Smart e-Learning as a Student-Centered Biotechnical System

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Abstract. The Smart e-Learning System (SeLS) should be designed and developed as a smart student-centered biotechnical system with certain features of smart systems (sensing, transmission, big data processing, activation of actuators) and levels of "smartness" (adaptation, sensing, inferring, learning, anticipation, self-organization). In order to provide higher efficiency of learning process in general, and, SeLS, in particular, SeLS should use multiple parameters of student psychophysiological state.

Keywords: e-Learning · Smart system · Student psychophysiological state

1 Introduction

A combination of smart systems with e-learning – Smart e-Learning – is a nascent area that potentially can combine the features and advantages of both areas, and, as a result, in the future provide learners and instructors with non-existing functionality and features.

1.1 Smart Systems for Learning: Examples

Various smart systems for learning have been designed and developed recently; relevant examples include but are not limited to the following ones: Smart Classroom based on Reconfigurable Context - Sensitive Middleware (RCSM) [1], Context Aware Smart Classroom [2], Open Smart Classroom [3], Smart Classroom for Tele-education [4], smart environments for learning [5], and other.

The performed analysis of [1–5] as well as multiple additional publications shows that currently the developed prototypes of smart systems with applications in eduction and/or learning are predominantly technical systems with a major focus on software-hardware solutions, components, mobile devices and machine-to-machine data exchange protocols. However, based on authors' active involvement into e-learning from 1994, multiple completed research projects and gained experience, the Smart e-Learning Systems (SeLS), first of all, should be considered as biotechnical systems.

G. Vincenti et al. (Eds.): eLEOT 2014, LNICST 138, pp. 167–175, 2014.
DOI: 10.1007/978-3-319-13293-8_21

In those systems a human being - a student or a learner with particular abilities to read, write, understand, learn, process data, make logical conclusions, retain knowledge - should be placed into a center. Secondly, as a smart system, SeLS should demonstrate certain smart features and levels of "smartness".

1.2 Research Project Goal and Objectives

The main goals of ongoing research project are (1) to define various types of smart entities relevant to education and/or learning, (2) to define levels of "smartness" of those entities, (3) to identify features and characteristics of smart systems for education and/or learning, (4) identify student/learner psychophysiological characteristics that should be actively used by advanced SeLS. Those aspects are important for advanced and sophisticated SeLS successful design, development and highly effective use by both learners and instructors.

2 Smart e-Learning: Smart Entities

The above-mentioned examples of smart systems with applications in education and/or learning as well as numerous additional examples of smart entities could be classified using the "systems thinking" approach, i.e. in terms of "system = objects + activities + technology/services" software architectural hierarchical model:

(1) level of systems: examples of smart systems in education/learning may include but are not limited to smart classroom, smart lab, smart e-learning system, smart university, smart school, etc.;
(2) level of smart objects (as components of smart systems): SeLS user/learner, smart phones, smart video cameras, smart sensors (transducers), smart mobile devices, etc.;
(3) level of smart activities/processes (as components of smart systems): smart curriculum, smart teaching, smart learning, smart testing, smart compilation of learning modules into courses and curriculum based on student/learner specific – in some cases, limited - psychophysiological parameters, etc.;
(4) level of smart technology/services (as components of smart systems): smart computing, smart sensor technology, smart grid technology, Internet-of-Things, etc.

This proposed classification of smart entities, particularly, enables designers and/or users to identify the "maturity" level of proposed and/or to-be-developed or existing SeLS in terms of smart objects, processes and technologies.

Despite a great variety of known and emerging smart entities, their scopes are defined by main features of smart systems [6]; the proposed adjusted and extended version of that classification is presented in Table 1.

Based on the ideas of "intelligence" levels that were introduced in [7], and in order to categorize smart systems based on their "smartness" maturity level, the improved and detailed classification of "smartness" levels of a smart system (including SeLS) is given in Table 2.

Table 1. Classification of general features of a smart entity

Feature	Goal	Components
Acquisition (sensing) of real-world raw data, and, possibly, a local pre-processing of raw data	To collect raw data needed for an appropriate sensing, and, thus, monitor a situation, condition, object, system, environment, etc.	Sensors, smart phones, smart devices, transducers, machine-to-machine communication, etc.
Transmission of raw data and/or pre-processed sensory information	To transmit the sensor raw or pre-processed data to the local and/or central control unit	Smart phones, smart devices, transmitters, wide area network, Internet, etc.
Big data processing and smart analytics at central control units	To manage and control the entire system	Central processing unit (CPU), invariant analysis systems, big data storage units, etc.
Transmission of instructions	To transmit the decisions made and the associated instructions to actuators	Smart phones, smart devices, transmitters, wide area network, Internet, etc.
Activation (triggering) of physical and/or virtual actuators (devices)	To initiate or perform activities to provide system's reaction on received raw data	Actuators, smart devices

Table 2. Classification of "smartness" levels of a smart system

Ability to	Details	Who/what is involved
Adapt	Ability to modify characteristics to fit the environment or better survive in it	SeLS, adaptive hyper media
Sense	Ability to identify, recognize, understand and/or become aware of process, action, object, etc.	SeLS user, sensors, software/hardware intelligent agents
Infer	Ability to make logical conclusion(s) on the basis of raw data, processed information, observations, evidence, assumptions, rules, and reasoning	SeLS user, reasoning systems, inference engines
Learn	Ability to acquire new or modify existing knowledge, experience, behavior to improve performance, effectiveness, skills, etc.	SeLS user, software intelligent agents, genetic programming
Anticipate	Ability of thinking or reasoning to predict what is going to happen or what to do next	SeLS user, intelligent tutoring systems
Self-organize	Ability of a system to change its internal structure (components), in purposeful (non-random) manner under appropriate conditions but without an external agent/entity	SeLS, smart technology and objects at the cellular or nano-technology level

The proposed classification in Table 2 clearly shows a difference between (a) existing prototypes of smart systems for education and/or learning that are pure technical software/hardware systems with their only smart abilities “to adapt”, “to anticipate”, and “to self-organize”, and (b) advanced SeLS as student-centered biotechnical systems with their additional important smart abilities “to sense”, “to infer”, and “to learn”.

3 Smart e-Learning: Student Psychophysiological Parameters

A student/learner is a key component of advanced SeLS; he/she has specific abilities to read, write, sense, understand process and/or data, infer, make logical conclusions, learn, and retain and use knowledge. The optimization of those activities involves obtaining maximum learning outcomes in a minimal time period with the highest retention factor possible. However, this process can be effective and optimal under the condition that student psychophysiological functional state is optimal [8].

3.1 Learner’s Mental Working Capacity

The learning load and intensity should not lead to a reduction of student’s psychophysiological functional state, including learner’s mental working capacity (MWC). In order to predict it, it is necessary to distinguish the following MWC phases and corresponding activities:

(1) getting started (i.e. forming a new functional system focused on achieving identified outcomes); a certain tension of regulatory mechanisms is needed;
(2) optimal MWC (in this case, the tension level of physiological systems corresponds to mental stress);
(3) full productivity (with possible initial signs of tiredness but without decrease of MWC);
(4) unstable productivity (with clear signs of tiredness and decrease of MWC);
(5) progressive decrease of MWC with fast increase of tiredness and obvious decrease of efficiency of learning.

These identified phases fit well into a classification of degrees of regulatory mechanisms’ tension, specifically (a) tension and/or stress, (b) overload or burden, and (c) tiredness.

In order to evaluate learner’s MWC we actively use the Heart Rate Variability (HRV) method.

3.2 Heart Rate Variability (HRV) Method

The HRV method is focused on monitoring of learner’s regulator mechanisms (a) before, (b) during, and (c) after learning experience. This method is based on (a) recognition and measurement of RR-intervals between the high-amplitude peaks of electrocardiogram (R-peak), (b) construction of time series of RR-intervals between two neighboring peaks, and (c) numerical analysis of obtained R-peak data [9–11]. The most informative parameters of the HRV method are (1) Heart Rate (*HR*), (2) Stress Index (*SI*), and (3) Centralization Index (*IC*).

The *SI* parameter is calculated based on the RR-intervals' histogram:

$$SI = \frac{Amo \cdot 100\,\%}{2 \cdot Mo \cdot MxDMn} \tag{1}$$

where *Mo* – mode, *AMo* – mode's amplitude, *MxDMn* – variation range. The *SI* parameter is sensitive to increased sympathetic nervous system tone; as a result, a small physical, emotional or mental overload may increase *SI* values by 1.5–2 times.

The *IC* parameter is associated with psycho-emotional stress and the functional state of brain; it is calculated as follows:

$$IC = \frac{VLF + LF}{HF} \tag{2}$$

where *VLF* – spectral density of RR-intervals in a very low frequency range, *LF* - in the range of low frequency, *HF* - in the high frequency range.

3.3 The Varikard Software/Hardware System

In order to actually calculate all designated parameters of the HRV method, and, therefore, monitor learner's MWC, the Varikard software/hardware system – the Varikard system - has been used in performed experiments; its Web-based graphic user interface is presented at Fig. 1.

Time	sum(RR)	RR	HR	SI	IC
19:09:59.264	29546	721	80	41.51	24.81
19:10:00.265	29421	693	80	37.73	26.79
19:10:01.169	29319	691	80	33.96	26.13
19:10:02.84	29985	666	82	33.13	22.8
19:10:02.949	29845	654	82	44.68	21.95

Fig. 1. The web-based graphic user interface of the Varikard system

Its main functions include but are not limited to:

(1) obtaining learner's functional state and health related signals,
(2) signals' filtering using various applied algorithms,
(3) identification of R-peaks,
(4) identification of RR-intervals,
(5) mathematical formation of dynamic series of RR-intervals,
(6) calculation of numeric values of *HR, SI, IC* parameters,
(7) direct transfer of obtained data to learning management system,
(8) visualization of processed data.

An example of the Varikard system in action – i.e. RR-intervals, and values of calculated parameters *HR, SI,* and *IC* - is presented on Fig. 1.

4 Experimental Data Obtained and Research Outcomes

In order to test the effectiveness of proposed approach – i.e. a consideration of SeLS system as a biotechnical system which effectiveness significantly depends on learner's functional state including MWC – we randomly selected and divided first-year students into two groups:

(1) experimental group EG of 46 students – a group of students who used the SeLS system for learning and testing, whose psychophysiological functional states were carefully measured, collected, processed and analyzed during learning process;
(2) regular group RG of 23 students – a group of students who also used the SeLS system for learning and testing; however, students in this group were not informed about the fact that their *IC* parameter "crossed the border" in terms of elevated *IC* parameter values; it was expected that due to complexity of learning content and to-be-taken comprehensive exams, tiredness, stress, and individual psychophysiological characteristics some of students probably would not be able to effectively learn, understand and retain new knowledge, i.e. values of their *IC* parameters will "cross the border" and stay above the allowed highest level of $IC = 9.5$ (Fig. 2).

Students in both groups were asked to take a 4-week long "Methods of Information Coding" online course using a learning management system. Course main topics included but were not limited to mathematical methods of data encoding/decoding, data transmission protocols, data processing algorithms, methods of information storage, data structures and algorithms, etc.

Each class in that online course included a set of tests and/or quizzes for (a) a new course topic, and, if necessary, (b) revised assignments for a previous topic in case *IC* parameter "crossed the border" and was above the recommended maximum one ($IC = 9.5$) for a particular student during previous test/quiz (Fig. 2).

Students of both groups took pre-course and post-course comprehensive exams. Each exam contained 45 problems and was 45 min long. Multiple experimental data have been obtained using the HRV method and the Varikard system; those data precisely reflected student psychophysiological state during both designated exams.

A summary of obtained experimental data is presented in Table 3.

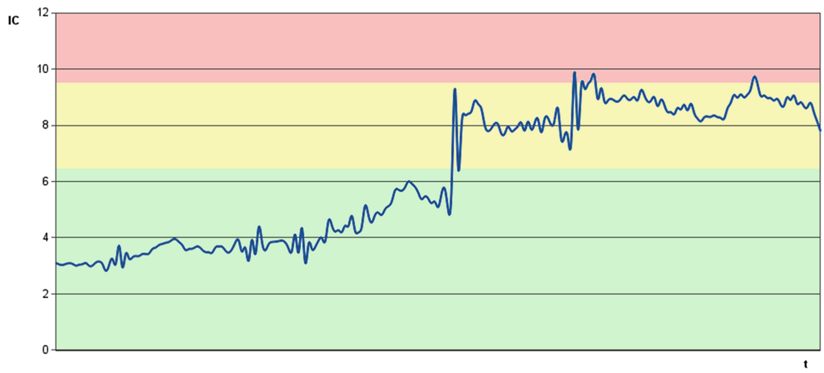

Fig. 2. The Varikard system: *IC* parameter values "crossed the border" case (with *IC* > 9.5)

Table 3. Obtained experimental data.

	Student groups	
	Experimental group (EG) with 46 students	Regular group (RG) with 23 students
Pre-course online exam		
Average score	42 %	42 %
Average IC	4.9	4.9
Post-course online exam		
Average score	86 %	79 %
Average IC	4.5	5.1

Outcome # 1. Students of both EG and RG groups had the same average scores (42 %) and average values of *IC* parameter (4.9) during a pre-course exam. However, during a post-course comprehensive exam EG students demonstrated better average scores (86 % in EG group versus 79 % in RG group) and smaller values of *IC* parameter – 4.5 in EG group versus 5.1 in RG group (as on Fig. 2, smaller value of *IC* is better). As a result, in general, an average student in EG group used fewer psychophysiological resources to achieve better learning outcomes than an average student in RG group; these obtained data strongly support the proposed approach.

Outcome # 2. Based on (a) obtained specific values of HRV method's indicators for a particular student for a particular learning assignment, and (b) range of "normal" HRM method values for this type of students, the SeLS system will get additional useful criteria to smartly compile an individual e-learning trajectory for a particular student. In other words, it will be able to automatically generate an individual sequence of reusable information and learning objects and atoms, pre- and post-tests, learning modules, learning assignments, types of problems in tests/quizzes to be taken, etc. in order to provide maximum efficiency of student learning outcomes [12].

5 Conclusions

The performed experiments and obtained data and outcomes enable us to make the following conclusions:

(1) The Smart e-Learning System (SeLS) should be designed and developed as a student-centered biotechnical system with a student/learner as a key central component in the advanced SeLS.
(2) Main features of a smart entity (such as sensing, transmission, big data processing, activation of actuators) and “smartness” levels (such as adaptation, sensing, inferring, learning, anticipation, self-organization) must be required characteristics of advanced SeLS.
(3) Multiple parameters of student psychophysiological state should be actively used in advanced SeLS for higher efficiency of (a) SeLS usability, (b) student learning process, and (c) student learning outcomes and knowledge retention factor.

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