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AFFECT-BASED, MULTIMODAL, VIDEO TUTORING SYSTEM FOR A NEUROMARKETING

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Abstract

Considerable research has been conducted globally showing how study results are substantially conditional to the interest and productivity of a learner in the studies and the emotions and stress the learner experiences. Scholars emphasize that learning should be pleasing, enticing, and emotionally positive leading to increased effectiveness of the studying. Tests were conducted regarding the effectiveness of the MSc Property management studies process among students. Development of the ARTSY Model involved five iterative phases over the course of the research. ARTSY Model, intelligent

and physiological technologies that had helped as the foundation for creating the Affect-based, Multimodal, Video Tutoring System for a Neuromarketing (ARTSY) were applied for this research. The research motivation and one of the main purposes are to increase students learning productivity, interest, emotions and decrease stress levels. According to this research motivation, ARTSY was developed. Upon comparison with the most advanced, existing affective tutoring systems, two innovative elements are distinguishing ARTSY. First, automatic means to develop and select the most effective variants from thousands of textual and video learning material alternatives by considering learner interest, productivity and stress levels. Secondly, exams or tests are unnecessary for assessing student knowledge levels by employing the newly developed Calculating a Student's Self-assessment Grade. ARTSY's future betterments are expected to achieve comprehensive and dependable, real-time information, not only about student needs but also about existing opportunities. A consequent outcome could be greater flexibility in the study process for students. This paper composed of Introduction (Section 1), Research background (Section 2), ARTSY Model description (Section 3) and the Construction of ARTSY (Section 4). The conclusions and notes for future study provide the ending to this article in Section 5.

Keywords

Neuromarketing, Tutoring System, Affect-based, Multimodal, Affective Tutoring System, Arousal, Valence

1. Introduction

History proposes that the worldwide economy after a major emergency like coronavirus will probably be different in a number of important means. Emergencies, counting epidemics, can promote the implementation of innovative tools. In this case, the e-learning and e-delivery of education issue are raising and this is important to ensure the continuous learning process (Wang, 2020; Carlsson-Szlezak et al., 2020; Mibe, 2020; Hazari, 2020; Parker, 2020). Procedures to end the dissemination of the coronavirus have become an unforeseen benefit for at minimum one business: online tutoring (Wang, 2020). For example, Hong Kong schools locked over Covid-19 use distance learning, audiovisual conferencing to continue lessons and advice students (Hazari, 2020). With many schools and universities locked, students are turning to the distance learning to last their tutoring (Parker, 2020). According to Wang (2020), China's distance learning leaders add \$3.2 billion as Covid-19 worries run students' distance.

An analysis was conducted on affective tutoring systems (Hernandez et al. 2007; Hernandez et al., 2008; Latham et al., 2014; Latham et al., 2012; Mao & Li, 2010; Moridis & Economides, 2008, 2009; Qi-rong, 2010; Sarrafzadeh et al., 2011) along with different methodologies for measuring self-assessments.

Meanwhile, the analyses conducted on biometric technologies were applied for the development of the Affect-based, Multimodal, Video Tutoring System for Neuromarketing (ARTSY). There is a proposal from Qi-rong (2010) for resolving the lack of emotional interactions in e-learning. His proposal is for an intelligent tutoring system with an affective computing model as its basis. Such a model presents descriptions of four basic emotions and definitions of moods and emotions; it also mapped out the link between emotions and learning psychology (Qi-rong, 2010).

The adaptations of ITSs have customarily been in accordance with the existing knowledge of a student. However, the factors that have currently been integrated due to their affecting learners include emotions, personality and learning style. Incorporation of three techniques is difficult for ITSs due to their complexity, which proves time-consuming (Latham et al., 2012). A major goal for artificial intelligence in education relates to the construction of computerized mechanisms with an ability to recognize the affective states of individual learners correctly, instantly and recurrently. Plus, these mechanisms must follow their recognition with a suitable response based on integrated pedagogical models (Moridis & Economides, 2009).

Our neuromarketing studies, as well as those done by other researchers, look at emotional states, valence and arousal (Boz et al., 2017; Golnar-Nik et al., 2019), affective states (Zurawicki, 2010; Gupta & Falk, 2016) and physiological states such as medium respiratory rates (Brown et al., 2010; Gallego et al., 2010; Balanou et al., 2013), heart rates (Brown et al., 2010; Gallego et al., 2010; Balanou et al., 2013; Mileti et al., 2016), pupil sizes (dos Santos et al., 2015; Ko et al., 2017; Ungureanu, 2017), and facial temperature (Brown et al., 2010; Balanou et al., 2013; Mileti et al., 2016).

These show that ATS investigations and increases in effectiveness are occurring in numerous directions. The worldwide uniqueness of the Affect-based, Multimodal, Video Tutoring System for a Neuromarketing (ARTSY) is primarily that it develops many alternative personalized text and video learning materials relevant to a concrete student, completes a multi-criterial analysis of these alternatives and chooses the most rational ones for that learner. This is accomplished in an integrative fashion in consideration of a learner's level of stress, emotions, learning efficiency and attraction in learning. Personalized, rational learning materials are selected in an integrated manner by considering the emotions, valence and arousal of a learner (see examples provided in Figures 3 and 6 and their descriptions) along with his/her blood pressure and heart rate.

2. Research Background

A number of researchers highlight emotions, pleasure and interest as key factors to an increase in learning ability and effectiveness (Gilbert, 2002; Gough, 2002; Rushton & Larkin, 2001; Snow et al.,

2005). Certain teaching manners stimulate enjoyment and curiosity, while others prove to be intensely boring. Desirable teaching outcomes are possible, according to Gough (2002), when a teaching strategy corresponds with pertinent student interests. Academic advancement becomes possible when emotions are recognized as influencers and motivators in addition to cognitive abilities, as Snow et al. (2005) have proclaimed.

When Goetz et al. (2010) examined situations that are involved in academic achievement, they discovered a distinct negative relationship between the course subject being taught and tediousness. Once studies become interesting, minds tend to function more efficiently, and attention becomes more focused, something which a number of scholars have noted, including Ainley & Hidi (2006), Hidi & Harackiewicz (2000), Jalongo (2007) and Nelson (2007). Even children process information much better, as found by Ainley & Hidi (2006), whenever teaching materials capture their interest. This way they are found to persevere with their work and remember their lessons better. Conversely, studies reveal that bored learners realize their difficulties about keeping their minds on their work (Sparks, 2012).

Customarily learning systems have focused on the cognitive abilities of learners, with no attention whatsoever on emotions (Qi-rong, 2010). Still, direct, one-on-one teaching proves more effective at teaching than using Intelligent Tutoring Systems (ITSs) do. Now it appears that future teachers will probably incorporate the emotions of their learners in their work (Sarrafzadeh et al., 2011). Provisions of a personalized, friendly learning environment seem to constitute a key trend when it comes to developments relevant to Intelligent Tutoring Systems (ITSs) (Mao & Li, 2010).

This research integrates Damasio's Somatic marker hypothesis (Damasio, 1994), Text Mining (Kaklauskas et al., 2014), DAM, CODEC, COPRAS and DUMA methods (Kaklauskas, 2015), biometric methods and systems (Kaklauskas et al., 2018a; Kaklauskas, 2015) and multiple criteria analysis methods and decision support systems (Kaklauskas, 2015; Kaklauskas, 2016, Kaklauskas, 1999).

That the guidance of behaviour and decision-making relates to emotional developments seemingly stems from the somatic marker hypothesis, which Damasio (1994) had formulated. Damasio's (1994) idea was that this term is a "marker" of an image. His term relates to the body in the broadest sense. A person may receive a somatic marker denoting a positive outcome, which would then stimulate happiness. This good feeling is inspirational, stimulating a person to seek the same feeling again from the similar or same behaviour. Conversely, a somatic marker may signify a negative outcome, leading to a feeling of sadness. Such a negative feeling alarms the individual, thereby diverting him/her from behaviour that resulted in this negative sensation. The feeling serves as a warning, an internal system of stopping related behaviour (Damasio, 1994).

The examination presented herein examines all the above-named factors. Its integrated study also presents the manner for the multivariant planning of variants. Aspects, which have not undergone previous analysis, may be interrelated, a matter distinguished by the research herein.

3. ARTSY Model

Affect-based, Multimodal, Video Tutoring System for a Neuromarketing (ARTSY) Model comprises an introduction, general explanation and exact necessities for an Intelligent Database Management System, an Intelligent Database, a Knowledge Base Management System, a Knowledge Base, an Equipment Subsystem, a Model Base Management System and an Intelligent Model Base and User Interface (see Figure 1). The basis for the development of the ARTSY was the aforementioned review of performed scientific research applying the hybrid approach. Thus, the hybrid methods approach is the basis of the ARTSY, and its application was for developing an Intelligent Model Base, described next:

- Domain Model holding the 54 a neuromarketing computer learning systems created by the authors and their colleagues. The foundation of these systems consists of DAM, CODEC, COPRAS and DUMA methods (Kaklauskas, 2015). Students can easily develop their own new a neuromarketing computer learning systems as needed. The above methods were applied to carry out some research with the authors' participation.
- Development of the Method for Calculating a Student's Self-assessment Grade aimed to establish the levels of student knowledge and a preliminary grade on an exam. This method, based on the self-report for ascertaining emotion and mood, is also a composite part of the Affective Tutor and Testing Model (ATTM).
- Data Mining determines the meaningful patterns among stress level, learning productivity and engage in learning of the students under research and their gathered physiological data. Data Mining involves calculating and determining numerous multi-modal, physical parameters of students. These include student's facial expressions (see Figures 3 and 6), systolic blood compression (see Figure 2) and diastolic blood compression and heart rate (see Figure 2) depending on their interest in learning, stress and productivity levels.
- Additionally, there is an application of Text Mining (Kaklauskas et al., 2014) and DAM, CODEC, COPRAS and DUMA methods (Kaklauskas, 2015).
- Recommendations Model.
- Clustering Model. Development of the Clustering Model involved the application of the Clustering Technique.

A Method for Calculating a Student's Self-assessment Grade was additionally developed; it can serve as the basis to assess students' levels of knowledge without using an exam or a test. Biometric approaches contained the basis for the measurements of learners' physical signs. Harley et al. (2015) worldwide investigation demonstrate that facial expressions may be the best one technique for correctly recognizing emotional conditions; using supplementary approaches to exactly categorize an emotional condition naturally marks in only modest additive improvements to correctness assessments. The establishment of learners' states (happiness, sadness, anger, surprise, scare, disgust and a neutral state) was with the automatically influence recognition software FaceReader 7.1 (see Figure 3). Measurements of valence and arousal levels were taken each two seconds (Fig. 6). The developers of FaceReader (2015) hold the opinion that this implied influence measurement software can identify facial expressions with an accurateness of 90%. During the research conducted by these authors, the high agreement between automatic facial affect detection software FaceReader 7.1 recognition and affective self-report was also established.

What can affect a student's behaviour and attitude in an examination in addition to personal expectations is that certain student's level of self-assessment. A means to measure this is by an application of the Self-assessment Measurement Model. Do the acquired knowledge and practical skills correspond with that student's true expectations? The extent to which these match the other is exceedingly important for student achievement. It has been shown that better learners tend to self-assess their accomplishments by merely an average grade. This has been confirmed by studies conducted by Lejk & Wyvill (2001), Papinczak et al. (2007), Sung et al. (2009), and other researchers. Meanwhile, students who perform at lower rates have a tendency to overestimate themselves. Low achievers and high achievers, as Sung et al. (2009) have found, often rate the quality of their efforts as too high or too low, respectfully. The authors of this work also confirm such a correlation by their research (Kaklauskas et al., 2010). They found that students performing with better e-test grades had rated themselves as worse on their self-assessments, and vice versa.

There are numerous, different questionnaires compiled to gain self-assessments, such as those devised by Pullmann & Allik (2008), Rahmani (2011), Saadat et al. (2012), and others. The questionnaire devised for measuring student self-assessments has similarities with all these other questionnaires. A 20-question questionnaire (see <http://iti.vgtu.lt/ilarning/charakteris.aspx>) was devised with the assistance of Rasa Pališkienė, who is a psychologist. This one determines a student's self- assessment (1) by basing it on analyses of pertinent scholarly literature and psychological techniques. The basis is this:

$$800x600K_s=0,055a+0,05b+0,045 c (1)$$

where a = number of responses to: “Disagree, the statement has little in common with my personality”; b = number of responses to: “I think the statement fits me in part, depending on the situation”; c = number of responses to: “Agree, the statement fits my personality”.

Other physiological signals (systolic blood compression (see Figure 2) and diastolic blood compression, heart rate (see Figure 2)) and their established dependencies with learners’ levels of stress, attentiveness in learning, and efficiency were used to guarantee the correctness of the levels of emotions, valence, and arousal received from FaceReader 7.1. These dependencies were gained, as learners used the affective, self-report questionnaire-based method while measuring their physiological signals (heart rate, systolic and diastolic blood compression) in parallel.

4. The Construction of ARTSY

Affect-based, Multimodal, Video Tutoring System for a Neuromarketing (ARTSY) involves the next parts (see Fig. 1): Intelligent Database Management System, Intelligent Database, Knowledge Base Management System, Knowledge Base, Equipment Subsystem, Model Base Management System, and Intelligent Model Base and User Interface.

The construction of the ARTSY is briefly analyzed in Subsections 4.1 - 4.3.

4.1. Smart Database and Knowledge Base Management System

Tables store all the data in the databases and organize them by relational database principles. The Intelligent Database holds the created Historical database, Domain model, Student (profiles, learning, personal information) database, e-Portfolio database, Question database, Self-assessment database, Exam process database, Student’s Affective Database, and Intelligent Database engine. All the data in the databases are interdependent. The Historical database gathers historical data. The information gathered and stored by the Question Database includes questions as per modules, possible responses to a question, and assessment of possible versions of correct responses. Meanwhile, real and integrated examination results accumulate in the Exam Process Database for storage including 1) time for replying to each question 2) a number of changes when replying to a test question, and 3) question difficulty from not confusing to most confusing. The Database then provides an assessment of this information. Additionally, a VSA assessment is provided with both while the student is replying as well as during the total time spent on the exam. There is also the Video, Calculators, and Computer Learning Systems Database, which includes numerous videos, calculators, and computer learning systems that assist in retaining learner interest.

The Domain model (theory, exercises, homework, coursework, examination questions, etc.) holds data and the knowledge that a tutor is teaching. This database was formed based on the VGTU Civil

Engineering Faculty. Over the three semesters of MSc courses, learners finish 7 main modules and 5, not obligatory modules. Learners select an optional from twenty-one modules in “Property Management”, an MSc degree study program, and they must optionally hold 5 exams. Throughout the 4 semesters, learners prepare a final thesis. The Student database holds information that is concrete to each learner.

The e-Portfolio database collects student e-portfolio information on the qualification certifications and diplomas a student has and that student’s achievements, goals, and experience. It also holds other personal entries about that student that can be provided to employers.

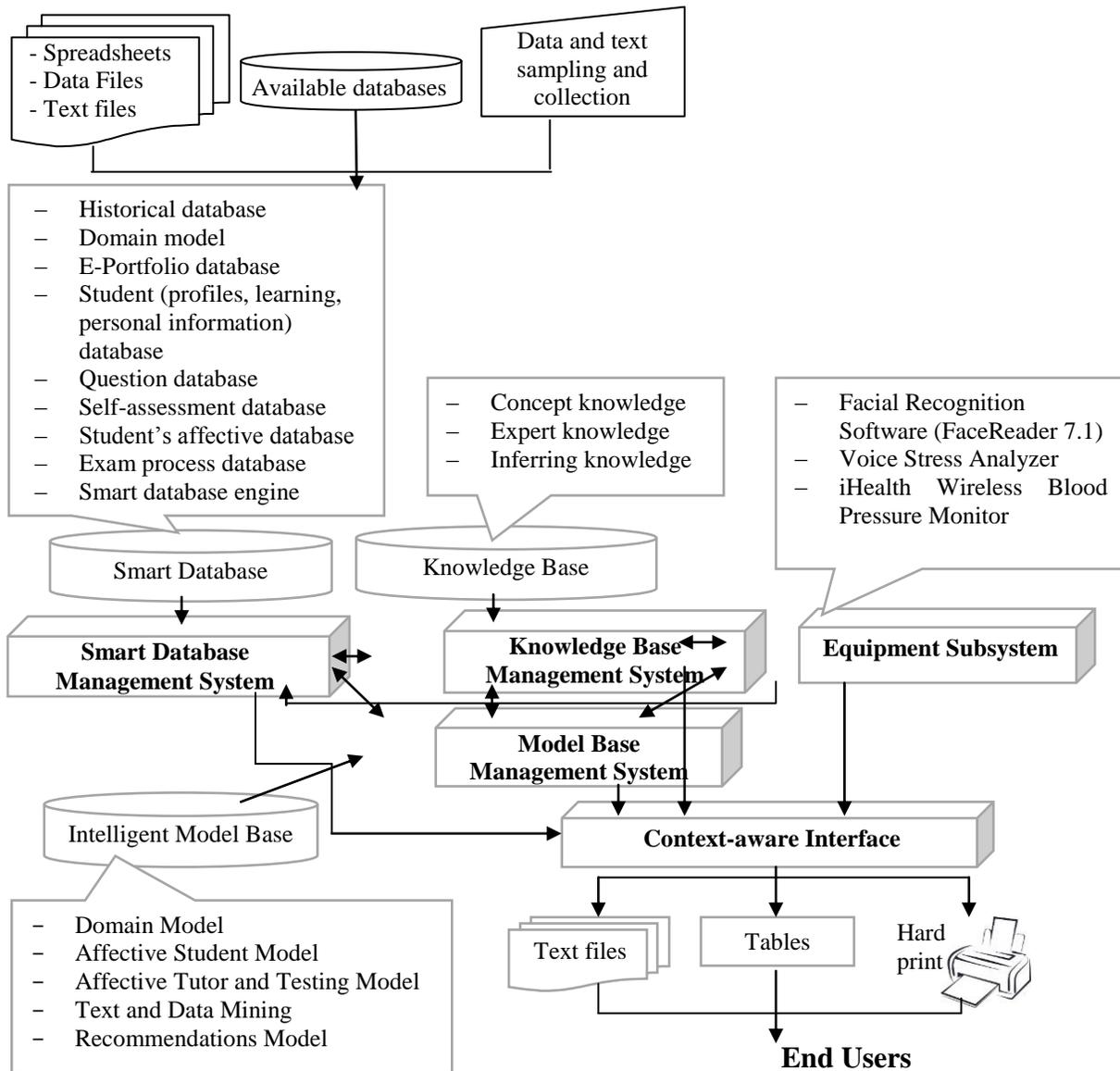


Figure 1: Construction of ARTSY
 (Source: composed by the authors)

A learner fills out his/her self-assessment questionnaire and presses the button marked “Start Learning”. Then the equipment subsystem starts collecting biometric data, which is stored in the Student’s Affective Database. The stress level, learning interest, and learning productivity experienced by different students differ. Therefore, the use of this way permits accumulating and storing the biometric parameters of different students in a Student’s Affective Database. A correlation analysis was performed in an effort to establish the interrelationship between the stress a student experiences, the biometric parameters of learning interest and learning products, and his/her self-assessment.

The storage of all the information in a database is in tables prepared by principles for relational databases. It uses an intellectual management system for a standard relational database. All data in a database are interrelated. The Knowledge Base (concept, expert, and inferring knowledge) represents facts and rules about the rational teaching process.

The ARTSY Intelligent Database is partly able to dealing and integration statistical, biometric and textual data along with the information and performing data mining. These principles automatically assess the student's stress, learning efficiency, and attraction in learning by using Ordered Logit, KNN, and Anova. The Data Mining collects and analyses the next data: (a) historical data describing individual student interests: grades earned for course work and exams; evaluations of course work and exams by points according to their interestingness, complexity, and stress caused to students; student level of advancement within the group and student self-assessment results according to the Multiple Intelligences Self-Assessment scale; (2) historical physiological data defining individual and situational interests of a student: student learning and his/her assessment of stress during an exam and learning interestingness (low, average, high); (3) statistical information on module keywords on exams passed at levels of good, average, and poor and defining individual student interestedness; (4) biometrical data. The model involves calculating and determining numerous multi-modal, physical parameters of students, including their facial expressions, systolic blood compression, and diastolic blood compression, heart rate, belonging on their attraction in learning, stress, productivity levels and determining the reliability of these dependencies with reference to the LOGIT, KNN, and Anova methods.

The Student Model establishes the specific dependence of interest, productivity, and stress on student learning by virtue of a student’s changing physiological parameter by consuming the Student’s Affective Database with the assistance of the LOGIT method. For example, 587 measurements were taken in the effort to establish the dependency between student learning and stress as per its physical factors (systolic blood compression and heart rate) by applying the LOGIT method. A learner would fill out the self-analysis questionnaire during all these 587 measurements, thereby evaluating his/her own learning productivity and interest as well as stress experiences on a 10-point scale (selecting from 1 to 10

points). These data were accumulated in the Self-assessment database in the Student Module. Since most counting systems in the world are based on 10, people are accustomed to assessing different matters within the limit of 10 points. Thus, use was also made of a 10-point, verbal-numerical scale where 1 and 2 mean poor, 3 and 4 mean fair, 5 and 6—good, 7 and 8—very good, and 9 and 10—excellent. The LOGIT subsystem of the Student Module can establish the stress of a student’s learning over any particular learning period according to the established dependency between student learning and stress by its physiological parameters (systolic blood compression and heart rate). A 41% recognition level was gained with a 0-point probability of error, and a 98% recognition level was reached with a 1-point probability of error (see Figure 2).

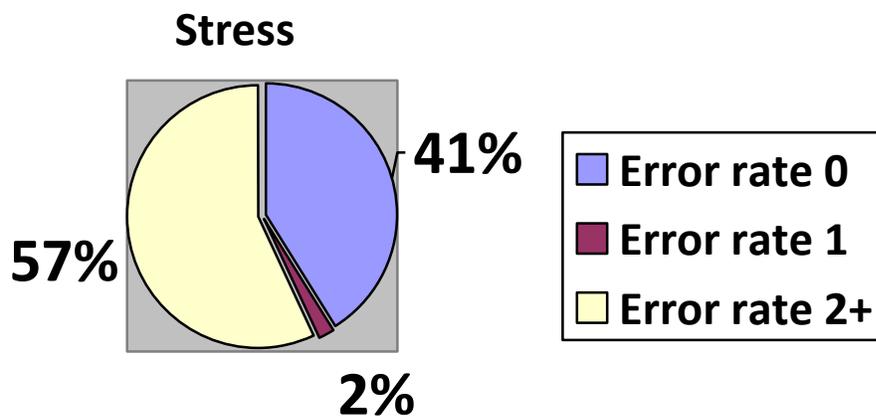


Figure 2: *Dependency between Stress and a Student’s Physical Parameters (Systolic Blood Compression and Heart Rate)—the Recognition Level established at the time of Research by using Ordered Logit*
(Source: Composed by the Authors)

Students are able to use neuromarketing computer learning systems for handling their assignments, homework and final course project: (1) ViNeRS1 is the computer learning system for analyzing and assessing the impact of electronic advertisements under composition. This computerized learning system permits grasping more about the efficiency of an ad at each phase of its composition. It assists in determining the advantages and disadvantages of an ad and revealing the significance of the enrichment to achieve the most attractive variation for a target viewer. This system helps to make an accurate assessment of the part of the audiovisual that has the highest impact on temporary and permanent memory. Furthermore, it identifies the objects in a clip, which generate the toughest effect and feelings; (2) ViNeRS2 is the computerized teaching system for broadcasting electronic, already composed advertisements. This computerized teaching system allows viewers to assess an integrated, neuro-biological response and select the most effective variation of an advertisement in real-time; (3) Create their own neuro-advertising property, housing purchase, building refurbishment, building life cycle,

facilities and property management, sustainable real estate development, and other video recommendation systems; (4) Calculate passive house customer-perceived, emotional, hedonistic and utilitarian values.

4.2. The Equipment Subsystem

The Equipment Subsystem consists of Facial-Recognition Software (FaceReader 7.1), Voice Stress Analyzer, and iHealth Wireless Blood Pressure Monitor. For example, FaceReader 7.1 procedures a web camera to identify the learner's states (happiness, sadness, anger, surprise, scare, disgust, and a neutral state) (see Figure 3) and the learner's valence and arousal levels every 2 seconds (Fig. 6). The valence specifies whether the learner's emotional position is positive or negative, and arousal specifies how dynamic the learner is. The value of valence varieties from very positive to very negative, whereas the value of arousal varieties from relaxing or comforting to thrilling or agitating (Lang et al., 1993; Kensinger, 2004). If the subsystem identifies emotions with high arousal and high valence (thrilled, surprised, etc.), it proposes ongoing with the present learning video, but if the emotions are looking after to negative (e.g., unhappy, uninterested, exhausted), it proposes shifting to the following audiovisual lecture. Once the FaceReader 7.1 Subsystem identifies a low level of valence in a mentee, the ARTSY presents to that mentee the next, more interesting study material (based on the compiled "mini video curricula"). Otherwise, it can permit the mentee to select for him/herself the material he/she would prefer to study at that time, which increases situational interest and learning effectiveness. In this instance, the red dot on the valence axis moves from the left to the right side, which indicates a mentee's level of interest and, at the same time, the increase in learning efficiency. The developed ARTSY continuously makes modifications pertinent to the education materials with regard to situational and individual mentee interest.

Students who participated in the experiment used the university's computers with the Equipment Subsystem for learning and data capture. Three channels of data were recorded and collected, while learners networked with ARTSY on themes of real estate management: 1) FaceReader 7.1 was employed for gathering data on facial expressions, 2) psychophysiological stress responses were recorded by Voice Stress Analysis (X13-VSA), and 3) pulse, blood pressure, etc. were measured by the iHealth Wireless Blood Pressure Monitor. In our research, the Voice Stress Analysis Subsystem was used to gather information on micro tremors in voices of tested students. While students were engaged in their self-assessments, they would experiment with ARTSY. Their responses would be imaginary, having nothing to do with reality. Nonetheless, the Voice Stress Analysis Subsystem would annul these sorts of untrue responses. Therefore, whenever the microtremor frequency of a student would rise above 11 Hz while answering a question, the answer would be discarded and unused in any further calculations. A voice stress analyzer would be employed to perform an analysis of the stress in a student's voice.

4.3. Intelligent Model Base and Its Management Subsystem

The Intelligent Model-based consists of six models (subsystems): Domain model, Affective student model, Affective tutor, and testing model, Text and data mining, Recommendation model (see Figure 1). The analyses of these models (subsystems) in brief follow.

The Domain Model consists of the 21 modules within “Property Management”, 54 neuromarketing computer learning systems, and a pedagogic module to prepare the rational teaching material. This subsystem uses standard Microsoft Framework 4.0 and SQL Server 2008 apparatuses.

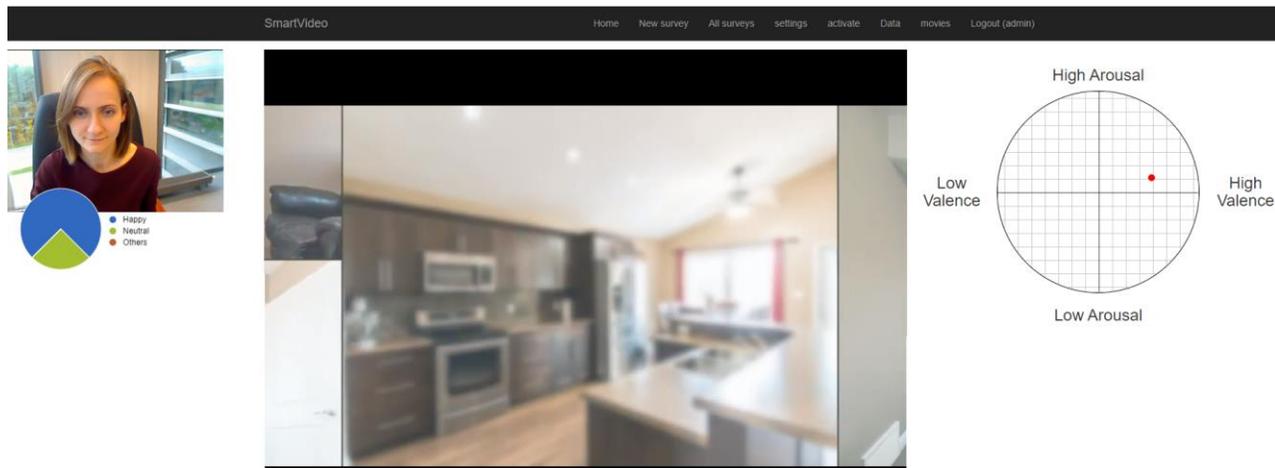
The information collected and stored in a student’s model includes completed education, previously taken exams and their grades, schedules of lectures and exams, study needs, stress, the level of interest for different subjects and topics, and the student’s physiological data. Such physiological data includes emotional expressions on a student’s face, systolic blood compression (Fig. 2), diastolic blood compression, pulse (Fig. 2), and their dependencies on a student’s interest and efficiency in education as well as the level of experienced stress. Thus the student’s model collects all the information about the course of a student’s studies along with changes in his/her physiological parameters. First, the student’s model assists in evaluating a student’s level of knowledge and attentiveness in his/her studied classes. A comparison of the existing knowledge with expert knowledge establishes the deviance in a student’s level of knowledge from expert knowledge. This deviance, the level of interest a student has in the studied subject matter, the level of stress experienced while studying this subject, learning productivity, and the emotional learning and testing model—all these constitute a basis. Such a basis establishes, what study program modules or module divisions (subdivisions to add to the program for the subject of studies and the means of presenting such material (by texts, use of multimedia, computerized learning systems, and so forth). The Affective Student Model makes use of response data to derive a depiction of the knowledge and learning process pertinent to some individual students. It is able to differentiate that student's knowledge from the knowledge of an expert. Such differentiations serve as the basis for deriving a student's level of interest, stress and learning yield. This way the system determines the best curriculum module or module chapter (subchapter) to introduce and the best manner of its presentation, whether by text, multimedia, a computer learning system, or some other means. All accumulated data must be useable by the Affective Tutor and Testing Module because its data provisions constitute the main objective of the Affective Student Model.

The Affective Tutor and Testing Model (ATTM) offers a model of the education procedure and cares about the changeover to a novel knowledge state by applying data and text mining. E.g., this model monitors the data about when to the exam, when to introduce a new theme, and which theme to introduce (see Fig. 3). The teaching experiences of associate professors or professors provide the input into the

ATTM. The Affective Tutor and Testing Model, on the other hand, provide output on the various needs, stress levels, and learning yield pertinent to every individual student.

The difference between the existing knowledge (as per a test prior to studies) and ultimate knowledge (as per a test following studies) defines obtained knowledge. The objective of the Tutor and Testing Model is to provide explanations about the correctness/wrongness of each answer. Furthermore, it recommends literature and multimedia to a better understanding of the topic relevant to a wrong response to a question. The level of difficulty of an exam is left to the choice of the student. Some learners, e.g., have a weak mathematical orientation so they may not wish to be examined on mathematical formulas used for decision-making.

The Tutor and Testing Model stores a base consisting of the following: (1) Modular questions; (2) Possible responses to the question; (3) Assessments of possible right or wrong response variants — scoring zero for wrong; (4) Answers, one for each correct one and 0 to 1 for intermediate answers; (5) Level of question difficulty based on previous test results from other students; (6) Links to related study materials relevant to a question; (7) Testing time allocations (Figure 4).



time	Neutral	Happy	Sad	Angry	Surprised	Scared	Disgusted
2s	0.10%	99.40%	0.40%	0.00%	0.00%	0.00%	0.00%
4s	0.13%	99.87%	0.00%	0.00%	0.00%	0.00%	0.00%
6s	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
8s	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
10s	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
12s	0.13%	99.87%	0.00%	0.00%	0.00%	0.00%	0.00%
14s	0.37%	99.63%	0.00%	0.00%	0.00%	0.00%	0.00%
16s	0.90%	99.10%	0.00%	0.00%	0.00%	0.00%	0.00%
18s	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
20s	21.63%	78.30%	0.00%	0.00%	0.00%	0.00%	0.00%

Figure 3: Emotions, Valence and Arousal Investigation Outcomes

(Source: composed by the authors)

The mentee’s model of analytical data analyzes and establishes connections between a learner’s interestedness (emotions, valence, and arousal), his/her physiological parameters, and the contents of the material in a mentoring video. The content of viewed videos is grouped by its potential to interest (very interesting, average, and uninteresting chunks of an educational video). Based on this information, affective and physical maps of videos are created. Additionally, this model accumulates data on how many times and in which places a termination of a shown video recording occurred (Fig. 3) due to its insufficient importance and interest to the learner. Conversely, it also gathers data on how many times some certain video had been viewed to its end. These data can be used in an effort to improve the quality of mentoring video films.

The Mentee Model accumulates statistical data on the interestedness of mentees (measures of their emotions, arousal, and valence) in video materials. The Mentee Model accumulates data on the number of terminations and the places of such terminations in mentoring videos being viewed due to their insufficient relevance and interest to a learner. Additionally, data are also gathered on how many times a video had been watched entirely, to its end. Analyses of the level of interest of such mentoring resources for mentees clearly show which videos and which of their composite parts are the most popular. The composite parts that need greater expansion or improvement can also be pinpointed. Furthermore, those that should be eliminated from the studies process can also be identified.

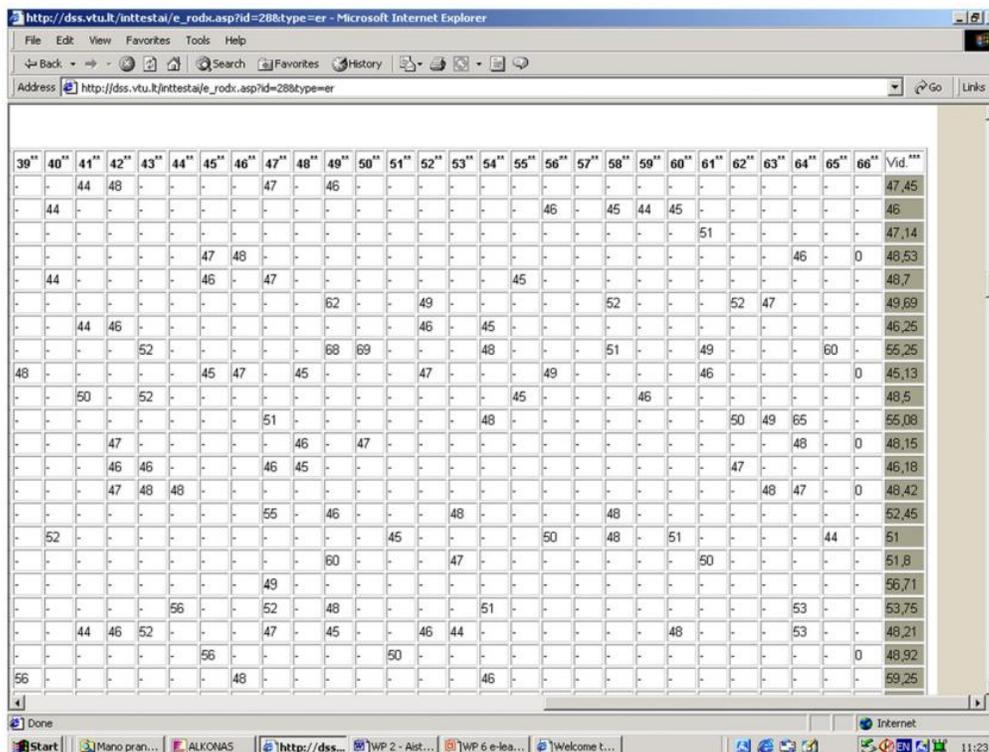


Figure 4: *Question Timespan, where Rows indicate Specific Questions and Columns, Specific Students*
 (Source: composed by the authors)

The Affective Tutor and Testing Model (ATTM) decide whether to show the selected video lecture. If the learner’s physical factors (heart rate, systolic and diastolic blood compressions) show that the student likes (i.e., a learner’s interest in the studies is greater than average, while a learner’s experienced stress is less than average) that specific educational video, the ATTM proposes ongoing with the same audiovisual lecture. If not, the system proposes skipping to the next selected educational video (see Figure 5 Stage 4).

The valence specifies the learner’s emotional state, and arousal specifies the strength of emotions. If the subsystem determines positive valence in the student viewing an educational video, it proposes ongoing with the present audiovisual lecture. However, if the emotions incline to be more negative than positive, the subsystem proposes shifting to the next educational video (see Figure 6) (see Figure 5 Stage 6).

The ATTM only shows certain audiovisual lectures, when the emotions, valence, arousal, and physical factors of a learner approve that the student enjoys the educational video.

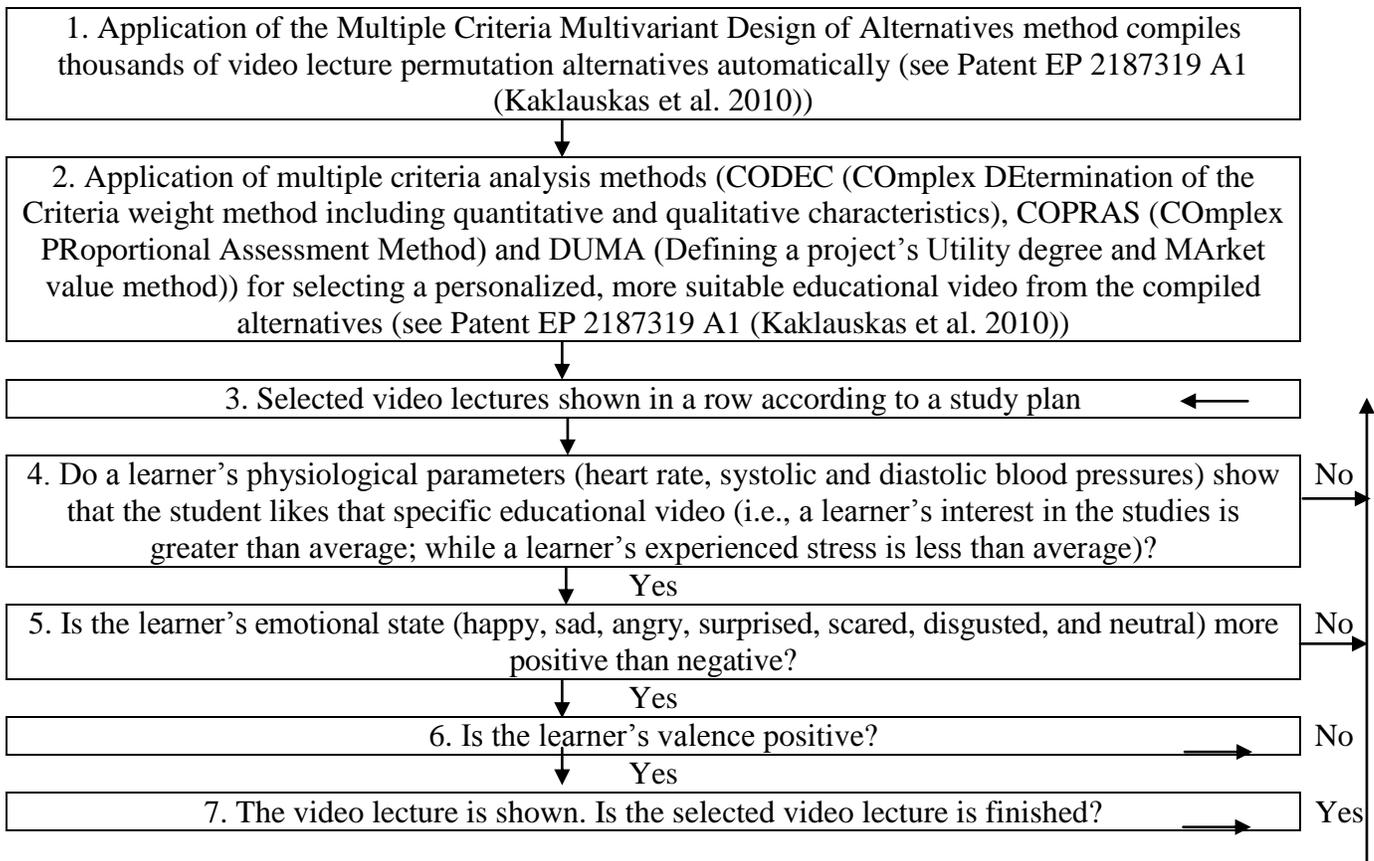
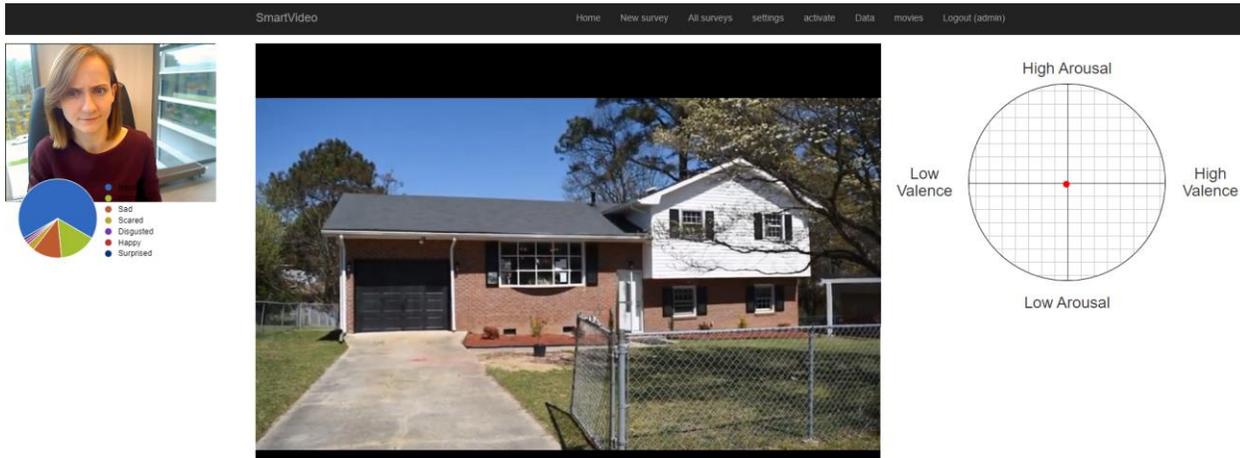


Figure 5: *Compiling Video Lecture Alternatives, establishing Rationality and the Process of showing them to Learners—a Block Diagram*
 (Source: Composed by the Authors)

A compilation of text alternatives is analogical to the video lecture (see Figure 6). The establishment of their rationality and the process of showing them to learners are the same.

It also establishes the level of stress experienced relevant to the various topics of the studied subject and the strengths and gaps in a student’s knowledge. Then ATTM generalizes the novel knowledge acquired during the course of his/her studies and offers different recommendations for further studies.



time	Neutral	Happy	Sad	Angry	Surprised	Scared	Disgusted
2s	0.10%	99.40%	0.40%	0.00%	0.00%	0.00%	0.00%
4s	0.13%	99.87%	0.00%	0.00%	0.00%	0.00%	0.00%
...							
22s	66.97%	31.83%	0.63%	0.03%	0.00%	0.00%	0.03%
24s	60.10%	38.90%	0.35%	0.00%	0.00%	0.00%	0.00%
26s	96.30%	0.40%	2.00%	0.60%	0.00%	0.00%	0.00%
2s	45.45%	54.40%	0.05%	0.00%	0.00%	0.00%	0.00%
4s	70.27%	28.37%	1.20%	0.03%	0.00%	0.00%	0.00%

Figure 6: Alteration in a video lecture, when the neurobiological evaluation of facial emotions, valence and arousal shows insignificance for learner needs

(Source: composed by the authors)

5. Conclusion

Upgrading learning efficiency via emotions, pleasurable sensations and interest is a topic that different researchers highlight, including Gilbert (2002), Gough (2002), Rushton & Larkin (2001) and Snow et al. (2005). The topics of analyses basing the development of the Affect-based, Multimodal, Video Tutoring System for a Neuromarketing (ARTSY) include Affective tutoring systems studied by Hernandez et al. (2007, 2008), Latham et al. (2014, 2012), Mao & Li (2010), Moridis & Economides (2008, 2009), Qi-rong (2010) and Sarrafzadeh et al. (2011), numerous self-assessment methodologies and student self-assessment scores, and biometric technologies. Although ITSs generally conform to the

current knowledge of students, learner affect factors such as emotions, personality, and learning style have been included lately. Not many ITSs are capable of including all three techniques because their developments have been complicated and time-consuming (Latham et al., 2012).

The ARTSY Model, intelligent and physiological technologies that had helped as the foundation for creating the Affect-based, Multimodal, Video Tutoring System for a Neuromarketing (ARTSY) were applied for this research.

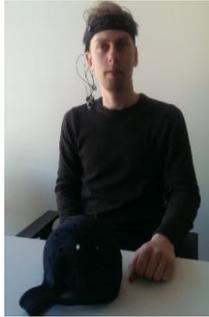
ARTSY analyses the interest students have in learning, their productivity, emotions, and stress levels. The ARTSY was verified using data originating from tests taken by 87 MSc students recruited from Lithuania and Belarus from MSc students aged between 22 and 41 years studying “Real Estate Management” and “Construction Management” at Vilnius Gediminas Technical and Belarusian State Technological Universities while interacting with the ARTSY learning environment. Students were questioned at the end of the experimentation. This feedback from the students advised that learners benefited from the additional use of the ARTSY learning environment for learning inspiration and pleasure. Furthermore, they noted that the application of this System in practice would generate circumstances for rationalizing the studies process, enriching the quality of the studies, growing the productivity of the learning, and decreasing stress.

Upon comparison with the most advanced, existing affective tutoring systems, the innovation of ARTSY is that this System could automatically develop and select the most effective variants from thousands of textual and video learning material alternatives by considering learner interest, productivity, and stress levels. Secondly, exams or tests are unnecessary for assessing student knowledge levels by employing the newly developed Calculating a Student’s Self-assessment Grade. Presently the ARTSY Intelligent Database (see Figure 7) is partly able to manage and merge information on historical statistical and biometrics data (e.g., see Figure 3), texts (e.g., keywords defining student individual interests), charts (see Figure 6), a neuromarketing computer learning systems, results of tests and exams, diagrams and videos (see Figures 3 and 4) as well as to perform data mining. Further improvements on the integration of such Intelligent Database data and information and data mining are foreseen in the future to increase the system’s effectiveness.

The existing e-learning infrastructure still contains gaps. This research identifies them so that affective tutoring technologies would be able to address them. The specific demonstration of this research is how a selected domain can best utilize the learning concept by vigorously exploring and controlling environmental variables. ARTSY is at its early developing stage, it has some research limitations: not only lack of studies in investigating all cognitive aspects, but also a lack of factors that are considered in constructing an overall student profile.

Fragment of Equipment Subsystem

Enobio Helmet (wearable and wireless electrophysiology sensor system for recording EEG)

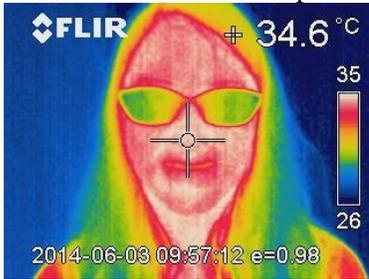


Miramatrix S2 Eye-Tracker (MRS2)

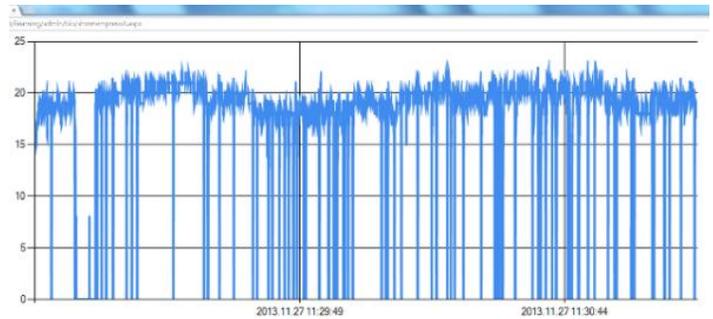


Fragment of Student's Affective Database

Student's face temperature and a student's iris size, iris blink frequency



...



EEG data



Fragment of Student's Affective Database

User	001
Parameter A	Right eye pupil diameter
	Right eye pupil diameter
	Right cheek temperature
	Diastolic blood pressure
	Humidity
	Left eye pupil diameter
	Left hand temperature
	Left hand middle finger temperature
	Left cheek temperature
	Forehead temperature
	Oxygen saturation
	Body temperature
	Respiration rate
	Nose temperature
	Heart rate
	Systolic blood pressure
	Chin temperature
	Finger temperature
	Skin conductance

Fragment of Affective Tutor and Testing Model

Time-span per question (rows show specific questions; columns show students)

	39"	40"	41"	42"	43"	44"	45"	46"	47"	48"	49"	50"	51"	52"	53"	54"	55"	56"	57"	58"	59"	60"	61"	62"	63"	64"	65"	66"	Vid
44	48	44	47	46																								87,85	
44																												88	
44																												87,74	
44																												80,53	
44																												88,7	
44																												89,69	
44																												86,25	
48																												85,28	
48																												85,13	
48																												86,5	
48																												86,08	
48																												86,15	
48																												86,19	
48																												89,48	
48																												82,48	
48																												51	
48																												51,8	
48																												86,71	
48																												83,75	
48																												86,21	
48																												89,88	
48																												59,25	

Fragment of Computer Learning Systems

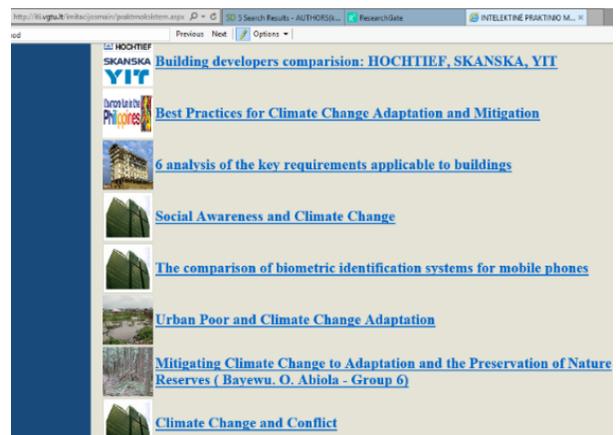


Figure 7: Foreseen Intelligent Database Improvements for Managing and Merging Data more effectively

(Source: Composed by the Authors)

The means to acquire real-time information pertinent to student needs and current opportunities still require an upgraded ARTSY. Such future betterments should result in comprehensive and reliable study processes, which would be more adapted to student needs. Furthermore, additional criteria may be added to evaluate the students' physiological and affective conditions. A selection is made of the best lecturer video to show a student, which best conforms to the individual needs of that student. This is possible upon completion of a multiple criteria analysis on the most appropriate video alternative that targets a certain student segment.

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