Article

Deployment and Dynamics of a Biofeedback System for Anxiety Awareness during Online Examination Activities

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Abstract: The presented paper examines the deployment of a cost-effective biofeedback system that provides anxiety awareness during online examination activities. Human anxiety is classified by evaluating biosignals related to skin conductance, skin temperature, and heart rate. The first aim of this study is to check the presented system performance. Thus, we test the convergent validity of the system regarding self-report measures of anxiety. Moreover, the system is validated against a commercial tool of anxiety detection. Fifteen (15) postgraduate students took part in the relevant psychometric test. The convergent validity of the system is found to be satisfactory. The second aim of this study is to identify the participant's personality dimensions according to Technology Readiness Index (TRI) which affects their academic performance and their real-time anxiety, as provided by the biofeedback device, during academic examinations. Thirty-five (35) postgraduate students, who were taking examinations in the form of synchronous online tests in the classroom for one of their lessons, took part in this stage of the research. The examined relationships are presented via a path model showing mainly that insecurity causes academic performance to decline, which in turn has a significant negative effect with increasing anxiety.

Keywords: technology readiness; academic performance; biofeedback in learning; student state anxiety

1. Introduction

Biofeedback is a modern technique that provides human affective state recognition, including anxiety awareness. It involves a mind–body technique and is used as an umbrella term to describe strategies that enable individuals to be aware of their own physiological responses in real-time, for the purpose of improving their physical, mental, emotional, and spiritual health [1–3]. Thus, biofeedback helps people identify their affective states and motivates them to apply cognitive processes, such as self-control and/or self-regulation. The importance of human affective state awareness in education has been presented by Mayer, Roberts, and Barsade [4], who claim that an educational system which does not include student strategies for stress regulation, associated with learning and test-taking, is clearly deficient [5].

Moreover, it could be argued that students who continuously monitor their anxiety levels may then utilize this information to support the development of their self-regulation skills. A recent review of strategies dealing with high anxiety in educational contexts revealed that the various effective methods to handle stress conditions included behavioral interventions that took into account the students' emotional states, such as biofeedback [5,6]. However, research into the effect of biofeedback on university students is very limited and has shown no clear results [5]. Thus, the present paper aims to examine the dynamics produced by applying biofeedback techniques during university students' examinations. More specifically, the purpose of this study is to identify the participant's personality dimensions according to Technology Readiness Index (TRI) which affected their academic

performance and their real-time anxiety, as provided by biofeedback, during academic examinations. Technology Readiness (TR) refers to "people's propensity to embrace and use new technologies to accomplish goals in home life and at work". It is a set of technology-related beliefs. These beliefs coexist, vary among individuals, and point to an individual's predisposition to interact with new technology. Four dimensions of these beliefs have been identified: optimism, innovativeness, discomfort, and insecurity [7,8]. According to Parasuraman and Colby [9], the four dimensions are independent, each of them making a unique contribution to an individual's Technology Readiness Index (TRI).

The following paragraphs present (a) the relationship between personality traits and academic achievement and (b) the need for a deeper exploration of the relationship between test anxiety and performance in modern academic testing contexts.

1.1. Relationship between Personality Traits and Academic Achievement

Some researchers consider that student personality traits are critical factors, which influence learning and academic performance [10–12].

Taking into account that anxiety is one of the personality traits that are included in the dimension of neuroticism, both in Eysenck's and in the Big Five taxonomy of personality dimensions [13,14], on the one hand, and the lack of established results regarding the relationship between personality traits and academic achievement, on the other hand, we attempted to investigate the aforementioned relationships during examinations, while considering anxiety as an additional important factor.

According to Lazarus [15], many emotions can be covered beneath the label of anxiety. The terms trait emotions and trait affectivity are "used to signify dispositional tendencies of the individual towards the experience of either specific emotions or even positive versus negative emotions in general" [16–18]. From this perspective, to say someone is a test-anxious person implies that he or she tends to see the testing situation in a manner that generally results in feeling anxious [16]. In addition, state test anxiety refers to the momentary context-specific appraisals, "right now" emotions and strategies, that emerge during a person-environment transaction [16–19]. Furthermore, research has shown that test anxiety is a multidimensional term [20]. Liebert and Morris [21] have suggested that test anxiety consists of two major dimensions, (a) the cognitive dimension labeled as "worry", which refers to concerns about being evaluated and possibilities of failure, and (b) the affective dimension labeled as "emotionality", which refers to the perception of the autonomic reactions evoked by test conditions [22]. The emotionality dimension refers to the classification of physiological biosignals that occur during evaluative situations and are expressed through: (a) an increased galvanic skin response, (b) an increased heart rate, (c) dizziness, and so forth [23].

The present study deals with real-time student emotionality within a context of an online academic activity, examining state anxiety and utilizing the state part of the State-Trait Anxiety Inventory (STAI) [24] for the convergent validity test of the biofeedback system.

1.2. The Need for a Deeper Exploration of the Relationship between Test Anxiety and Performance in Modern Academic Testing Contexts

Many researchers argue that increased test anxiety is one of the main causes of poor performance [25–29]. The negative relationship between anxiety and academic achievement has also been verified in research by Pekrun et al. [17,18]. A number of experts have stated that it would be better to view the relationship between test anxiety and performance as reciprocal [20,30]. More specifically, Zeidner [20] has stated that test anxiety may affect performance, but test performance may also affect anxiety. The aforementioned theories lead us to the consideration that although the aforementioned relationship is reciprocal, a definite causal relationship has not yet been established between these two variables, and further research is required [31,32].

Nowadays, learning environments are starting to utilize more technological tools, such as computer-assisted learning, distance learning, and even computer-supported col-

laborative learning (CSCL). Moreover, academic testing conditions in many cases now differ from the traditional methods of writing exams, which utilized computer assistance (i.e., multiple-choice tests). According to Baig et al. [33], improved technological awareness and the utilization of computer-based examinations at a preparatory level for both teachers and students can reduce students' test anxiety. In addition, it could be suggested that personality dimensions may differ, with regard to their effect on student behavior, depending on the learning environments. Within this context, there is a need for more current research activities that deal with the relationship between student personality traits, such as anxiety, and performance in computer-based examinations.

2. The Biofeedback Device and Application

Taking into account the dynamics of the anxiety provided by biofeedback during academic examinations, the present study attempted to initially investigate the deployment of a cost-effective biofeedback system that provides anxiety awareness during online examination activities. This section briefly presents this device.

The design of the biofeedback device was based on an analysis and modeling of the users, and on the relevant activities and suitable usage scenarios as well. Next, we proceeded with an application of the biofeedback tool by creating a prototype version and evaluating it. The biofeedback device (Figure 1a) was used to collect, identify, and utilize biosignals, which were the result of physiological reactions to stressful situations, such as skin sweating (GSR), heart rate (HR), and skin temperature (SKT).
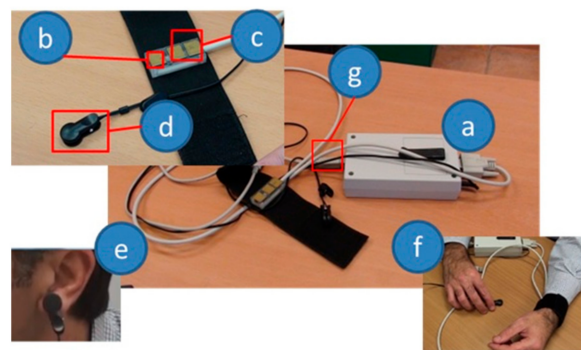
Figure 1. The biofeedback device. (**a**) Device, (**b**) Skin temperature, (**c**) GSR, (**d**) Heart rate ear clip, (**e**) User connected to heart rate ear clip, (**f**) user wearing bracelet with skin temperature and GSR sensor, (**g**) USB cable.

In our effort to construct a convenient device, we embedded the skin temperature (Figure 1b) and GSR (Figure 1c) sensors on the surface of a bracelet. We also used a heart rate sensor in the form of a clip, which we attached to the individual's ear lobe (Figure 1d). The clip was part of the Grove ear clip kit, which collects photoplethysmographic (PPG) signals and calculates the values of the interbeat interval (IBI) time series, which result in heart rate values. Figure 1e depicts the user wearing the heart rate sensor. Figure 1f depicts the user wearing the bracelet with the skin temperature and GSR sensor.

During this study, the collected raw biosignals are first normalized and then filtered. A low pass filter is applied to the PPG signal. In addition, low pass and moving average filters are applied to the GSR and skin temperature signals in order to remove the high frequency components. The resulting values of the GSR and SKT signals and the calculated heart rate (HR) are added to the biosignal vectors, which are transferred to the biofeedback application (Figure 2).
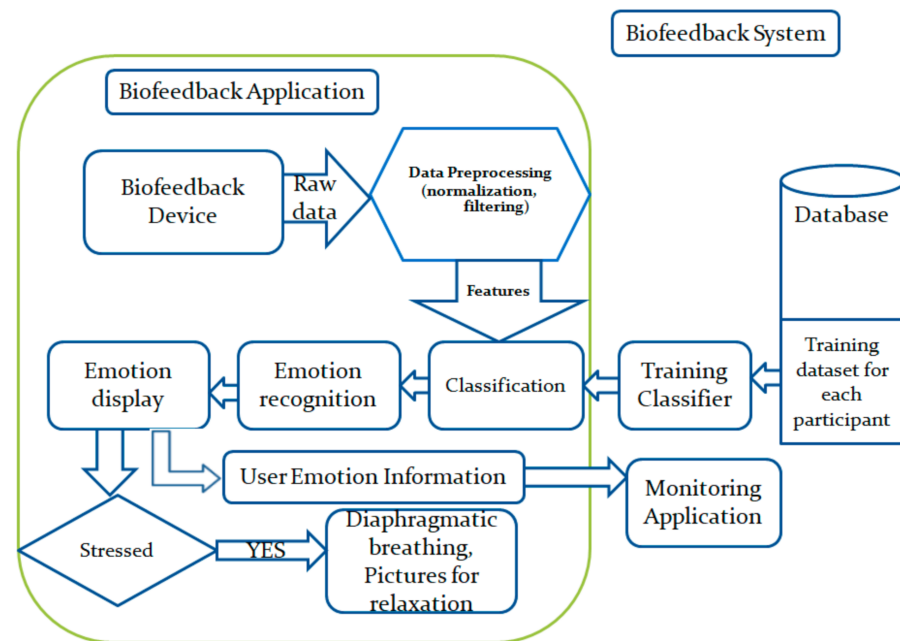
Figure 2. The biofeedback system.

The heart rate sensor has a range of measures $\geq 30/\text{min}$. A TMP36 (analog system) is used as a skin temperature sensor which is sufficiently accurate, affordable, easy to use, and also operates under a broad range of environmental conditions (-40 to $150\,°\text{C}$). As the temperature increases, the voltage across a diode also increases at a known rate. This sensor has $\pm 2\,°\text{C}$ accuracy over temperature and a scale factor of $10\,\text{mV}/°\text{C}$. The resolution of the Arduino board is 4.9 mv. The measurement sampling rate is 10 Hz. Both the bracelet and the ear clip are connected to the main body of the system, which consists of an Arduino board and a separate processing board for the heart rate sensor. The whole system costs approximately 100 Euros, which is quite low compared to other similar, well-known systems. All measurements took place at a normal environmental temperature, ranging from $20\,°\text{C}$ to $25\,°\text{C}$. The biofeedback tool (Figure 1) uses the Arduino platform as an analogue to digital converter; it is connected to a computer through a USB cable (Figure 1g) or via a Bluetooth connection. This device collaborates with dedicated software (biofeedback application). This application classifies real-time biosignals, using the Gaussian regression algorithm [34], to human anxiety levels. The real-time raw biosignals and the resulting anxiety level are displayed on the screen.

Biosignal values and anxiety levels are stored in an online database for record-keeping purposes (Figure 2).

Before the case study activities take place, the regression algorithm is trained for every user. Then every derived model is used to determine the specific participant's anxiety level during the activities, on the fly. The biofeedback application has a graphical interface (Figure 3) that either appears on screen or embedded in a web environment. The graphical part of the application displays the result of the regression procedure as a visualized response on the computer screen, where users can see their personal code (Figure 3a) and recognize their anxiety states through a chromatic code (red for anxiety, green for relaxation, orange for a little anxiety) along with their anxiety level percentage (Figure 3b). During the real-time measurement, when high anxiety levels are reached, the application encourages users to apply diaphragmatic breathing (Figure 3c) and shows them pictures so as to get them to relax (Figure 3e). Furthermore, the application informs the users about whether the sensors are working properly (green color next to the sensor's name) or not (red color next to the sensor's name) (Figure 3d).
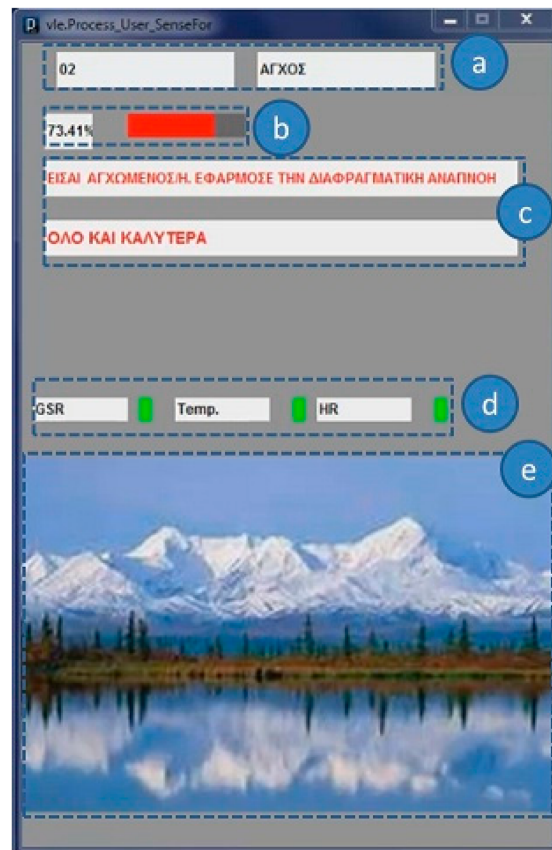
Figure 3. Biofeedback application user interface. (**a**) Biofeedback application interface, (**b**) Anxiety level percentage, (**c**) Encouragement for diaphragmatic breath, (**d**) Indication of well-functioning sensors, (**e**) Display pictures for relaxation.

The tutor can monitor the students' stress level in real-time with the monitor user interface depicted in Figure 4. The user interface of this monitoring application shows the names Figure 4a and user codes (Figure 4b). Moreover, their anxiety level is depicted in color code (Figure 4c) followed by the relevant percentage (Figure 4d). The meaning of the colors is displayed at the bottom of the screen (Figure 4e).
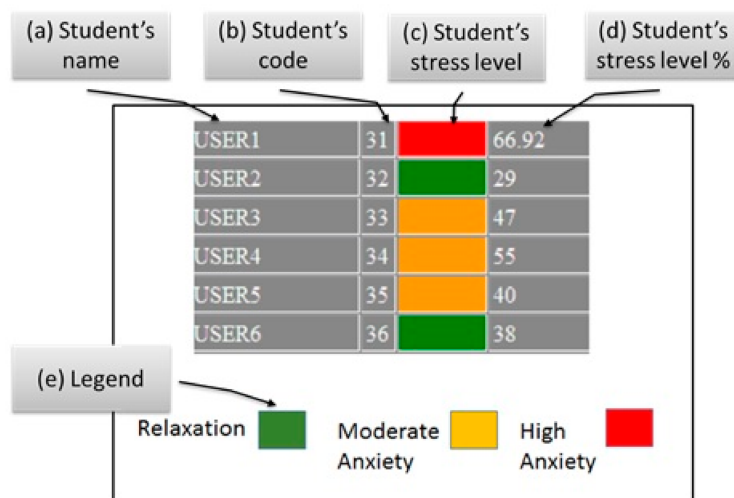
Figure 4. Instructor monitoring application.

3. Research Goals

As stated in the previous section, the present study is an attempt to carry out a preliminary investigation of the deployment of the biofeedback system during online examination activities. Using the term preliminary is meant that this study describes our first attempt to deploy the biofeedback device during an online educational activity. A validation phase (first experiment) was decided to precede the deployment in order to check the device performance. The results of the validation phase were satisfactory for establishing the conditions to proceed to the deployment activity (second experiment).

The first research goal (RG1) of this study involves testing the convergent validity of the used biofeedback system regarding measures of anxiety, and more specifically, regarding (a) the anxiety level as provided by the Neurosky Mindset (http://www.neurosky.com) and, (b) the state part of the State-Trait Anxiety Inventory (STAI) [24], which is a self-report measure of anxiety.

The second research goal (RG2) of this study involves exploring the relationship between the participants' personality dimensions according to TRI (Technology Readiness Index), their academic performance, and their real-time state anxiety, as provided by biofeedback during online academic examinations.

In order to achieve our research goals, two experiments were conducted:

- Experiment 1: Test of convergent validity of the biofeedback system.
- Experiment 2: Deployment of the biofeedback system during online academic examinations.

The following sections present both experiments, with regard to the materials and instruments used, and their results.

4. Experiment 1: Test of Convergent Validity of the Biofeedback System

4.1. Materials

During this evaluation activity, each student (participant) was connected to the biofeedback device (Figure 1) and to the Neurosky Mindset [35].

Anxiety Level Measurement Using the Biofeedback Device and the Neurosky Mindset

The anxiety level measurements of the biofeedback device follow a similar logic to the Mindset anxiety level indications, which are based on Neurosky's eSense algorithm. This algorithm uses a value range from 1 to 100; the values increase when the users are relaxed and decrease when the users are stressed. According to Neurosky's eSense algorithm, every value produced represents the user's level of relaxation. More specifically, a value between 1 and 20 corresponds to a strongly increased anxiety level, 21 to 40 corresponds to increased anxiety, 41 to 60 is considered "neutral", 61 to 80 corresponds to considerably reduced anxiety, and 81 to 100 is considered "relaxed". Biofeedback device anxiety measurements also have a range from 1 to 100. The only difference in the measurement logic of the biofeedback device compared to the Neurosky Mindset is that the values decrease when the user is relaxed and increase when the user is stressed. Thus, in order to maintain a compatibility level between the biofeedback system and the Neurosky Mindset, when a value x (anxiety level) was received by the Neurosky device it was transformed to $(100 - x)$. The anxiety level is received by the Neurosky Mindset after calling the Mindset library. The Neurosky averaged signal quality was between 80% and 100%.

4.2. Instruments

State Anxiety Inventory

This is the state part of the State-Trait Anxiety Inventory (STAI) [24] that consists of 20 items. It is commonly used to measure adults' state anxiety and is "among the most widely researched and widely used measures of general anxiety, and is available in many different languages" [36]. The term "state anxiety" refers to an assessment of the intensity of one's current anxiety. In other words, it assesses the intensity of the anxiety one feels at the moment s/he is completing the questionnaire. Each item-question is rated on a 4-point

Likert scale [37] (1 = not at all, 2 = somewhat, 3 = moderately so, 4 = very much so). The STAI result-score is the sum of every item score. Some of the items are reverse scored when anxiety-absence is implied [36]. This study administered the state portion of the STAI inventory in a Greek adaptation with a Cronbach's alpha internal consistency of .93 [38].

4.3. Method

4.3.1. Participants

In order to examine the convergent validity of the biofeedback system measurements as regards the state part of the STAI questionnaire and the Neurosky Mindset anxiety level, 15 postgraduate students (with a mean age of 26.06 years, SD = 2.3) participated in the psychometric test examination. Before this experiment, all participants signed a consent form. It should be noted that during the experiment with three subjects, there were connection problems to the Neurosky mindset. This causes unreliable Neurosky mindset measurements. Thus, the three (3) subjects were excluded from our experiment.

4.3.2. Procedure

The design of this experiment consists of a psychometric protocol (Figure 5) tapping into general cognitive ability, also known as the g factor, which was first mentioned by Spearman [39]. Psychometrically, the g factor is described as "a construct which refers to the overall mental capacity behind a person's performance on any number of cognitive tasks" [40]. Thus the use of the aforementioned protocol, as part of a valid general intelligence test causes anxiety, since it has been stated that "one variable that may be particularly detrimental toward validly assessing IQ is the experience of anxiety-related responding" [41]. This is in line with extensive research that examines the impact of anxiety on cognitive experimental tasks [41–43].
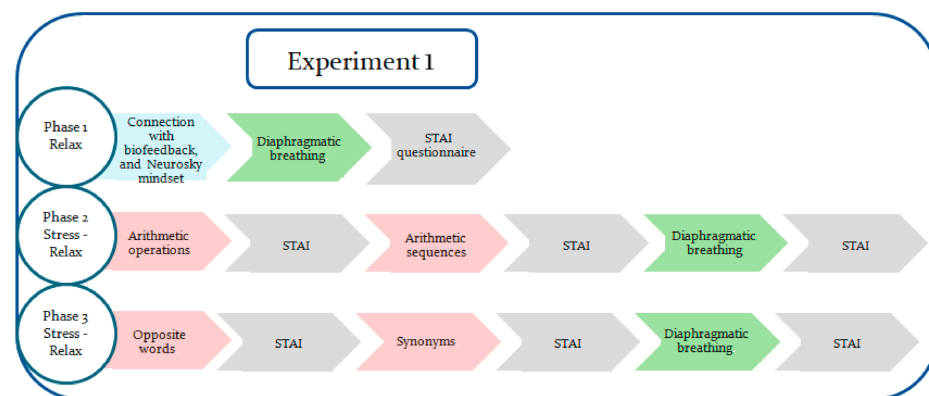
Figure 5. Procedure protocol of Experiment 1.

The psychometric procedure was applied individually on every student participating in the following evaluation activity. During this procedure, the student was simultaneously measured using two sets of biosignal technology equipment. One was our biofeedback device and the other was the mobile Mindset from Neurosky, which is a commercial electroencephalography (EEG) biosensor solution. The psychometric procedure of the training phase included the following stages. Some of these stages consisted of stressful tasks and some tried to encourage relaxation by applying diaphragmatic breathing [5]:

- The participant was connected to the biofeedback device and to the Neurosky Mindset.
- The participant completed the TRI questionnaire, which consisted of optimism, innovativeness, insecurity, and discomfort technology beliefs.
- The participant was asked to apply diaphragmatic breathing three times.
- The participant was asked to fill in the twenty items referring to the state part of the State-Trait Anxiety Inventory (STAI).

- The participant was asked to complete a set of sixty (60) arithmetic operations in 2 min. This task is part of the cognitive ability/intelligence tasks battery. It is called the Number Facility test (NF) and taps into arithmetic operations fluency [44].
- The participant was asked to fill in the state items of the STAI questionnaire.
- The participant was asked to complete a set of twenty (20) different arithmetic sequences in 4 min. This task is part of the cognitive ability/intelligence tasks battery. It is called the Number Series test (NS) and taps into fluid intelligence [45].
- The participant was asked to fill in the state items of the STAI questionnaire.
- The participant was asked to apply diaphragmatic breathing three times.
- The participant was asked to fill in the state items of the STAI questionnaire.
- The participant was asked to fill in a form of 10 words with as many opposite words as s/he could manage in 3 min. This task is part of the cognitive ability/intelligence tasks battery. It is called the Opposites test (OP) and taps into verbal/semantic fluency [44].
- The participant was asked to fill in the state items of the STAI questionnaire.
- The participant was asked to fill in a form of 10 words with as many synonymous words as s/he could manage in 3 min. This task is part of the cognitive ability/intelligence tasks battery. It is called the Synonyms test (SYN) and taps in verbal/semantic fluency [44].
- The participant was asked to fill in the state items of the STAI questionnaire.
- The participant was asked to apply diaphragmatic breathing three times.
- The participant was asked to fill in the state items of the STAI questionnaire.

4.4. Results

This experiment examines the convergent validity of the used biofeedback system in relation to the Neurosky Mindset measurements and the responses to the state part of the STAI questionnaire.

The statistical analyses were conducted using SPSS version 20.

In order to test the concurrent validity of the biofeedback device, we first examined the existence of a significant correlation between:

(1) the biofeedback device measurements regarding galvanic skin response (GSR), heart rate (HR), and skin temperature (SKT) that were received during the training activity while applying the psychometric test.

(2) the state part of the State-Trait Anxiety Inventory (STAI) scores (STAISCORE) based on each student's responses, each time s/he was asked to complete this questionnaire during the training phase as part of the psychometric protocol.

The data used for this evaluation was collected during the training phase, as aforementioned. Thus, the users were connected to the biofeedback device and the Neurosky Mindset while completing the STAI questionnaire at the same time. The biofeedback device provided us with raw galvanic skin response (GSR), skin temperature (SKT), and heart rate (HR) values. From the Neurosky Mindset, we collected anxiety levels and from the STAI questionnaire the corresponding responses. We applied a statistical analysis between these three types of measurements for every student identically at specific time windows (the time period needed for each completion of the state items of the STAI questionnaire during the psychometric protocol procedure). More specifically, we applied Spearman's rank correlation between the STAISCORE variables and the GSR, HR, and SKT biofeedback. The significant moderate correlations found for 12 out of the 15 participants are shown in Table 1.

Table 1. Significant correlation coefficients between the State-Trait Anxiety Inventory (STAI) scores and biofeedback device measurements for each participant.

User Code	Spearman's Correlation (STAI Scores—Biofeedback Measurements)		
	HR	**SKT**	**GSR**
User 03		−0.368 **	0.248 **
User 04		−0.538 **	0.374 **
User 06	0.277 **	−0.259 **	0.234 **
User 07	0.361 **		0.550 **
User 08	0.362 **		0.369 **
User 09	0.221 *	−0.297 **	
User 10	0.496 **	−0.202 **	
User 11	0.237 *		0.521 **
User 13	0.351 **	−0.281 **	0.268 **
User 14			0.306 **
User 15	0.277 **	−0.422 **	0.604 **
User 16	0.497 **	−0.381 **	

*, **—This sign is used by the statistical tool SPSS and it means that the correlation is significant.

Moreover, we examined whether there is any significant correlation between:

(1) The biofeedback device's raw measurements for GSR, heart rate (HR) and skin temperature (SKT) during the training phase, while applying the psychometric test.
(2) The Mindset brainwave anxiety measurements during the training phase, while applying the psychometric test.

All measurements were collected within the same time period.

We used Spearman's Rho correlation between the TRAINLABEL (100 − (Neurosky Mindset anxiety level)) variable and the GSR, HR, and SKT biofeedback. The significant moderate correlations found for 12 out of the 15 participants are presented in Table 2.

Table 2. Significant correlation coefficients between the Mindset device and the biofeedback device measurements for each participant.

User Code	Spearman's Correlation (Mindset—Biofeedback Measurements)		
	HR	**SKT**	**GSR**
User 03	0.250 **	−0.290 **	
User 04		−0.383 **	0.228 **
User 06	0.250 **		0.216 *
User 07	0.289 **		0.424 **
User 08	0.248 **		0.342 **
User 09	0.207 *	−0.258 **	
User 10	0.392 **	−0.198 *	
User 11	0.292 *		0.617 **
User 13	0.195 *	−0.230 *	0.382 **
User 14			0.310 **
User 15	0.330 **	−0.397 **	0.384 **
User 16	0.268 *	−0.303 **	

*, **—This sign is used by the statistical tool SPSS and it means that the correlation is significant.

In addition, we examined the correlation between the STAI scores and the values of the aforementioned TRAINLABEL variable during the training phase, while applying the psychometric test for each student. The purpose of this analysis was to discover whether the two valid tools used for the biofeedback system validation and calibration actually measure similar anxiety components. The significant positive correlations found for 12 out of the 15 participants are presented in Table 3.

Table 3. Significant correlation coefficients between the STAI score and Mindset measurements for each participant.

User Code	Spearman's Correlation (STAI Scores—Mindset Measurements)
	Trainlabel
User 03	0.770 **
User 04	0.561 **
User 06	0.741 **
User 07	0.564 **
User 08	0.678 **
User 09	0.923 **
User 10	0.715 **
User 11	0.626 **
User 13	0.501 **
User 14	0.941 **
User 15	0.617 **
User 16	0.548 **

**—This sign is used by the statistical tool SPSS and it means that the correlation is significant.

The resulting significant correlations for 12 (out of the 15) users are moderate or high and support the convergent validity of the used biofeedback device regarding the other two measures of anxiety.

4.5. Discussion

In order to examine the concurrent validity of the presented biofeedback system regarding the two valid tools of anxiety detection (Neurosky's measurements and the response scores to the state part of the STAI questionnaire), we applied Spearman's Rho correlation analysis to the data received from each participant individually. More specifically, each student responded to the STAI questionnaire during specific phases of the psychometric procedure. Each student's answers were kept in a database under the participant's code. During the time windows of the students' responses, their biosignals provided by the biofeedback and $(100 - (\text{Neurosky anxiety value}))$ were kept in the database under their relevant codes. The correlation analysis for every participant showed that the majority (12/15, 80%) presented significant positive or negative correlations between the STAI assessment score or the $(100 - (\text{Neurosky anxiety level}))$ provided by the Neurosky eSense algorithm and the biosignal measurements provided by the biofeedback device. Thus, as the anxiety detected by the STAI score or the Neurosky EEG increases,

- the galvanic skin response correspondingly increases. This is confirmed by Fowles [46,47] and Venables and Christie [48],
- the heart rate correspondingly increases. This is in line with De Geus et al. [49], and Boutcher and Stocker [50],
- the skin temperature correspondingly decreases. This is confirmed by Cannon [51].

More specifically, the moderate correlations that we found between the biosignal values provided by the biofeedback device, on the one hand, and both the STAI and Neurosky Mindset, on the other hand, were in the predicted direction. The Neurosky Mindset is a well-known commercial tool which is used in several EEG research projects dealing with brain activity in various control tasks [52–54] or more specifically in learning processes [55–57]. The findings showed that the biofeedback device's measurements of the emotionality component of anxiety displayed a satisfactory convergent and divergent validity.

5. Experiment 2: Deployment of Biofeedback System during Online Academic Examinations

5.1. Materials

This experiment consisted of two steps.

During the first step (training phase), each student was connected to the biofeedback device and the Neurosky Mindset.

During the second step (examination activity), each student (participant) was connected to each one of the copies of the biofeedback device (Figure 1). The biofeedback application was running on each student's computer, based on the architecture depicted in Figure 2.

5.2. Instruments
5.2.1. Anxiety Awareness

During the construction of the training sets (training phase), biosignal measurements were received from the biofeedback device and the anxiety level was detected by the Neurosky Mindset filling vectors in the form of <GSR, SKT, HR, Anxiety-level>. Every completed student training set was used to produce his/her trained anxiety prediction model. During the examination activity (second step), the anxiety level was detected by the biofeedback system using the specific prediction model for every measurement subject.

5.2.2. Technology Readiness Index

The Technology Readiness Index (TRI) [8] is a multi-item scale that includes 36 technology belief statements, which tap into the four dimensions of technology beliefs that impact on an individual's level of techno-readiness. For the translation of the TRI Scale in Greek, we followed the International Test Commission (ITC) guidelines (www.intestcom.org). A back translation procedure was also followed in order to eliminate any inconsistencies that would disrupt the accuracy of the results.

5.2.3. Knowledge Test—Academic Performance

The knowledge test, which was used in the present study for the evaluation of academic performance, mainly included multiple-choice questions relevant to the syllabus of the course during which the experiments took place. The course with the title "Open and Distance Education Using Multimedia and Internet Technologies" was offered as part of the "Interdepartmental Program of Postgraduate Studies in Information Systems". The questions were displayed on the computer screen and answered by using a customized application. The tests were constructed by the instructors of the examined courses. There were a number of short-answer questions involving computations, and others requiring students to use their reasoning skills to complete a multiple-choice assessment. The reliability of the knowledge test was estimated on the basis of the Kuder and Richardson [58] Formula 20 (KR-20) measure that checks the internal consistency of measurements with dichotomous data. The KR-20 score for the knowledge test was 0.86.

5.3. Method
5.3.1. Participants

In order to evaluate the relationship between the students' TRI personality traits, the state anxiety levels provided by the biofeedback system and academic performance, 35 participants (with a mean age of 26.04 years, SD = 1.6) took examinations in the form of online tests for one of their lessons.

The examination phase took place at the same time and venue, namely in the students' classroom, under the supervision of two of the authors. Before this experiment, all participants signed a consent form.

5.3.2. Procedure

The experiment followed a procedure consisting of two steps (Figure 6).
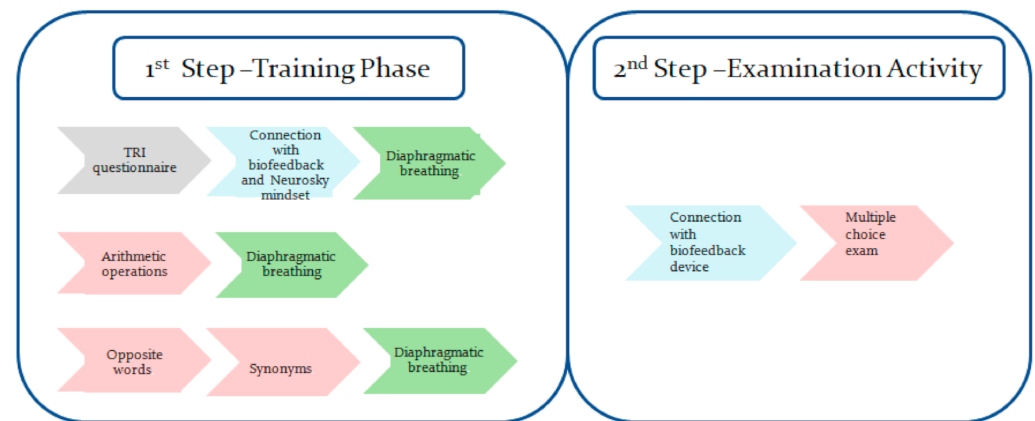
Figure 6. Procedure protocol of Experiment 2.

First Step:

The first step is the training phase, which is an attempt to apply a calibration procedure for the biofeedback device in order to create training biosignal sets for every participant. Thus, during this step, biosignal measurements were collected in order to train the regression algorithm for each participant. In parallel to the biosignal measurement collection procedure, real-time student anxiety levels were detected by the Neurosky Mindset (brainwave measurements). Every detected anxiety level is used as a label for each corresponding galvanic skin response (GSR), heart rate (HR), and skin temperature (SKT) biosignal that is measured by the biofeedback device.

Moreover, according to Johnson [59], every person presents different areas of emotional and mental sensitivity when they try to interpret and respond to current situations by deploying their past experience. Thus, it is assumed that every participant has a unique human physical organization and personality, with its own specific biosignal measurements. For this reason, it was decided that a psychometric protocol, inducing and provoking mental stress, supervised by a psychologist supporting the research, should precede the scheduled examination (second step) and follow a specific experimental design. This design is very similar to the protocol followed in the first experiment. Nevertheless, there are two main differences between the two designs followed by the two experiments under examination. In the first experiment, we used the STAI questionnaire, which was not used in the second experiment. Moreover, we used the TRI questionnaire in the second experiment but not in the first experiment.

Second Step:

The second step is the examination phase. The students' test anxiety during this phase was measured using the biofeedback device (Figure 1) that can detect biosignal measurements and classify these measurements into anxiety levels. The Neurosky Mindset equipment was not used during this step, since the training set and the relevant anxiety prediction model for every participant had already been formulated. During the examination activity, every measured student had to answer certain multiple-choice or computational exercises, which were displayed one at a time (left part of the screen), while watching his/her anxiety measurements provided by biofeedback (right part of the screen).

5.4. Results

The present experiment tries to discover and put forward a preliminary model of the relationships between the students' personality traits, their current anxiety level as detected by the presented system, and their performance.

The path analysis was conducted using SPSS AMOS version 20. The data used for this evaluation was collected from 35 participants during the examination phase. We therefore collected the classified anxiety levels provided by the biofeedback device, the students' TRI questionnaire responses, and their academic performance. The anxiety levels were collected within the same time window with the examination taken.

We initially examined the factor structure of the Greek version of the four subscales that measure each of the TRI dimensions. More specifically, we conducted Confirmatory Factor Analyses (CFA) in EQS 6.1 [60], in order to compare the a priori factor structures, as implied by previous theoretical and empirical research, as follows:

- Optimism Scale: The Optimism scale captures positive feelings about technology and consists of 10 items. In the present study, we excluded the item referring to "You like the idea of doing business via computers because you are not limited to regular business hours." from the outset, since the sample used for our research was not familiar with a regular business context [7,61]. The one-factor structure of the scale, based on the nine remaining items, was not verified by the initially applied CFA. The initial one-factor model results with the Satorra-Bentler scaled χ^2 (27, N = 35) = 103.95, p = 0.00, CFI = 0.11, and RMSEA = 0.26 (CI90% 0.20 to 0.31). Consequently, a second CFA was performed, using a revised item set of the scale. In the revised item set, according to the suggested modifications, as indicated by the Lagrange Multiplier and Wald tests, and the Largest Standardized Residuals as well, the one item (item 10 of the original scale) that failed to come up with a one-factor solution corresponding to the Optimism Scale was dropped. The model using the revised item set yielded a noticeably better fit to the data than the first model [Satorra-Bentler scaled χ^2 (16, N = 35) = 16.78, p = 0.40, CFI = 0.99, and RMSEA = 0.03 (CI90% 0.00 to 0.14)]. Thus, with respect to that one factor—consisting of 8 items—, we came to the conclusion that its variance is probably explained by the users' optimism related to the studied biofeedback system.

- Innovativeness Scale: This scale measures the extent to which the individuals perceive themselves as being at the forefront of technology adoption. The one-factor structure of the scale, based on seven items, was not confirmed by the initially applied CFA. The initial one-factor model results with the Satorra-Bentler scaled χ^2 (14, N = 35) = 78.02, p = 0.00, CFI = 0.33, and RMSEA = 0.33 (CI90% 0.25 to 0.39). Consequently, a second CFA was performed, using a revised item set of the questionnaire. In the revised item set, according to the suggested modifications, as indicated by the Lagrange Multiplier and Wald tests, and the Largest Standardized Residuals as well, two items (item 4 and 6 of the original scale) that failed to come up with a one-factor solution corresponding to the Innovativeness Scale were dropped. The model using the revised item set yielded a better fit to the data than the first model [Satorra-Bentler scaled χ^2 (4, N = 35) = 1.63, p = 0.80, CFI = 1.00, and RMSEA = 0.00 (CI90% 0.00 to 0.14)]. Thus, we derived one factor—consisting of five items—, which could be explained by the users' innovative attitude according to the system under study.

- Insecurity Scale: It taps into concerns people may have when faced with technology-based transactions. The one-factor structure of the scale, based on nine items, was not confirmed by the initially applied CFA. The initial one-factor model results with the Satorra-Bentler scaled χ^2 (27, N = 35) = 142.12, p = 0.00, CFI = 0.53, and RMSEA = 0.32 (CI90% 0.26 to 0.36). Consequently, a second CFA was performed, using a revised item set of the scale. In the revised item set, according to the suggested modifications, as indicated by the Lagrange Multiplier and Wald tests, and the Largest Standardized Residuals as well, four items (items 1, 2, 5, and 8 of the original questionnaire) that failed to come up with a one-factor solution corresponding to the Insecurity Questionnaire were dropped. The model using the revised item set yielded a better fit to the data than the first model [Satorra-Bentler scaled χ^2 (2, N = 35) = 1.13, p = 0.57, CFI = 1.00, and RMSEA = 0.00 (CI90% 0.00 to 0.25)]. We derived one factor—consisting of five items—, which is probably explained by the users' insecurity related to the biofeedback system under study.

- Discomfort Scale: It captures the inconvenience people may experience because of the biofeedback system [8]. The one-factor structure of the scale, based on 10 items, was not confirmed by the initially applied CFA. The initial one-factor model results with the Satorra-Bentler scaled χ^2 (35, N = 35) = 278.40, p = 0.00, CFI = 0.27, and RMSEA = 0.40

(CI90% 0.35 to 0.44). Consequently, a second CFA was performed, using a revised item set of the questionnaire. According to the suggested modifications, as indicated by the Lagrange Multiplier and Wald tests, and the Largest Standardized Residuals as well, five items (items 2, 5, 6, 8, and 10 of the original questionnaire) that failed to come up with a one-factor solution corresponding to the Discomfort Questionnaire were dropped. The model using the revised item set yielded a better fit to the data than the first model [Satorra-Bentler scaled χ^2 (4, N = 35) = 0.31, p = 0.99, CFI = 1.00, and RMSEA = 0.00]. Thus, we derived one factor—consisting of five items—, which could be explained by the users' discomfort in relation to the system under study.

Cronbach's alpha internal consistency estimates, obtained for each of the aforementioned scales/factors, were found to be higher than or equal to 0.77. This finding is comparable to a sound reliability with Cronbach's alpha ranging from 0.74 to 0.81 as found by Parasuraman [8] and to a replication in Great Britain that has further strengthened the soundness of the TRI. More specifically, Tsikriktsis [62] extracted the same four-factor structure, with Cronbach's alpha ranging from 0.74 to 0.88.

We then used structural equation modeling (SEM) analysis in order to test the relationship between the students' TRI personality traits, as described by optimism (9-item average, OPTAVG), innovativeness (7-item average, INNOAVG), insecurity (5-item average, INSAVG) and discomfort (5-item average, DISAVG), the state anxiety levels provided by the biofeedback system and academic performance. A total of four parameters (optimism, insecurity, anxiety, and performance) were estimated as being statistically significant in the path model. The confirmed relationships between the derived parameters are shown in Table 4.

Table 4. Relationships between optimism, insecurity, anxiety, and performance. Sign (***) indicates the statistical significant relationships.

			Estimate	S.E.	C.R.	p
INSAVG	<—	OPTAVG	−0.569	0.126	−4.502	***
Performance	<—	INSAVG	−1.667	0.422	−3.949	***
Performance	<—	OPTAVG	0.870	0.393	2.213	0.027
Anxiety	<—	Performance	−4.498	0.453	−9.935	***

The confirmed path model is displayed in Figure 7 with an excellent overall fit, χ^2 (2, N = 35) = 0.11, p = 0.95, CFI = 1.00, GFI = 0.99, NFI = 0.99, and RMSEA = 0.00.
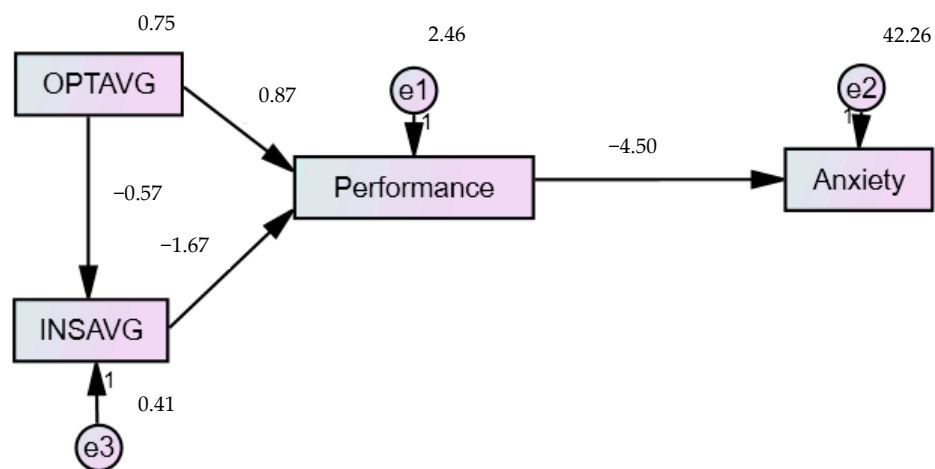
Figure 7. The resulting path models.

5.5. Discussion

SEM analysis was applied in order to examine the relationship between the students' Technology Readiness (TR) personality traits, anxiety, and academic performance. The

results showed that optimism has a significant negative influence on insecurity. This result is in line with Yuan and Wang [63], who support that "insecurity is negatively associated with mental health and this relation is mediated by optimism". Moreover, insecurity has a significant negative effect on performance, whilst optimism has a positive but not significant effect on performance. Furthermore, optimism is a positive psychological construct [64]. Optimism is a control belief, which represents general positive outcome beliefs, rather than identifying specific routes through which one can achieve specific outcomes, such as academic achievement [65].

Moreover, the derived path model showed that insecurity causes academic performance to decline, which in turn has a significant negative effect with increasing anxiety.

Zeidner [20] states in his book "Test Anxiety, The State of the Art", that the relationship between test anxiety and performance is of a cyclical nature. In our case, the derived path model shows one part of the cyclical relationship between performance and test anxiety. More analytically, the student's realization of his/her poor current performance during the examination causes an increase in test anxiety. In this case, the realization of poor performance precedes the test anxiety increment and thus we could support that this is in line with Zeidner [20], who claims that test anxiety can very possibly occur as a result of previous performance. Moreover, this is in line with another study, which claims that poor performance can lead to additional anxiety over time [66].

Apart from research in learning environments, there is a similar and very interesting study applied in the job environment, dealing with personality traits, organizational anxiety, and job performance. In more detail, the results of this article showed that job insecurity has a negative impact on job performance and the organizational anxiety mediates the effect of insecurity on performance [67].

6. Limitations

The present study has certain limitations that should be taken into consideration when interpreting the findings. The sample of presented studies is relatively small; this means that more experiments should be conducted. However, it is unfortunately not possible to prepare a study with a larger group of students, since the number of biofeedback devices is limited. Furthermore, the majority of participants in this survey fall within a similar age range. This fact may have influenced the results and, thus, future research should extend to samples of older students (e.g., in the field of lifelong learning) and non-student samples.

Although additional research is needed to further validate and refine the biofeedback device, the results of our studies, in conjunction with the size of the sample used and the breadth of the variables examined, show that the biofeedback device, apart from being cost-effective, is also a useful instrument for measuring the emotionality component of anxiety.

7. Conclusions

The present study is linked to the research area which deals with the development of a biofeedback system for anxiety awareness. The said system was used in relation to the students' anxiety awareness during online examination activities and attempts to integrate affective computing into education. It could be claimed that anxiety awareness can significantly support a distance learning activity, where there is no face-to-face contact and it is very difficult to identify the participants' emotions. The present research results can contribute to the design of a supportive intervention framework, which could be applied in the case of intensive autonomous or collaborative learning activities in order to deploy the said biofeedback, combined with a constructive reappraisal strategy and pedagogical methodologies. The anxiety level provided by biofeedback can be utilized as a trigger to activate the appropriate interventions.

This research focused on two research goals.

- The concurrent validity of the presented biofeedback system as regards Neurosky's Mindset and the STAI questionnaire (RG1).

- The relationships between the students' TR dimensions, the anxiety detected by the biofeedback system and academic achievement (RG2).

According to the results obtained and analyzed from both experiments, the following conclusions can be reached per research goal:

RG1: The first research question is answered by the statistically significant correlations found between the biosignal measurements provided by the biofeedback device, the students' scores in the STAI state-questionnaire and the Neurosky measurements for the majority (80%) of students. Thus, we could support that the biosignal measurements of the biofeedback system are significantly related to those detected by a well-known commercial EEG device (Neurosky Mindset), and also to the responses given to a widely-used and accepted anxiety detection questionnaire (STAI). Thus the biofeedback system performance is quite satisfactory. Furthermore, the presented biofeedback device is less expensive than similar better-known commercial systems.

RG2: The second research question is answered by the derived relationship model pertaining to the students' Technology Readiness (TR) beliefs, state anxiety, and performance. According to this model, less optimistic students feel more insecure, since this is a psychological condition that negatively affects their academic achievement. Moreover, students become more anxious or even stressed when they realize that their performance is declining.

8. Future Work

It would be very interesting to apply the deployment of the biofeedback system on demanding and challenging job environments. These environments are characterized by tense work conditions which are crucial factors for increasing job stress. Thus, it would be very interesting to explore the relationships between an employee's personality, job stress, and performance.

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