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- THE DOCTORAL THESIS SUMMARY-

SISTEM ADAPTIV DE INSTRUIRE ASISTATĂ DE CALCULATOR

AN ADAPTIVE FRAMEWORK FOR COMPUTER-BASED TEACHING TECHNOLOGY

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Contents

Abbreviation List - English - Romanian

AES	**Adaptive E-Learning System**	Sistem E-Learning adaptiv
AI	**Artificial Intelligence**	Inteligență artificială
AR	**Augmented Reality**	Realitate augumentată
BASN	**Body Area Sensor Network**	Rețeaua senzorilor zonei corpului
BL	**Blended learning**	Instruire mixtă
BLE	**Bluetooth Low Energy**	Bluetooth cu energie redusă
BMI	**Body Metabolic Index**	Indicele metabolic al corpului (IMC)
BVP	**Blood Volume Pulse**	Pulsul sanguin
CART	**Classification and Regression Tree**	Arborii de clasificare si de regresie
DSP	**Digital Signal Processing**	Procesarea digitala a semnalului
Edu 4.0	**Education 4.0**	Educația 4.0
ERS	**Early Recognition System**	Sistem de Avertizare Timpurie
GUI	**Graphical User Interface**	Interfață grafică
HRV	**Heart Rate Variability**	Variabilitatea bătăilor inimii
ICT	**Information and communication technology**	Tehnologia informației și comunicațiilor
IND 4.0	**Industry 4.0**	Industria 4.0
IoT	**Internet of Things**	Internetul lucrurilor
IoP	**Internet of People**	Internetul oamenilor
IoS	**Internet of Services**	Internetul serviciilor
IoWT	**Internet of Wearable Things**	Internetul lucrurilor purtabile
ITS	**Intelligent Tutoring Systems**	Sisteme inteligente de tip Tutor
KDD	**Knowledge Discovery in Databases**	Descoperirea cunoștințelor in baze de date
KPI	**Key Performance Indicator**	Indicator cheie de performanță
LA	**Learning Analytics**	Analiza învățării studenților
LLL	**Lifelong Learning**	Învățarea pe tot parcursul vieții
LMS	**Learn Management System**	Sistem de management al învățării
LO	**Learning Object**	Material de instruire

MAD	**Mean Absolute Deviation**	Media abaterii absolute
MCU	**Microcontroller**	Microcontroler
ML	**Machine Learning**	Învăţarea automată
MOOC	**Massive Open Online Course**	Cursuri de învăţare online f. mari
NFC	**Near Field Communication**	
NN	**Neural Network**	Reţea neuronală
OS	**Operating System**	Sistem de operare
PASS	**Personalized Adaptive Study Success**	Succesul studiului adaptiv personalizat
PNS	**Parasympathetic nervous system**	Sistemul nervos parasimpatic
PPG	**Photoplethysmography**	Fotoplestimografie
rMSSD	**Root Mean Square of the Successive Differences**	Rădăcina medie pătratică a diferenţelor succesive
RQ	**Research Question**	Întrebarea de cercetare
SKT	**Peripheral skin temperature**	Temperatura periferica a pielii
SNS	**Sympathetic nervous system**	Sistemul nervos simpatic
SRL	**self-regulated learning**	Instruirea autoreglată
SVM	**Support Vector Machine**	Maşini cu suport vectorial
STEM	**Science, Technology, Engineering and Mathematics**	Ştiinţele Naturii, Tehnologie, Matematică şi Inginerie
TEL	**Technology Enhanced Learning**	Instruirea îmbunătăţită cu ajutorul tehnologiei
DIT	Technische Hochschule Deggendorf	
USB	**Universal Serial Bus**	Bus serial universal
VR	**Virtual Reality**	Realitatea virtuală

1. Introduction

The digitization in higher education is at the beginning. The extracted data and knowledge are the new gold of the period we live in. The Fourth Industrial Revolution is forcing us to rethink the way we live, work and learn. The teaching process for the future is designed with evidence-based decisions from learning analytics design and machine learning methods is becoming more and more up-to-date. This is necessary because Industry 4.0 is creating a demand of high-quality education, teaching and learning also in quantitative terms. On the other hand, the success of Artificial Intelligence (AI) has recently led to an increased demand for technology for 4.0 elements in teaching. The Higher Education 4.0 uses elements from different disciplines: electronic technology, artificial intelligence, medicine, education, etc. The Education 4.0 helps the university management and professors to understand students experience by offering them adaptive and personalized training necessary for Industry 4.0 future-ready engineers.

The future engineer who will master the Industry 4.0 requirements is a so-called "*Tall Thin Engineer*" [o2] with the skills of innovation, artificial intelligence (AI) methods, creativity, AI support decisions and leadership. The VDE Tec Report 2018 results presented at the Hanover Messe: companies called for a strong AI innovation as a key technology for the digital transformation and to remain at level of international competition. According to survey results, 73% of questioned companies, institutions and universities want to adapt training courses in the field of AI needs [VDE]. Each branch (logistics, industry, services, administration, etc.) will face the challenge of 4.0 (networking, digitization and artificial intelligence) in the coming years and must react with 4.0 concepts in order not to endanger their own existence. Every industry has a need for academic 4.0 skills [o8].

Due to the large number of medium-term qualification and retraining courses are required and due to the growing demand for higher education graduates, **traditional teaching and training methods have reached their limits.** This requires new paradigms of teaching and learning a new way of transmitting knowledge. An answer to these is also offered by my contribution **to the Education 4.0 with adaptive training, modern technology and teaching methods adapted** to **requirements of Industry 4.0** [o2]. There are three key challenges for higher Education: electronic technology, adaptive instruction and creation laboratories for free innovation.

The importance of this thesis is more stressed during the pandemic crisis COVID-19. Around the world, the technologies powering the fourth Industrial Revolution and speeding up innovation in higher education. The use of sensors integrated in wearables provide us with information about a person's physiological signals and location in real time. Applying artificial intelligence methods make us possible to analyze student's health, better identify clusters of strategic importance and to alert the students at-risk.

1.2 Thesis objectives

This thesis introduces new paradigms, methods and a prototypical implementation of an adaptive computer training system. It addresses three main objectives: First, **helps** students to be qualified and specialized for Industry 4.0. Second, **motivates** students to improve performance, to pass the examination taking advantage of artificial intelligence and machine learning methods. Third, gives them **confidence** in new technologies and the ability to use them. The thesis solution includes: the use of wearable devices, embedded sensors and artificial intelligence in the field of **Education 4.0**; an Internet of Things (IoT) system for the Education 4.0, and an *"Early Recognition System"*, with machine learning algorithms for students at-risk to fail the examination.

1.3 Thesis outline

In Chapter 1, we provide the motivation for this topic as well as the purpose of the thesis. In Chapter 2, we provide a brief overview over the development of programmed instruction (assisted teaching) and the field of artificial intelligence and machine learning algorithms relevant to this thesis, as well as Data Mining methods for data exploration.

In Chapter 3, we review sensors of wearable devices, methods of measuring of physiological signals obtained with the help of embedded sensors. These, assisted by artificial intelligence, aim to a better academic performance and wellbeing of students. Techniques for acquiring physiological data and non-invasive measurement of physiological signals without medical personal, as well as some background information's of human anatomy and physiology are also presented.

In Chapter 4, we present revolutions in higher education and introduced Education 4.0, that requires the methods of artificial intelligence and the seven stages of the learning process that we identify for the training of future engineers ("*Tall Thin Engineer*") [o2]. In order to understand the criticism, we have levelled at earlier formulations of the concept of Education 4.0, it was necessary to look back at the evolution of educational technology. We present revolutions of industry until today Industry 4.0 and their analogy to higher education. New paradigms of teaching, instruction and learning are needed, as well as the use of hardware for data acquisition. Educational activity is increasingly moving online and course contents are becoming available in digital format [o4]. It allows the collection of data and their use for "Learning Analytics". For the 4.0 Revolution in higher education, an active and interactive presence of students contributes to a superior learning quality [o4].

In Chapter 5, we present our experiments on the implementation of IoT architecture in Education 4.0, using non-invasive and real-time measurements, physiological signals using smartwatches and smartphones taking advantage of embedded sensors. Using machine leaning algorithms, we found a correlation between heart rate, daily activity (number of steps taken daily) and mental stress, energy level and learning efficiency of students. We proposed and developed an "IoT Adaptive

System" for Education 4.0, the acquisition in real time of environmental parameters was implemented with of the Raspberry Pi board and Grove Pi+ sensors.

In Chapter 6, we used an "*Early Recognition System*" based-on Machine Learning binary classification algorithms with neural networks. We aim at estimating student performance during the learning process, 6-8 weeks in advance before the examination and we could alert students at-risk by email. This chapter presents our results from Education 4.0 process, didactically implemented with an efficient blended learning . During the reflection phase Edu. 4.0 process we built up an Early Recognition System. The results were promising, because more than half of those alerted by the system passed the exams.

In Chapter 7, we present contributions, the list of scientific publications and the conferences I have attended and, future research directions for Education 4.0 with value added by wearable devices and Artificial Intelligence. Selectively, also contains few papers how cited my publications.

Chapters 5 and 6 present the prototypical implementation of the Early Recognition System with Machine Learning algorithms in Python and R, block diagrams and sensor diagrams for IoT with Raspberry Pi 3.0 and Grove Pi, as well as the results of experiments. This thesis delivers a detailed analysis of sensors integrated in wearable devices, identification of physiological signals and opportunities that opens by using them in everyday life and especially in adaptive learning instruction of students through Academic Education 4.0.

The research was conducted at the University Politehnica of Bucharest and at the Faculty of Informatics of the Deggendorf Institute of Technology, and a large part of the thesis was published in **16 scientific** German and English papers, as well as in **5 research reports** in Romanian language.

2. The development of Programmed Instruction and Artificial Intelligence

Pioneers of modern programmed instruction educational model are considered Burrhus Frederick Skinner and Norman Allison Crowder, who issued the first ideas about assisted teaching instruction in the 1950s. This can be done in two ways: through linear instruction (Skinner's model) and branched instruction (Crowder's model).

B. F. **Skinner**'s linear instruction model is the oldest and most commonly used one. Figure 2.1 presents the logical scheme of Skinner's linear instruction by applying the learning sequence: stimulus - (question i), answer, comparison - confirmation (feedback), the following stimulus (question i + 1).

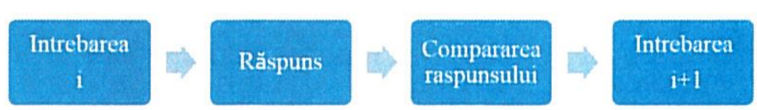

Fig. 2.1 *Logical scheme of Skinner's linear instruction model*

During "linear" type of instruction, each student progresses along the same fixed sequence of tasks. **Skinner** concluded **that the confirmation of the answer has a positive impact on learning success**. In traditional education the teaching methods are those of the linear method. The **disadvantage** of the method: a student who learns quickly does not have any possibility to skip parts of the training. The **double positive effect of the method** is that the correct answer is learned and the student is motivated to learn further. **Skinner's model** capitalizes on **the law of effect, if the connection is followed by success, its force increases** *("the law of positive effect"),* and if it is **followed by failure, its force decreases** *("the law of negative effect").*

Crowder's model aims to **prevent mistakes and treat them through negative reinforcement methods**, which reorients the student's activity in the direction of recovery, reselection, reinterpretation, reapplication of information necessary to complete the respective "*step*". At the beginning the student gets the learning material where a concept or idea is explained, followed by a question that verifies the student's understanding of the concept or idea, his answer determines in which direction he will go further in the training. When the answer is correct, the next step will be taken, and when it is not correct, the student receives feedback explaining the nature of the error and is asked to return to choose the correct answer.

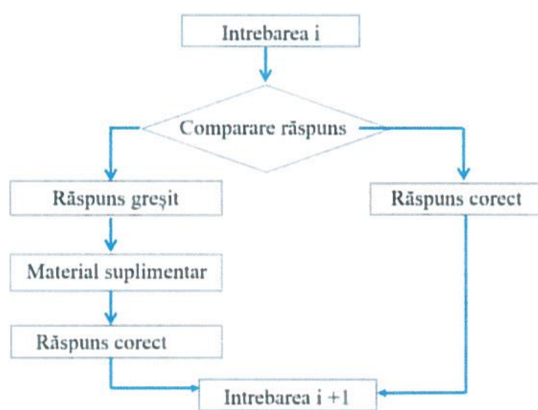

Fig. 2.2 *Logical scheme of Crowder's model for branched instruction*

Promoting *"**self-regulated instruction**"* in Academic Education is an important skill for students` success. Self-regulated learning skills include self-motivation, anticipatory planning and self-assessment ("feedback"). Zimmerman's model of self-regulated learning is a cyclical model that presents information about the stages and process of self-regulated learning, providing a variety of established methods for evaluating training [Panadero]. In Chapter 4 of the thesis, we used this model to find ways to motivate and support students to become *"self-regulate"* as a skill for life, not just for the university environment, so that students can continue to learn in a practical way even outside the classroom.

3. Technologies, intelligent sensors from wearable devices and physiological signals

The first part of Chapter 3 presents the current state of intelligent sensors of wearables, the fundamentals of the cardiovascular system and the autonomic nervous system through an analysis of the current literature. Another element we dealt with is the body area sensor network (BASN). The second part of Chapter 3 presents contributions as answers to research questions.

3.2 The cardiovascular and the neurovegetative system

In order to understand the methodology and functionality of the proposed adaptive training system, it is necessary to understand the basic anatomy notions of the cardiovascular system and the vegetative nervous system (VNS). The vegetative nervous system consists of three systems: the sympathetic nervous system (SNS), the parasympathetic nervous system (PNS) and the digestive nervous system. SNS and PNS are functionally opposite: the **sympathetic nervous system** gives the body an increase in **activity and energy** level *("fight and flight" potential)*, the **parasympathetic nervous system coordinates sleep and regeneration** level, **including digestion** *("rest and digest" potential).*

The **heart rate variability (HRV)** analysis is used by professional athletes for optimizing training. HRV has proven to be an effective way to track the body's recovery potential after exercise. The parameter used to track recovery is **rMSSD** (mean value of the roots of successive differences). That is used in the scientific literature as an accepted measure of **parasympathetic activity**. Stress, lack of sleep and inactive life are indicators for an imbalance between SNS and PNS. HRV is a non-invasive measure for identifying this imbalance. **HRV** is an indicator of the state of tension, which is not only extremely sensitive to stress, but also to relaxation. A good result in measuring HRV is **a healthy balance between energy** (SNS) **and relaxation** (PNS) levels. In recent decades, numerous scientific studies have demonstrated the importance of HRV measurement for stress assessment [M. Buchheit], [Welltory], [J.G. Dong].

Table 3.2 presents a contribution, developed on the basis of the normal values of the standard HRV measures [S. Samito, I. Böckelmann], [ESC Task Force].

***Tab. 3.1** HRV parameters average values*

Name	Description	
	Definition / Indicator	***Aver. Values***
Heart Rate	HR or blood volume pulse (BVP)	56-84 bpm
rMSSD	Strong general fitness indicator; Analysis time: 10-15 seconds for HR, 30 sec. for HRV; 60 sec. provides more reliable measurement, 120 sec. provides more reliable spectral analysis.	>>40 ms
LF (low frequency) 0.04-0.15Hz	**Energy and tension level**; Responsible for blood pressure regulation, sympathetic and parasympathetic nervous systems are involved, but the **sympathetic system is overconfident**. The higher values show more energy and much higher indicated stress.	700-1600ms
HF (high frequency) 0.15-0.4Hz	**Rest and regeneration level** / Shows only the parasympathetic part. The higher values are indicator for more relaxed person, less stress HF <<700 ms.	700-1200ms
LF/HF	It is one of the indicators of healthy balance between tension and recovery. During the day shows the vegetative balance between PSN and SNS; higher value means stress. For chronical stress predominates the sympathicus.	1.5-2.0

3.6 Sensors from wearable devices

Sensors form wearable devices provide students with:

- information about the concrete learning situation;
- increase the subjective perception about health, safety and well-being;
- the opportunity to get to know their body better and to find out how they can relax better in stressful situations.

Many aspects of using sensors are not yet clear, e.g. which non-invasive techniques can be applied in education and which are more easily accepted by students. The use of **wearable devices in** Academic Education 4.0 brings a lot of **advantages, contributing to the motivation and to the improvement in real time** of the quality of student instruction such as:

- taking advantage of heartbeat, pulse, and pedometer data for identifying a personalized activity type for each student (sedentary, mild, moderate, active, very active, extremely active);
- recognizing the need for movement after a certain period of time by offering movement and relaxation exercises;
- creating a healthy lifestyle by measuring and monitoring daily activity level - counting steps, heartbeat, calories consumed daily, climbed floors, water and coffee consumption, sleep duration, distance traveled, atmospheric pressure;
- motivation with personalized messages at the right time.

The GrovePi [1] is an Internet of Things (IoT) kit that connects sensors and equipment to the Raspberry Pi. GrovePi is a hardware system used to connect, program and control sensors for implementing our smart system. The algorithm was developed in the programming language Python. The set used contains: GrovePi board, microSD card for the Raspbian IoT operating system, as well as the following Grove sensors: ultrasonic ranger, sound sensor, temperature and humidity sensor, light sensor, potentiometer, LCD display with RGB backlight, 3 LEDs (red, blue, green), cables for connecting sensors with analog signal (standard 4-wire cable) and a cable for I2C digital signal.

Advantages of Grove Pi + hardware for Education 4.0:

- easy connection of smart sensors to the Internet of Things (IoT) via plug-n play;
- soldering is not mandatory, just plug the Grove sensor to the respective port via standard cable (4 wires) and start programming directly in Python;
- GrovePi + is an easy-to-use, low cost, modular system for hardware testing with IoT prototyping for RaspberryPi.

3.8 Contributions in Chapter 3

In order to answer the research questions (RQ1-RQ4) which have been raised, we analysed non-invasive methods of measuring physiological signals using sensors.

Our contributions to the Academic Education 4.0 are:

- identified physiological signals (which can be interpreted without medical staff) and embedded sensors from wearable devices;
- identified **heart rate variability (HRV) parameters** for real-time assessment of student health and for effective recognition of recovery potential after effort (rMSSD), energy level (LF), stress (HF), energy-stress balance (LF / HF). These contributions were used in the Chapter 5;
- highlighted wearable devices, which can be used to achieve **the adaptive IoT early recognition system** and which bring value to Education 4.0 [o13, M. Ioniță Ciolacu et al, IEEE 2019 a];
- analyzed and compared the sensors built in Android smartwatches and smartphones, and introduced the Raspberry Pi minicomputer with Grove Pi ambient sensors used later on in Chapter 5.
- identified embedded and non-invasive sensors from smartphones and smartwatches, such as accelerometer, barometer, gyroscope, pedometer, pulse, motion, and demonstrated that wearable devices have valuable features for Education 4.0 [o12].

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[1] https://www.dexterindustries.com/grovepi/

4. Artificial Intelligence in higher Education 4.0

There are several definitions of Education 4.0 at universities, such as for example those of [Scheer and Riebe] and [Schildhauer], where personalization and adaptation of the learning environment are the determining characteristics. Since empirical studies show a grade advantage of up to 0.4 degrees at blended learning compared to complete virtual teaching [Popp, Beer], the lectures at Education 4.0 should be in the form of blended learning with a very interactive presence part [o8].

4.2 Knowledge and competencies for Industry 4.0 engineers

The great potential of Industry 4.0 is data and its efficient use. Three trends have been identified in the Gartner emerging technology hype cycle: Artificial Intelligence Everywhere, Transparent Immersive Experiences and Digital Platforms [Gartner 2017]. Industry 4.0 requires a "*Tall Thin Engineer*" that must fit to the future industry [K. Morris]. Traditional methods of learning and teaching reach their limits when it comes to qualifying employees for the requirements of Industry 4.0. In the thesis we evaluated the technological and didactical methods of the fourth Revolution in Education. We see Education as an Industry that is disrupted by digital transformation (Fig. 4.7).

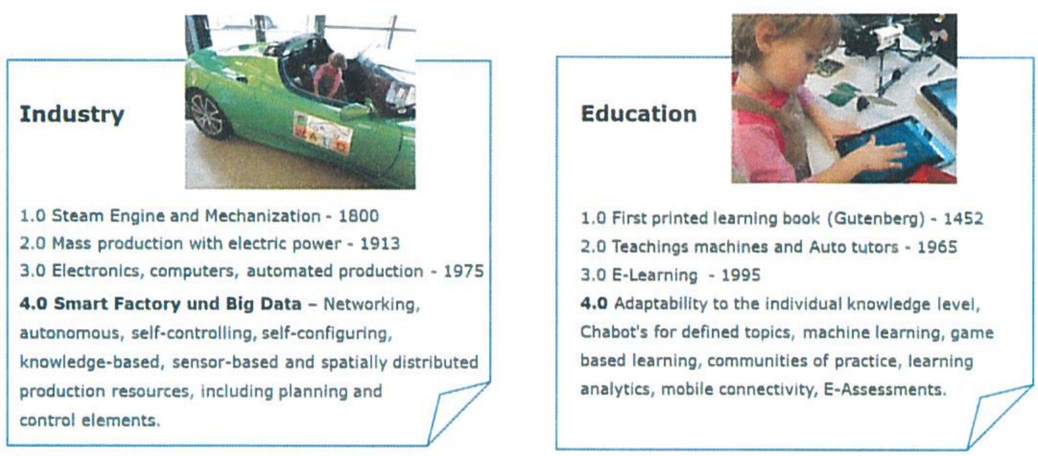

Fig.4.3 *Stages of four Revolutions in Industry and Education* [o2, M. Ioniță Ciolacu et al, IEEE 2017 a]

The growing need for knowledge and the skills of academics 4.0 in the digital society requires "*future-ready curricula*" and the adaptation of didactic methods [o8]. In this process, practical projects certified by the industry play an important role [Svasta].

4.4 Technological elements of higher Education 4.0

We defined higher Education 4.0 - given the four design principles of Industry 4.0 - interconnection, decentralized decision-making, information transparency and technical assistance [Hermann]. We characterize **Education 4.0** by virtual courses including an interactive presence in the form of blended learning and seven AI driven features as significant challenges in the education technology: a personalized training process, game based learning using virtual reality (VR) / augmented reality (AR), student-to-student collaboration communities like *"Community of Practice"* (CoP), smart support platforms such as *"Teletutor"* or *"Chatbot"*, adaptive technologies, learning analytics, and automated correction for the assessment of online exams *"E-Assessment"* [o4, M. Ioniță Ciolacu, IEEE 2017b].

4.5 Artificial Intelligence assisted Education 4.0 adaptive process

This chapter presents modern AI techniques, that we have implemented for two blended learning courses Mathematics and Information Management. Blended learning is the training method where students learn using digital materials, as well as traditional face to face teaching with a live session with the professor.

We defined the **adaptive process of Education 4.0** using Zimmerman's cyclic model of self-regulated learning (initial-, performance- and self-reflection level) to increase motivation and to reduce study drop-out [Zimmerman], [Panadero]. We implemented an early recognition system in blended learning courses based on the Zimmerman cyclical model with a personalized test at the beginning of the semester, adaptive courses based on B. F. Skinner [Skinner] and N. A. Crowder [Crowder], Autotutor with interactive book, interactive video and learning control with automatic feedback for reinforcement learning.

Figure 4.11 illustrates the adaptive process of Education 4.0 assisted by AI techniques and wearable devices. It consists of the following seven phases:

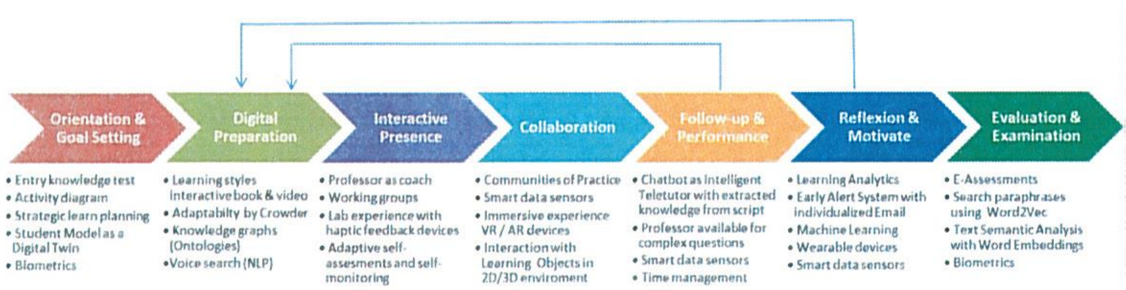

Fig. 4.41 *Artificial Intelligence assisted Education 4.0 process [o10]*

1. **Orientation:** Entry test of the initial competences and an overview of the course structure (anticipatory phase) [Popp, Beer], Activity diagram with the grades achieved for motivation and learning plan (strategic planning) and learning goals [o1].

2. **Digital preparation:** personalization of content according to two learning types: interactive book and interactive video [o2], learning control and self-monitoring with adaptability of responses [o11].

3. **Interactive presence**: group work and case study discussion [o3].

4. **Collaboration:** "Communities of Practice" (CoP) by students for students - document and learn [o3], [o14].

5. **Follow-up and performance:** control of quantitative and qualitative evolution of knowledge; chatbots - "intelligent" teletutors answer simple questions with expert knowledge from the script. Their intelligence comes from using an ontology [o11], [o13], [o15].

6. **Reflection and motivate:** early recognition system, based on neural networks. It is used for self-monitoring and self-observation to continue the educational process; Future scenario would be to extend a Learning Analytics cockpit from dynamic and static data from students [o8], [o13].

7. **Evaluation and examination:** e-assessments - part of the exams are automatic evaluated competence tests. We experimented with the latent Semantic Analysis (LSA) and Word2Vec in this phase [o11], [o12].

In the follow-up and reflection phase, students usually participate cyclically after this phase continues the digital preparation phase.

5. Adaptive IoT system for Education 4.0 with wearable devices and embedded sensors

In this chapter we developed the idea of the IoT adaptive training system with non-invasive sensors. We identified for various scenarios, through experiments with wearables, for following the student's evolution and experiences with new technologies during the training and learning process.

5.2 Jump to innovation with IoT in higher education

Through this contribution we lead students in the IoT world, helping them to understand technological concepts. We improve their subjective opinion about wearing non-invasive sensors, providing them with information in real time for their training, wellbeing and health. A contribution is the model "*Using the Internet of Things in Academic Education 4.0*" with: Education 4.0 (I) with feedback through learning analysis uses Smart Devices (II) such as: smartwatch, smartphone, Raspberry Pi, Health (III) with biofeedback methods and Artificial Intelligence (IV) [o13].

5.3 Block diagram of the adaptive IoT system for Education 4.0 based on multimodal data

Internet of Things (IoT) for Education 4.0 uses **student features, both physiological** ("biosignals") and **behavioral.** Physiological characteristics such as pulse (HR), heart rate variability (HRV), age, weight, height, gender, energy level (LF), stress resistance (HF), resilience after exercise (rMSSD) or fingerprint scanning. Behavioral features during the online training activity: the ongoing activity, the progress and the understanding of the subject by analyzing the answers to the test questionnaires [o10]. Another contribution is presented in the diagram in Figure 5.2:

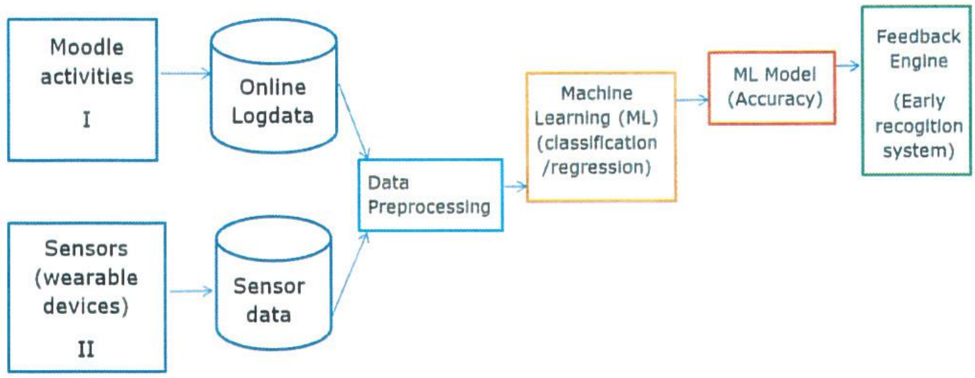

Fig. 5.5 *Block diagram of the adaptive IoT system for Education 4.0 based on multimodal data from online course activity (I) and physiological signals (II) [o10]*

The requirements of the "Adaptive IoT System for Education 4.0" are as follows:

- real-time monitoring with different sensors of students' physiological signals;
- easy to use, flexible, small size and low cost;
- should not disturb or distract students from their learning;
- to help students analyse their learning behaviour;
- improve students' understanding of their bodies respond to training and to learning conditions [o13].

5.6 Adaptive IoT system for Education 4.0

We proposed and implemented an adaptive IoT system for a rapid prototype, with commercial wearable devices and a Raspberry Pi minicomputer. The activities measured by the system can be divided according to the sensors that measure them: **physiological** (pulse, sleep duration, calories consumed, daily activity, sleep quality, etc.) or **environmental** (temperature, humidity, altitude, noise, light, etc.) [o21]. The advantages for Education 4.0 assisted by AI and physiological sensors are the following:

- students can monitor their activities in real time without being distracted or disturbed during teaching or learning;
- students learn self-control, self-observation, better use of time, lead a healthier and more active life, receive real-time feedback;
- students obtained digital skills and the necessary qualification for Industry 4.0;
- students are more motivated, learn more efficiently and better;
- teachers use smart digital technologies and provide real-time feedback;
- more students pass the exams and fewer drop outs.

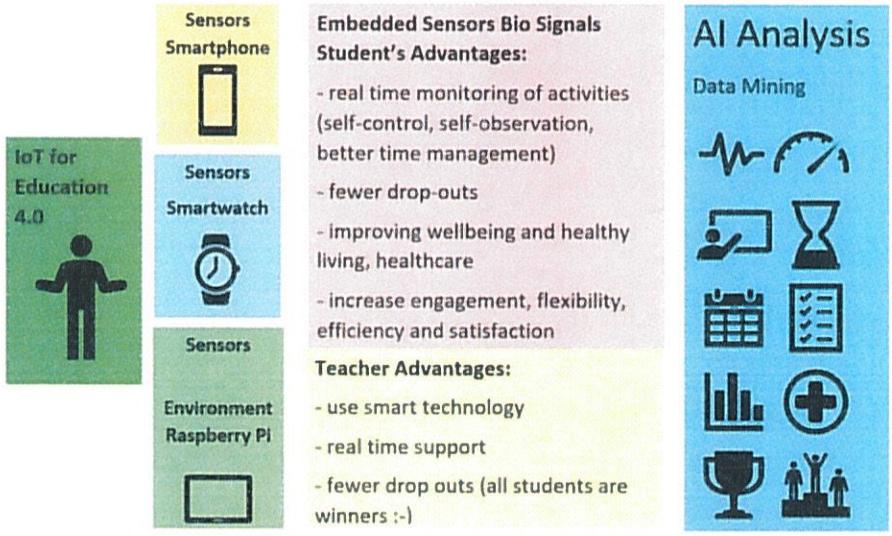

Fig. 5.6 *Advantages IoT adaptive System for Education 4.0 [o13]*

5.7 Experiments with smartwatch in Education 4.0

Participants wore a smartwatch from morning to evening on their wrists, which measured their pulse and steps. The pulse was permanently measured during the day with the HRM pulse monitoring sensor and then averaged for each month. Motion data were obtained from the accelerometer and gyroscope sensors. Numerous studies have shown that approx. 10.000 steps a day will bring many benefits, but they are at first difficult to achieve for students who lead a sedentary lifestyle; for this we started with 3.000 steps and as they made progress, the number of steps were increased to 6.500 daily.

For the experiments, we used an Android smartwatch, IoT protocols to collect data, and "Samsung Health" and "Withings" cloud applications for efficiently analysis of the collected data and gain more information. The "Samsung Health" app gives users the ability to view results and to export data collected in .csv format. We have learned about the sensors from the "Samsung Health Android SDK" API. Samsung Gear Sport Watch and Samsung Galaxy S8 Smartphone were used to collect data. Physiological data was automatically recorded with the smartwatch. We developed and implement an *"Education 4.0 User Experience Questionnaire for smartwatch"* for measuring physiological signals during learning [o12]. Students measured their values in the

Fig. 5.7 *Pulse measurement with smartwatch and motivation messages*

morning for the individual calibration of the measurements, wore the watch on their wrist during the day and visualized results at the end of the day after synchronizing the smartphone via Bluetooth. Figure 5.18 presents examples of measuring daily activity using a smartwatch for a healthy life-style.

All participant students synchronized the data from the smartwatch once a day with the health application "Samsung Health" using the BLE protocol. Figure 5.19 presents few views of smartwatch or smartphone that motivate to lead a healthy life through encouraging messages, personalized real-time interventions, as well as rewards in the form of medals and badges obtained for carrying out the activity and daily steps.

Through three scenarios we monitored the following physiological data of the participants: pulse (“*heart rate*” - *HR*), minimum pulse (“*HR_min*”), average pulse (“*HR_mean*”), maximum pulse (“*HR_max*”), creation time (“*create_time*”), number of steps (“*step_count*”), distance (“*distance*”), active time per day (“*active_time*”), walking time (“*walk_time*”), rest time (“*rest_time*”), calories actively consumed (“*active calories*”), basal metabolic rate i.e. the number of calories consumed by the body during a day if it did nothing (“*basal_metabolic_rate*” - BMR), age (“*age*”), weight(“*weight*”), height (“*height*”), and gender (“*gender*”). The data of each participant has been saved as .csv, processed and analysed using AI algorithms.

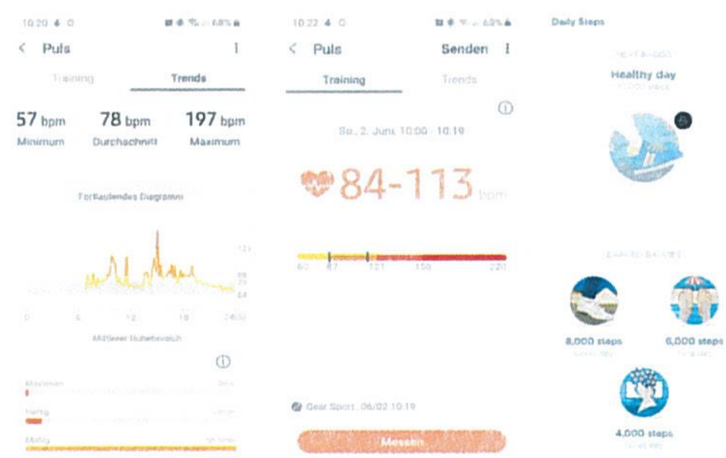

Fig. 5.8 *Motivating students with smartwatch: activity and health tracking, winning medals, badges and points for activity [o12, M. Ioniță Ciolacu et al, IEEE 2019 a]*

5.8 Experiments with smartphone in Education 4.0

Through experiments we answered the following research questions (RQ):

- RQ1: What is the students' experience in using wearable equipment in higher education?
- RQ2: Can we identify a significant correlation between HR and HRV?
- RQ3: Can sensors provide useful information during the learning process?

For experiments, we used Android smartphones, IoT protocols to collect physiological data and the cloud application "*ECG for Everybody*"[2] [Jokic] to measure HR, HRV, rMSSD, LF, HF values with the Photopletismography method described in subchapter 3.3.6. Hereinafter we will call it the HRV measurement. The "ECG for Everybody" application gives students the opportunity to see their results, and with the Biofeedback method described in subchapter 3.3.7 we helped them to become aware of their energy level (productivity), stress or recovery potential and to understand their physiological data.

Through it, the custom calibration has been made at the beginning of the experiment for measuring with smartphone embedded sensors reference values: gender, age, weight, height, heart rate (HR) and heart rate variability (HRV), respectively steps, calories consumed daily and of the pulse (see Appendix 5_Edu 4.0_smartphone). In parallel, a smartwatch was worn to check the accuracy of the measurements. Analogous to the experiments in subchapter 5.7, the participating students have been able to receive the results or discussed about their data. Participation in the study was not relevant to the exam grade and they did not receive any compensation for participating.

We have performed several Education 4.0 workshops with students (52 participants). We developed an online course and used "Education 4.0 User Experience Questionnaire with Smartphone" by considering the aspects for learning by measuring physiological parameters. Participation in the experimental study was voluntary, giving students the opportunity to describe their experiences and ideas during the interaction with physiological data measured by sensors in real time during training. During the LMS Moodle course, an online course with a database was created. The physiological signals measured during experiments have been gathered in the database.

Fig. 5.28 shows the exemplary workshop demonstration with a participant in front for the Photoplethysmography measurement ("PPG") methodology with the help of the back-smartphone camera (Fig. 5.28). Subsequently, the students performed HRV measurements themselves and noted the results in the online course.

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[2] www.ecg4everybody.com

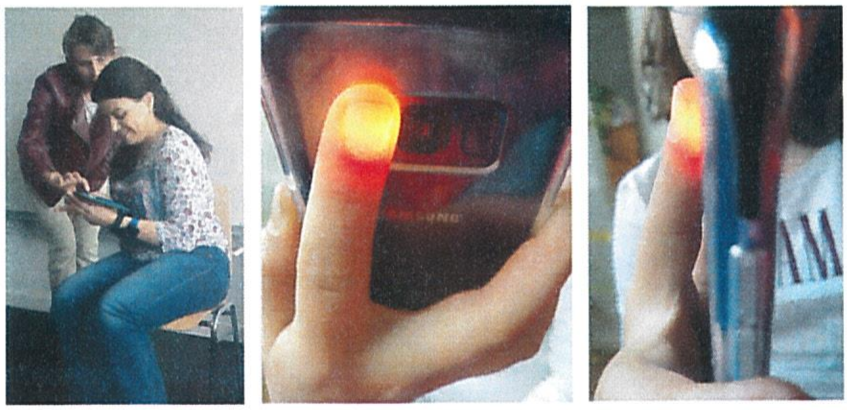

Fig. 5.9 *Measurement of heart rate (HR) and heart rate variability (HRV) using a mobile phone camera with the photoplethysmography method [o13]*

After measuring HR and HRV values, the survey was conducted with the online questionnaire. HRV measurement is simple, completely painless and takes about 2 minutes. Measurements were done in a relaxed atmosphere: upright (sitting on a chair) and measured the pulse HR, RMSSD, LF, HF, LF / HF. Fig.5.29 exemplifies the measured data for a healthy 45-year-old female participant (id. = F45), activity: rest, time: evening with measurement details.

Based on regular values presented in Table 3.2 and 3.3 we observe the following values: excellent values of HR = 78bpm (between 60-84) and with a low energy level (LF = 303) (reference between 754ms and 1.586ms optimal for energy), with low stress (HF = 573) (reference between 772 and 1,178 is relaxed) and low LF / HF which means fatigue (LF / HF = 0.5). The level of recovery after stress is very good rMSSD = 46 (reference> 35 is good). In general, the physical condition is good (rMSSD).

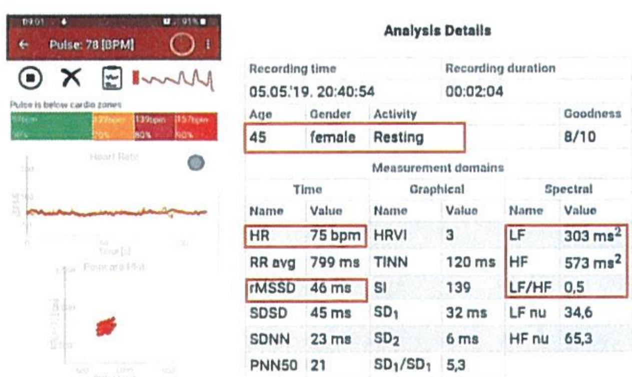

Fig. 5.10 *HRV values for a healthy 45 years old female participant measured with the application „ECG for Everybody" [o13]*

Figure 5.33 presents survey results regarding the acceptance compared to the measurement of physiological signals by considering aspects: acceptance, easy to use, utility and pleasure. It presents a comparison of the mean values of the acceptance assessments before and after the measurement for 52 participants. We notice that the students accepted the measurement of the "biosignals" very well, perceived the use as easier and more useful than they expected. Attitudes towards the future use of wearable equipment have changed positively, making them happy and they have begun to trust wearable devices.

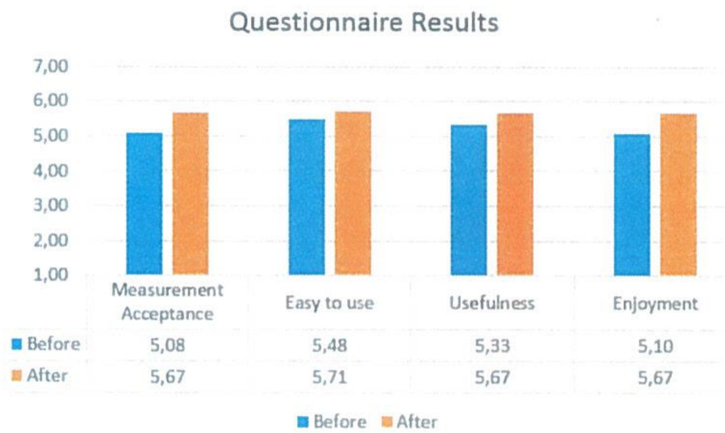

***Fig. 5.11** Survey results for scenario III – measurement acceptance before and after experiments with 52 participants [o13]*

Figure 5.34 presents scenario IV results for the measurement for 3 weeks with a healthy participant by considering the aspects of pulse, energy, fatigue, recovery after stress, steps, climbed floors (morning left up, noon right up). We used the correlation coefficient to find the connection between two measured values (r values between -1 and 1).

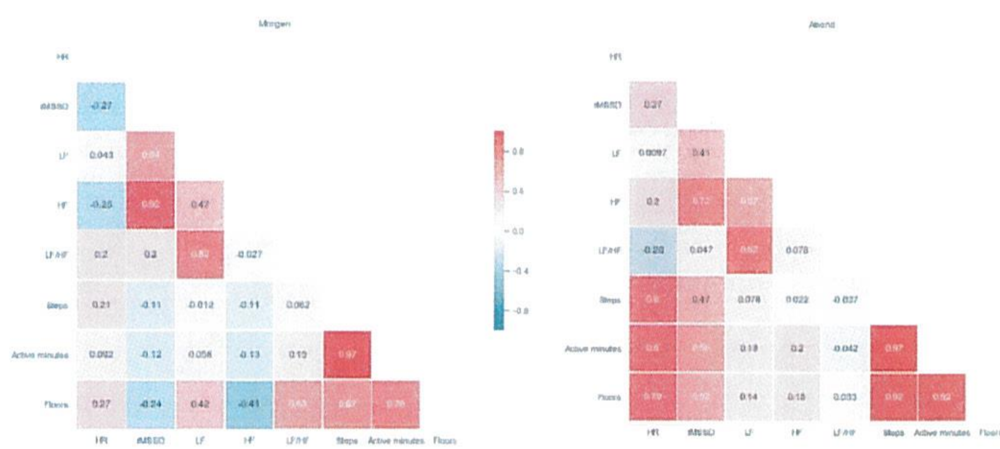

***Fig. 5.12** Study results correlation between HR, rMSSD, LF, HF, LF / HF, steps, active minutes, floors climbed [o13]*

5.9 Experiments with an adaptive IoT System based on RaspberryPi

The prototype of the "*IoT for Education 4.0*" adaptive system works stable. It is based on a Raspberry Pi 3.0 and Grove P sensors, and is programmed in Python 3.7.3 with the Raspbian operating system based on Debian (32 bit) Linux. The prototype makes the warnings spoken in Romanian, German and English by implementing the "Google

Text-to-Speech" application for reading the text displayed on the monitor screen. This application reads the text on the screen with support in several languages. The Raspberry Pi adaptive system uses Grove Pi sensors to identify environmental conditions in the room during training, announces whether there is too much noise, cold or hot, dark or light, humidity and gives recommendations [o21]. In case that established parameters are normal, nothing is communicated and the IoT prototype is on standby, constantly measuring with the help of intelligent sensors.

For the development of the prototype of an Adaptive IoT System, we used the ultrasonic sensor, the light intensity reading sensor, the ambient temperature and humidity sensor, the sound sensor, the RGB Backlight LCD display from the Grove Pi set, as well as serial, digital communication protocols, Wi-Fi and Bluetooth. The hardware implementation is illustrated in Figure 5.36 [o21].

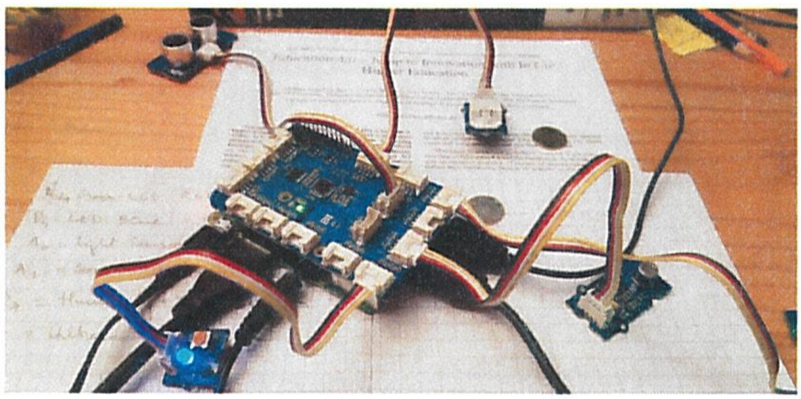

Fig. 5.13 *Prototype of an Adaptive IoT System for Education 4.0 [o21]*

6. Early Recognition System with machine learning algorithms to support student's success

This chapter presents the early recognition system based on data obtained from two online courses conducted with Education 4.0 process, and the results of experiments performed. In a traditional teaching scenario, the teacher can identify students who have not studied during the semester only after evaluating the examination papers. We focused especially on Artificial Intelligence with machine learning algorithms ("Machine Learning" ML), Data Mining (DM) methods and on learning analysis ("Learning Analytics" LA). Taking advantage of ML binary classification algorithms, we realized a classification of students 6-8 weeks before the exam.

Starting from the premise that the exam grade and the success of learning depend on the online activity, we made the following statements ("Hypothesis" H) which we presented and demonstrated in various papers:

H1: Self-regulated learning starts early in the semester [o4, M. Ioniță Ciolacu, 2017b].

H2: There is a relationship between the activity during the semester and the degree of success of the students' exam [o4].

H3: The use of online quizzes to check what has been learned influences the success of the exam [o10, M. Ioniță Ciolacu, IEEE 2018].

H4: Warning students at risk, respectively inactive during the semester, helps in increasing the success of the exam [o10].

H5: Access to multimodal data (see Fig. 5.2 and Fig. 6.17), obtained from the activity during the semester but also with the help of intelligent sensors, can lead to a higher accuracy of learning prediction [o14].

It presents the experiment's results with binary classification machine learning algorithms. The activity was carried out in three steps:

I. Identifying students with problems using unsupervised learning respective clusters;

II. Identifying students with problems as soon as possible during the semester by making a prediction (successful or unsuccessful in the exam) for students in a new semester, using a model with neural networks for attention to help them succeed in exams and motivate them not to give up the study;

III. Analysis of exam results after notification by email by the neural network early recognition system.

6.7 Results of Early Recognition System with neural network

In previous works, we investigated with different machine learning methods in scenarios where students use only digital materials, in order to be able to predict how much the exam success rate depends on their way of learning [o4]. Therefore, for the recognition system we considered only the results of the Machine Learning application for blended learning and only the supervised learning binary classification algorithm that get the best results in our tests, namely algorithms with neural networks.

Tab. 6.14 presents the number of data sets used to train, test and analyze the results of the early warning system ("#go live" and "#at risk"). Two types of experimental studies were performed:

I. Making a prediction for students for a new semester ("#go live"),

II. Live recognition of at-risk students ("#at risk")

We applied this methodology for two blended learning courses for the Mathematics and for the Knowledge Management.

Tab. 6.14 *Data sets used for the Early Recognition System and results obtained (identification of students at risk)*

Data set	Stages of Early Recognition System			
	No. of students #training	No. of students #evaluation	No. of students #go live	No. of students identified #at risk
Mathematics/ BA	115	111	91	21
Knowledge Mgmt. / BA	110	97	78	38
Knowledge Mgmt. / BI	60	53	35	20

We used the IDE ("Integrated Development Environment") R Studio Version 1.2.5019 to program Machine Learning algorithms.

From the experiments in subchapter 6.6 we conclude that, unlike complete virtual courses, the use of quiz clicks in blended learning courses provides little information. Therefore, we did not consider the clicks in the test questionnaires for each month as a separate entry, but we used the clicks of the monthly activity accumulated during the semester as an entry model in the WT 16/17 training phase. Also, the students' names were anonymized with the MD5 algorithm. When using the neural network, we considered only the data of the ongoing interaction (clicks for the first 2 months, respectively October and November). Figure 6.12 presents the methodology for implementing the system. In this way, students are informed as soon as possible about the danger of failing the exam, so that they have enough time to react.

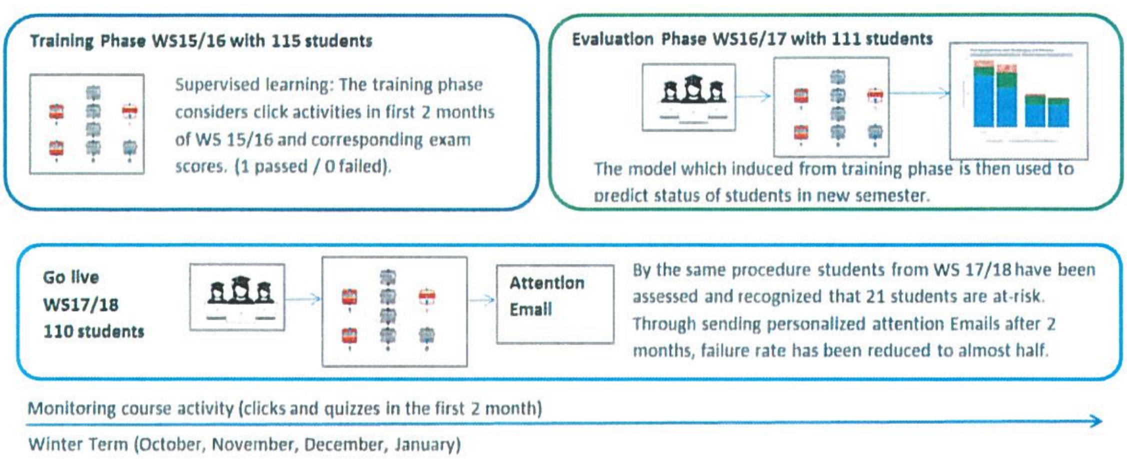

Fig. 6.14 *The methodology of Early Recognition System*

The experiments [o4], [o10] showed that the LMS activities of the first two months for first year students are more significant for success or failure than the whole period (75% accuracy for the first two months, compared to an accuracy of 70% considering four months). The correction of the Mathematics exam in January 2018 was as interesting as the evaluation of the laboratory results. The joy was great, as the **failure rate** dropped by almost half, to **11%** compared to previous years, with an examination as difficult as shown by comparative tests in other faculties. At the Faculty of Tourism and Psychology, the early recognition system was not used, and the failure rate was **31%** for the same exam. For the first time in 2018 the Artificial Intelligence has improved the performance of students on the DIT exam.

6.8 Contribution Chapter 6

Examining the content of this chapter, we mention the following contributions:

1. Idea, implementation and testing of the "*Early Recognition System*", which uses Machine Learning algorithms and student activity data from online courses. Through this they come to the aid of all students who do not learn enough, by offering personalized help before they are in danger of failing the exam or dropping out of studies, identifying them after 8-12 weeks depending on ongoing activity. The neural network identifies students with problems and warns them in a timely manner.
2. The use of binary classification algorithms we were able to identify and to explain students at-risk. That consequently help them to prepare properly for the exam.
3. By using models learned by means of neural networks, it is possible to recognize students at-risk and make them aware of their weakness by sending them an alert mail. We observed a decreasing failure rate by 50% and a reduction in terms of the number of students who did not participate in the exam. The scores obtained in the examination have been improved substantially compared to those who attended the same course, but studied at other faculties and have not been alerted by the system.
4. In the future, students can directly monitor their activity throughout the course through Learning Analytics that uses the warning system, an adaptive and personalized teaching interface.

The results of our researches offer enough promise:

- To continue the use of students' experience with Machine Learning algorithms and Learning Analytics, using a self-regulated model for student success;
- To identify students at risk and to be able to intervene early, before the examination.

7. Conclusions

7.1 Results

This chapter concludes the work presented in the thesis. The main objective was to improve the quality of the teaching and learning process through an adaptive framework to motivate students and change the way they learn, namely the transition to self-regulated learning. We were particularly interested in identifying in advance students at risk. We have analysed this problem mathematically with supervised and unsupervised machine learning (ML) algorithms - papers [o2], [o4], [o8], [o9] and chapter 6.

In addition, the thesis provides an overview over non-invasive embedded sensors from Wearables and RaspberryPi hardware with GrovePi for easy IoT prototyping using five sensors available for Education 4.0.

Chapter 4 presents the general scheme of operation of data acquisition for an adaptive framework using machine learning methods. Starting from the blended learning model and acquiring the **real data related to the students' activity in online course** (block I) as well as the **data obtained from the intelligent sensors** (block II) we proposed an Early Recognition System of the students at risk in the examination. We discussed block I *("data from moodle activities")* in detail in report 4, and block II *("data from sensors")* was the topic of report 5. The results were published in [o10].

Chapter 5 presents our analysis and an adaptive framework of **IoT** implementation in Academic Education - "*Enabling IoT for Education*" with computer-assisted teaching, with four facets: **smart devices *(smartwatch, smartphone, smart glasses)*, health, learning and artificial intelligence.** The results were published in [o13]. We developed an "*Adaptive IoT System for Education 4.0*", which measures non-invasive methods such as physiological data obtained from heart rate and heart rate variations (HRV) of the student in various conditions (rest, stress and during learning), the number of steps, calories consumed, and daily activity. The system highlights the pulse and measures the heart rate of the student in real time, in order to know his behavior and response to the conditions in which he/she learns. The results were published in [o13].

Chapter 6 presents results of the Early Recognition System. The proposed system provides information in advance about the student's activity to prevent dropping out and motivating success in the exam. We implemented the active and passive adaptability scenario, and also the scenario of personalization (recommendation) of the subject in two blended learning courses for helping students to evaluate their level of knowledge. Using unsupervised learning students were classified into three clusters: those who finish the course with good grades and are active throughout the course *("very active" - big success*), those who finish the course but learn less *("less active" - success*), those who leave the course early do not learn and are at risk of dropping the exam *("inactive" - early dropouts*). For this purpose, we acquired data from students from two faculties: Business Administration (BA) and Business Informatics (BI) who were taught the Mathematics course and the Knowledge Management course. We used supervised learning binary classification to identify students at-risk. This actually means classifying students according to passing or failing the exam by machine learning algorithms, namely support vector machine (SVM), decision trees (DT), clusters and neural networks (NN). We acquired the data of three academic years to create the necessary database. Therefore, the neural network learns from the click data and the achieved points in the quizzes (the first two months) as well as the pass / fail (classification) or the achieved points (regression) in the exam. We test the learned the neural network during the next execution of the learning course (achieved forecast accuracy 76%-100% in the classification) and use it again during the next semester. We have learned NN for three courses. We have been able to analyze the effects using the Early Recognition System in two simulations by carrying out the first successful applications in courses mathematics and information and knowledge management of business administration degree in WS 17/18 and SS 18. Based on these forecasts, warning e-mails were sent to students classified as at-risk. This almost halved the failure rate. The results were published in [o4], [o8], [o9], [o11] and [o13].

In conclusion, in this thesis we discussed a broad number of experiments with Artificial Intelligence methods such as user modeling, adaptability, chatbots, semantic text recognition tools, machine learning processes, and especially neural networks, have underlined that professors can use the Education 4.0 framework with very good performance. We are confident that once Higher Education takes these measures into account, they can add value to education.

An interesting further development of this project could be the combination of wearable equipment with other integrated sensors. This can identify additional information about the learning stage and strengthen students' subjective perception of health, safety and well-being. The first preliminary tests have already been performed.

Limitations

- access to student data has changed since 25.05.2018 due to "General Data Protection Regulation" (GDPR);
- ethical and data security reasons;
- limited battery life of wearable devices;
- limited budget necessary to perform experiments.

7.2 Contributions

The main achievements[3] of this thesis can be outlined as follows:

1. Identification of Academic Education 4.0 knowledge and competencies required for Industry 4.0 [o2], [o4], [o7], [o8] and in Chapter 4.

2. We developed the adaptive and personalized Education 4.0 teaching and learning framework aided by Artificial Intelligence with intelligent sensors and wearable equipment based on Zimmerman's *"self-regulated learning"* model [o8], [o9].

3. Identifying the stages of the Higher Education 4.0 process supported by electronic equipment and artificial intelligence [o9], [o10], [o13] and in Chapter 3.

[3] where [o] is the number of the original paper in which the contribution was published from the list in section 7.4.

4. We identified which sensors are relevant for Higher Education 4.0 by investigating in the "smartwatch" and "smartphone" sensors [o13] and in Chapter 3.

5. Starting from physiological signals from wearable devices' intelligent sensors, we proposed a scheme for analyzing the multimodal data obtained from students during learning [o10] and in Chapter 5.

6. We analyzed the biological signals and identified which of them are relevant for the analysis of students' activity in Academic Education 4.0 [o12], [o13] and in Chapter 3.

7. We developed and implemented an IoT prototype for Education 4.0 with the Raspberry Pi minicomputer and the Grove Pi development board using temperature and humidity sensors, the ultrasonic sensor, the light sensor and the sound sensor [o14].

8. We designed and developed an Early Recognition System customized, by e-mail, of students using machine learning algorithms [o4], [o8], [o9], [o11] and in Chapter 6.

9. The Early Recognition System have been tested with real students' data and we obtained the first results of the application of artificial intelligence (AI) with Machine Learning methods. The results were validated in the winter and summer sessions of the academic year 2017-2018 for the Mathematics course and in the summer session 2018 for the Information Management course. Through the Early Recognition System, we managed to motivate students, in the sessions of 2019 and 2020, to learn and reduce the number of students who did not pass the exams by half - [o8], [o10], [o12], [o13] and in Chapter 6.

10. We developed and implemented two Education 4.0 feedback questionnaires for students' experience during learning for smartwatch and smartphone, in order to identify the degree of acceptance by students of wearable equipment and Biosensors, in general, in Academic Education 4.0. These were published in [o12], [o13] and in Chapter 5.

This thesis demonstrates steps for the achievement of 4.0 skills and competencies. It focuses on the orientation, digital preparation, follow up , reflection and motivation phase in the Education 4.0 process. In the simulation of the Early Recognition System, first results of the use of NN for forecasting have already been achieved, which show that it is particularly efficient. This system motivates through grade and exam point forecasts, which reduces the failure rate in exams. A deeper analysis is aimed at identifying the changed interactions with the learning material. The Early Recognition System, integrated into the Education 4.0 process, helps students to individualize their self-regulated digital learning process and motivate themselves through grade point forecasts, as well as reducing their failure rate. A further development would be a "*smart monitor with biofeedback*" for sensor-based Learning to learn more about the emotional and cognitive state of a learner.

This thesis advocates that the usefulness of wearable devices, IoT, artificial intelligence and machine learning algorithms in an adaptive Early Recognition System with self-regulated learning brings promising results. In this regard, we noticed the increase of student's well-being and of confidence in their own competences and strengths. For online teaching and learning this system can offer personalized interventions and adaptable learning environments through the Internet of Things and artificial intelligence. That is the reason why AI should be integrated into the existing way of teaching future ready students as the workforce for Industry 4.0.

7.4 Original publications

The work leading to this thesis was published in **15 research papers**, of which **6 IEEE conference proceedings** and have been cited in over **98 scientific articles**, including:

- **the paper** [o1] was **cited in the book**: "*Redesigning Prediction Algorithms for At-Risk Students in Higher Education: The Opportunities and Challenges of Using Classification Techniques in a University Academic Writing*"[4] **in the article** "*Redesigning Higher Education Initiatives for Industry 4.0*".
- **the concept of Education 4.0** from [o2] and [o4] was **analysed in the journal** "*Brazilian Journal of Development*" **in the article** "*Education 4.0 in engineering: perception of professors from 3 Brazilian universities*"[5].
- **the paper [o10]** was **cited in the journal** "*Der Chirurg*" **in the article** "*Artificial Intelligence in Orthopaedics and Trauma Surgery*" ("*Künstliche Intelligenz in der Orthopädie und Unfallchirurgie*")[6].
- **the paper [o12]** was **cited in the article** „*Prescriptive Education im Zuge der Industrie 5.0*" on VDI Conference in Germany, 2020.

[o1] **Monica Ioniță Ciolacu**, Rick Beer, ***"Adaptive user interface for higher education based on web technology"***, Conference: 2016 **IEEE 22nd International Symposium** for Design and Technology and Electronic Packaging (SIITME), Oradea, Romania, Oct. 20-23, 2016, pp. 300-303, published: **2016**, cited by **14 authors.**

[o2] **Monica Ioniță Ciolacu**, Paul Svasta, Waldemar Berg, Heribert Popp, ***"Education 4.0 for Tall Thin Engineer in Data Driven Society"***, Conference: 2017 **IEEE 23rd International Symposium** for Design and Technology and Electronic Packaging (SIITME), Constanța, Romania, Oct. 26-29, published: **2017**, cited by **25 authors.**

[o3] **Monica Ioniță Ciolacu**, Heribert Popp, ***„Lehre 4.0: Effiziente virtuelle Weiterbildung /Open Innovation Education 4.0"***, Forschungsbericht 2016-2017,

[4] https://www.igi-global.com/chapter/redesigning-prediction-algorithms-for-at-risk-students-in-higher-education/224218
[5] http://www.brjd.com.br/index.php/BRJD/article/view/3245
[6] https://link.springer.com/article/10.1007/s00104-019-01091-9

Wissens- und Technologietransfer der Technische Hochschule Deggendorf, Germany, pp. 52-58, published: **2017**.

[o4] **Monica Ioniță Ciolacu**, Ali Fallah Tehrani, Rick Beer, Heribert Popp ***"Education 4.0 – Fostering Student Performance with Machine Learning Methods"*****,** Conference: 2017 **IEEE 23rd International Symposium** for Design and Technology and Electronic Packaging (SIITME), Constanța, Romania, Oct. 26-29, 2017, pp. 432-437, published: **2017,** cited by **37 authors.**

[o5] Heribert Popp, Erwin Semke, **Monica Ioniță Ciolacu,** ***"Virtueller, wissensbasierter und analytischer MINT-Coach (VWA-MINT)"***, In Book: Bayerisches Staatsministerium für Bildung und Kultus, Wissenschaft und Kunst (Ed). Erfolgreicher MINT-Abschluß an bayerischen Hochschulen, Publisher: Bayerisches Staatsministerium für Bildung und Kultur, Wissenschaft und Kunst, München, Germany, Oct. 2015, pp. 72-81, published: **2015**.

[o6] Heribert Popp, **Monica Ioniță Ciolacu,** ***„Lehre 4.0 revolutioniert E-Learning in Hochschule und Weiterbildung"***, Journal: Die neue Hochschule (DNH), (4), Germany, pp.12-15, published: **2017.**

[o7] **Monica Ioniță Ciolacu**, Heribert Popp: ***„Education 4.0: Künstliche Intelligenz gestaltet smarte Blended learning Prozesse"***, Forschungsbericht 2018-2019, Conference „6er Tag der Forschung", Technische Hochschule Deggendorf, Germany, pp. 51-59, 10. April 2019, published: **2019**, cited by **1 author**.

[o8] **Monica Ioniță Ciolacu**, Leon Binder, Rick Beer Heribert Popp, ***"Education 4.0 für Akademiker 4.0 Kompetenzen -Blended learning 4.0 Prozess mit Learning Analytics Cockpit"*** [5], Arbeitskreis Learning Analytics der Fachgruppe E-Learning in der Gesellschaft für Informatik (GI), "Digitalisierungs(wahn)Sinn? Wege der Bildungstransformation – DeLFI und HDI 2018, Goethe-Universität Frankfurt, Doctoral **Workshop**, http://ceur-ws.org/Vol-2250/WS_LA_paper7.pdf, German National Library for Science and Technology, published: **2018**.

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