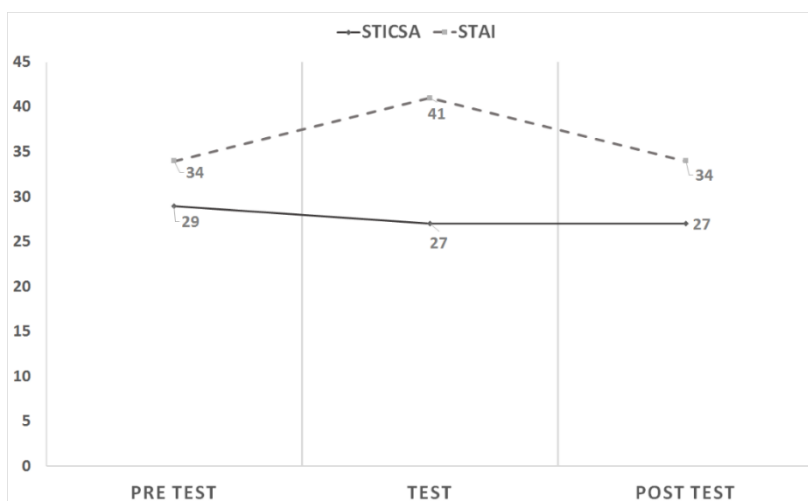


FIGURE 7. The results of two tests: STICSA and STAI for respondent 2 (without app for relaxing)

In both tests (STICSA and STAI), respondent 1 showed a higher level of anxiety in the period before the test and before relaxing using the well-being app. During the test and until the end of post-test, anxiety continued to weaken significantly, most likely as a result of the period of quality rest before the test itself and after the test using the well-being app. In the pre-test period, respondent 1 spent a total of 13.2 minutes using the mobile health application for well-being with relaxation content. Table 2 presents an overview based on the content and the time spent browsing certain content during the pre-test period.

TABLE 2. The time spent browsing well-being app content during the pre-test period for Respondent 1

Application content	Duration (minutes) in pre-test period
Fun sport	8.9
SPA music	3.1
Relax photos	1.2
Sum	13.2

TABLE 3. The time spent browsing well-being app content during the post-test period for Respondent 1

Application content	Duration (minutes) in post-test period
Fun sport	9.4
SPA music	5.6
Relax photos	0
Sum	15.0

Table 3 shows the time that respondent 1 spent using the mobile health application for well-being in the post-test period, i.e. in the period designated for rest and relaxation.

In the post-test period, respondent 1 spent all of the rest and relaxation time using the mobile health application for well-being with relaxation content, which most likely resulted in reducing anxiety to minimal levels. The longest amount of time was spent in the Fun sport section, featuring funny content from the world of sports, which was followed by listening to relaxing music.

The students' Spielberger STAI test scores were categorized into low (20 to 40), moderate (41 to 50) and high (51 to 80) (Ping, Subramaniam, & Krishnaswamy, 2008).

Respondent 2 showed a more noticeable difference in the STAI test after testing. Therefore, respondent 2 exhibits a moderate anxiety level after TSST. Pre-test and post-test values of the tests are equal (STAI) or nearly equal (STICSA).

The values of STAI and STICSA tests follow the skin conductivity values measured using the GSR sensor, with the values presented in Figure 6.

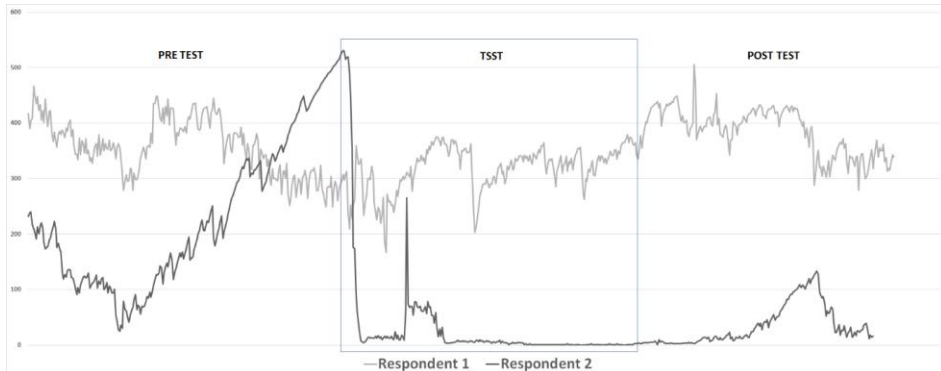


FIGURE 8. GSR data for respondent 1 and 2

GSR values present significant deviations in respondent 2 during TSST, with the most evident one corresponding to the part of the test with questions and the mathematical problem in TSST. Extremely low GSR values in respondent 2 may be a consequence of poor circulation, given that the respondent is a smoker, and her hands, when testing the functioning of the sensor, were very cold.

Respondent 1 shows no significant deviations in GSR values, and slight deviations can be noticed during TSST.

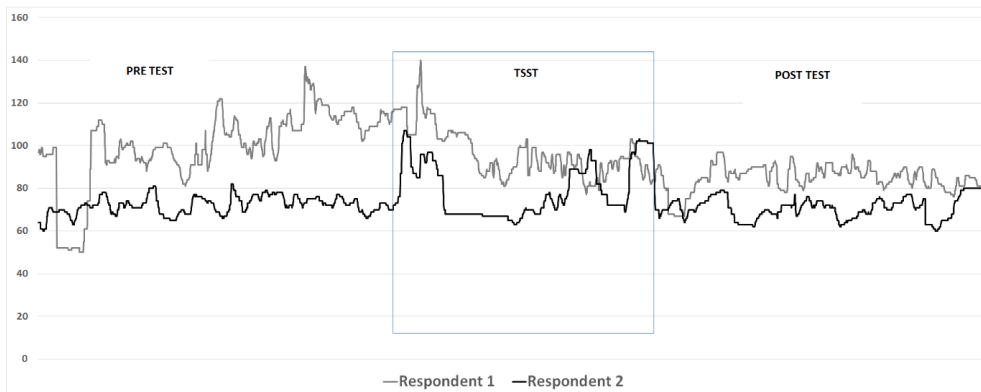


FIGURE 9. Heart rate values for respondent 1 and respondent 2

Figure 8 shows the heart rate values for both respondents at the same time. No significant deviations are noticeable in respondents' heart rate

values. Respondent 1 has a significantly higher physiological heart rate, unlike respondent 2. The average heart rate value of respondent 1 stood at 97 bpm, whereas that of respondent 2 amounted to 74 bpm. The average oxygen saturation (SPO2) in respondent 1 stood at 98%, whereas in respondent 2 it was somewhat higher, at 98.5%.

The mean measured heart rate values for both respondents during the different test stages are shown in Table 4.

TABLE 4. Means of heart rate measurement during the different stages in test for both respondents. The values in brackets show differences from one stage to the next

Respondent/Heart rate	Pre-test (bpm)	TSST (bpm)	Post-test (bpm)
Respondent 1	95	109 (+14)	90 (-19)
Respondent 2	72	81 (+9)	70 (-11)

Respondent 1 showed a more significant heart rate increase during TSST when compared to respondent 2.

The mean measured values of environmental parameters are given in Table 5.

TABLE 5. Environmental parameters for both respondents

Parameter	Respondent 1	Respondent 2
Temperature (C°)	26.5	23.5
Humidity (%)	44	55
Noise (dB)	41.5	43

Respondent 1 had more unfavourable conditions concerning air temperature, and somewhat more favourable conditions of humidity and noise.

CONCLUSION

The Internet of Things is the paradigm of the modern world in which people and devices are linked and communicate ones with the others. The human dimension of the Internet of Things is the fact that it has a role in the healthcare sector and it can change the healthcare system for the better. Until present, different technological solutions have been developed with the aim of improving healthcare and conducting preventive actions.

The proposed model demonstrates one of the ways of integrating the concepts of electronic health, mobile health, Internet of Things and wearable computing. The implemented wearable well-being system allows for the monitoring of respondents' vital parameters, as well as of the environmental parameters which can have an effect on increasing or decreasing stress in a respondent.

The wearable system solution proposed in this paper can be successfully applied in order to monitor stress levels in different life situations. In the research we have conducted, it has been shown how mobile healthcare applications (for well-being, with relaxation content) can have an impact on reducing anxiety in respondents (university students) during the presentation of term papers.

The values obtained in the research indicate that the use of a mobile health application for well-being with relaxation content had no significant impact on heart rate values. The heart rate significantly decreased in respondent 1 (13% from mean value in pre-test) during TSST in relative to respondent 2 where it decreased by 6.5%.

In reference to the variations in GSR values, we draw the conclusion that the well-being app with relaxation content can reduce nervousness and sweating of the palms, but with limitations, since the research was conducted on only one respondent, and the respondent was a smoker, which could have had an impact on poorer circulation and reduced galvanic skin response values.

The main limitation of the study is the small and homogeneous sample. The future development of the system should be directed towards implementation of a wearable system, small sized, and then monitor the vital parameter of respondents who stands during the defense of term paper or thesis.

Apart from heart rate, SPO2 and GSR sensors, future research should also include sensors for measuring blood pressure, respiration, body temperature and accelerometers. By analyzing the values obtained from these sensors, it is possible to analyze a respondent's psychological state more precisely. By implementing alarm systems or alerts, it is certainly possible to prevent adverse effects of stress or have an impact on reducing stressors in different life situations.

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