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# How Can Pedagogical Agents Detect Learner's Stress?

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**Abstract:** Learning analytics is aimed to analyze different types of data about the learning process of learners and to provide appropriate pedagogical intervention. However, existing research work on learning analytics mostly focuses on cognitive data (e.g., number of problems solved, number of correct answers, lessons visited) and physical data (e.g., clicks on specific media). The research question to be investigated is how to detect and analyze physiological data of learners in real-time. This paper describes an approach to detecting learners' stress using a pedagogical agent. For that purpose, a wearable wristband sensor is integrated into an existing pedagogical agent for developing human reasoning ability. The pedagogical agent analyzes the heart rate variability of the learner to determine the individual stress threshold. If the learner's stress exceeds the critical threshold, the pedagogical agent offers support with stress coping strategies. The evaluation study with the physiology-aware pedagogical agent shows that the heart rate variability in terms of RMSSD (root mean square of successive differences) can be used as a relevant indicator for measuring learners' stress in real time. The results of the evaluation study suggest deploying RMSSD if stress is taken into account in learning analytics.

**Keywords:** Learning Analytics, Physiology, Stress, Affect, Pedagogical Agents.

## 1. Introduction

Learning analytics is "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Long & Siemens, 2011). That is, learning analytics is aimed to analyze different types of data about the learning process of learners and to provide appropriate pedagogical intervention. However, existing research work on learning analytics mostly focuses on cognitive data (e.g., number of problems solved, number of correct answers, lessons visited) and physical data (e.g., clicks on specific media) (Chatti et al., 2014; Ferguson, 2013). In addition to the cognitive dimension, other researchers are currently paying attention to the cultural dimension of learning analytics, e.g., (Rüdian et al., 2019). Research on learning analytics using data on the physiological dimension has not gained much attention yet. Several researchers (e.g., Siemens et al., 2011) promoted considering emotional data in addition to cognitive and physical data because the emotional dimension is also important for effective learning. That is, a learner's emotion affects learning motivation and academic achievement (Mega et al., 2014). This paper aims to add learners' physiological data to learning analytics. One of the physiological responses that occur during learning is stress (Li et al., 2017).

The term "stress" has been introduced by Selye who defined stress as "the nonspecific response of the body to any demand for change." (Selye, 1976, p. 15). According to this definition, stress is not emotional valence or nervous tension. Selye differentiated between eustress and distress. The former describes stress that has positive effects and the latter is referred to as stress that is associated with negative effects. In the context of learning, according to this definition, if a learner is in a learning situation whose demand overwhelms her cognitive availability, thus, negative stress or distress would expose. Of course, depending on the individual situation, other negative consequences might also imply such as tiredness, monotony, lowered vigilance, and physical saturation (ISO, 2018). From the physiological point of view, the sympathetic nervous system reacts in a stressful situation and results in physiological responses, for example, the heart rate increases, because specific and relevant muscles will cause stronger blood flow. Academic-related stress can reduce learning achievement. An observational study (Kotter et al., 2017) with 456 medical students has shown that higher perceived academic-related stress was found to predict poor academic performance. Academic-related stress not only has an impact on academic performance but also learners' motivation (Pascoe et al., 2020). Thus, detecting and measuring stress that occurs while learning is relevant for technology-enhanced learning environments.

Different observation techniques have been proposed to track the stress of learners, e.g., facial detection and video monitoring (D'Mello, 2017). Giannacos and colleagues (Giannacos et al., 2020) suggest that physiological parameters, e.g., heart rate, blood pressure, temperature, and electrodermal activity (EDA) level can be used as a proxy to estimate learning performance. The monitoring of physiological parameters like heart rate variability (HRV) is considered a potential indicator for stress detection (Zangroniz et al., 2018). If one is in a stressful state, HRV will decrease (Kim et al., 2018; Mourenas et al., 2018). However, handling physiological data, to what extent they can be used to analyze learners' cognitive demands, and how they can be utilized in a learning context is still a research gap. The research question to be investigated in this paper is how HRV data can be used in real-time by a pedagogical agent to determine the stress level of the learner and to offer the learner stress reduction strategies within the context of technology-enhanced learning environments.

In the next section, the paper presents the methodology for investigating the specified research question. In Section 3, an evaluation study is conducted to test research hypotheses. In the final section, evaluation results are discussed and lessons learned are summarized.

## 2. Methodology

### *2.1 A Stress-Sensitive Pedagogical Agent*

To investigate the specified research question, the web-based pedagogical agent LIZA (Le & Wartschinski, 2018) that was aimed to improve human reasoning ability, is used. Since the pedagogical agent is intended to measure the physiological states of users, it is required to extend it with three new components. The first component provides a solution to generate, save and process the HRV data. The second one analyzes data regarding stress and the third one adapts the learning situation through selected stress reduction strategies.

### *2.2 Physiological Parameters of Stress*

To use HRV parameters as an indicator for stress, a physiological sensor is required. Such a sensor is provided e.g., by the Empatica E4 wristband that can be considered for a learning environment because it is compact and wearable. These features are required to reduce entry barriers while learning (Gjoreski & Gjoreski, 2017). The integrated photoplethysmography sensor in the wristband is utilized to determine the heart rate and to calculate the time interval between two consecutive heartbeats (i.e., NN intervals) (Empatica Inc., 2016). These data can be transmitted to a server by a mobile application provided by Empatica. The server is responsible for processing HRV and is the first component extended to the existing pedagogical agent LIZA (Le & Wartschinski, 2018).

To determine HRV, Standard Deviation of the NN intervals (SDNN) or the Root Mean Square of Successive Differences of the heart rate (RMSSD) can be applied (in addition to frequency-based parameters such as high frequency or low frequency). SDNN is suitable for long-term measurement that requires a period of about 24 hours, while RMSSD is a short-term measurement that requires between 0.5 and 6 minutes (Sammito, et al., 2014). Thus, RMSSD is chosen as a metric for HRV to be adopted in a pedagogical agent because the learning process through problem-solving can be monitored in short durations of every 5 minutes. RMSSD is calculated using the formula (Figure 1):

$$\mathrm{RMSSD} = \sqrt{\frac{1}{\mathrm{N}-1}\sum_{\mathrm{i}=1}^{\mathrm{N}-1}(\mathrm{NN}_{\mathrm{i}+1}-\mathrm{NN}_{\mathrm{i}})^2}$$

*Figure 1.* Root Mean Square of Successive Differences of the heart rate

## 2.3 Stress Induction

Since there are no generally accepted threshold values to determine a general stress marker for everybody, individual measurements need to be carried out (Sammito, et al., 2014). Thus, a specific individual threshold of stress level needs to be determined. Due to this reason, a stress induction phase was added to the pedagogical intervention process. The second component required to be integrated into the existing pedagogical agent LIZA serves to handle stress induction and stress analysis.

Castaldo and colleagues (2015) conducted a meta-analysis of assessment of stress factors in healthy adults using short-term HRV analysis, i.e., using RMSSD as an appropriate stress indicator. Punita and colleagues (2016) induced stress situations in daily life (e.g., car driving). Examination situations (Tharion et al., 2009) or playing video games (Li et al., 2009) also cause stress. Other stress situations that are more similar to learning settings are the Color-Stroop test (Endukuru et al., 2016; Visnovcova et al., 2014) and arithmetic exercises (Visnovcova et al. 2014; Taelman et al. 2011; Lyu et al. 2015). The stress factors like car driving, examination, and playing video games are not suited to an (online) learning environment that is constructed using a pedagogical agent. On the contrary, Color-Stroop tests and arithmetic exercises can be embedded into (online) learning environments quickly. For the study being investigated in this paper, arithmetic tasks were chosen as an induction method for stress, because they have been used widely to generate moderate stress levels (Schneider et al., 2003).

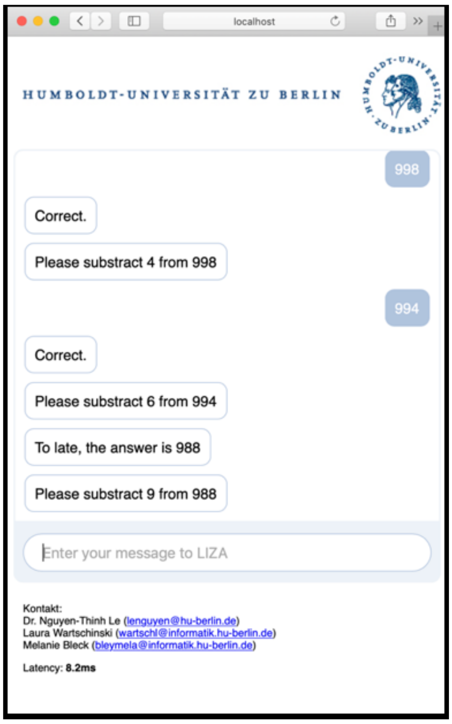


*Figure. 2.* Arithmetic Task in Stress Test 1

The stress induction phase has two arithmetic tests. The first stress test is aimed to derive an RMSSD value for a normal cognitive load. Test 1 represents a normal condition that requires attention for learning. The second stress test, which is designed with a higher difficulty level, is aimed to induce an excessive cognitive overload. Test 2 represents a stress condition. With stress test 1 (see Figure 2), the user has to subtract a random value from a certain number (e.g., starting from 1000) consecutively for five minutes (this period is appropriate for RMSSD measurement). The result of the previous equation provides the minuend of the following. For stress test 1, the time limit for each question is 15 seconds. The pedagogical agent can verify the user's solution as correct or not correct. The second stress test has a similar design but is more difficult to induce a higher cognitive load. The level of difficulty can be altered through three options: 1) reducing the time limit for solving an arithmetic exercise (e.g., less than 15 seconds), 2) increasing the digits of the random subtrahend, and 3) increasing the value of the start minuend (e.g., greater than 1000). The second and third options determine the number of shifts during arithmetic problem solving, which increases the cognitive load with a growing number.

In a range between the normal cognitive demand and the excessive cognitive overload, an individual stress threshold is required to be specified when a user steps into a stressful situation. Considering that an excessive cognitive overload may result in learning demotivation and a drop-out of learning in the long term, the learning situation has to be adapted before such a scenario may occur. Another factor, which has to be taken into account is that an adaption of the learning situation through stress coping strategies will interrupt the learning process itself. So, it should be carried out as little as possible but also as much as necessary.

A preliminary empirical test was conducted in advance, where the task solutions were known and therefore low stress was induced, showed, that a threshold at 50% of the range triggers an intervention nearly every time LIZA was used. This would lead to massive interruptions in the learning process. Based on the results of the preliminary test, the threshold was increased to 2/3 of the individually defined stress range, where the frequency of the intervention could be reduced. The threshold is defined according to the following formula and the stress threshold is illustrated in Figure 3:

$$\text{Threshold} = \max(\text{RMSSD}_{test1}\,;\text{RMSSD}_{test2}) - (\text{abs}(\text{RMSSD}_{test1} - \text{RMSSD}_{test2}) * 2/3)$$


*Figure 3.* Stress Threshold

## *2.4 Stress Coping Strategies*

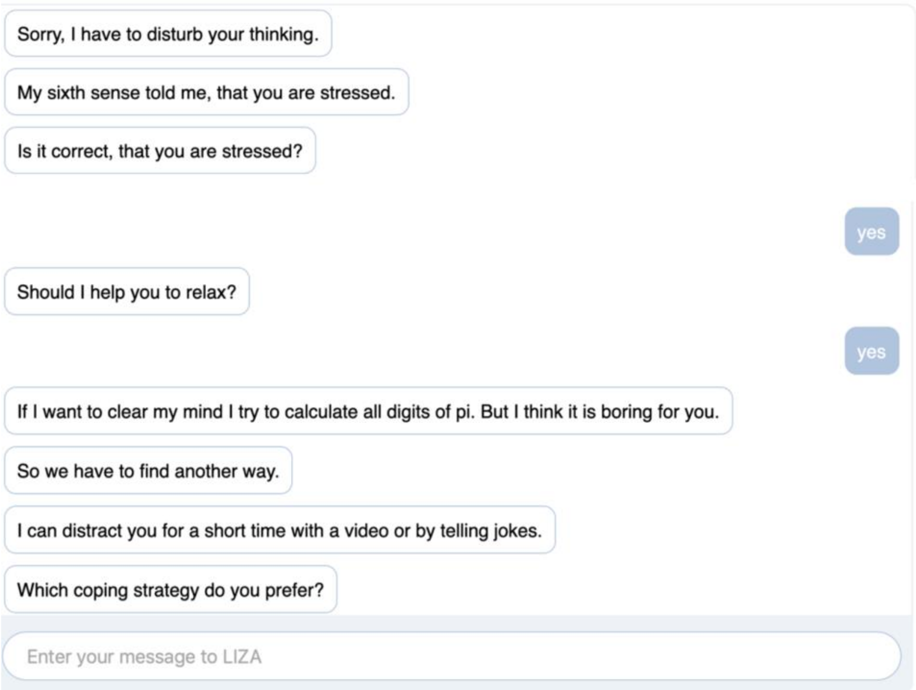


*Figure 4.* The Pedagogical Agent Proposes Two Strategies for Reducing Stress.

If the current RMSSD exceeds the stress threshold after a specific time, LIZA offers assistance through stress coping strategies. Among the twelve coping approaches classified by Skinner and colleagues (Skinner et al., 2005), the strategies “Isolation”, “Delegation”, “Opposition”, “Negotiation”, “Escape”, “Support seeking” seem to be not goal-oriented in the context of learning. The approaches “Information seeking”, “Self-reliance”, and “Accommodation” could be deployed in an (online) learning environment. “Self-reliance” methods could be mindfulness or autogenic training. These strategies require a longer period. Adopting those “Self-reliance” strategies, the pedagogical agent may prepare appropriate video sequences for mindfulness or autogenic training. “Accommodation” strategies could be telling jokes or showing a video. These strategies are adopted in the current version. The first one distracts the user by telling jokes, the second one shows a video with relaxing content. The user decides whether it is necessary to start the offered coping process and how long the strategies are used. If the stress level is significantly reduced below the threshold, pedagogical agent LIZA proposes the continuation of the learning process (see Figure 4).

### *2.5 A Dialogue Design*

As mentioned before, it was necessary to alter the pedagogical intervention process of the original pedagogical agent LIZA for analyzing the RMSSD data accordingly (see Figure 5). First, an inquiry for the declaration of consent for monitoring the heart rate was added to the greeting phase. After that, the user is requested to apply and activate the wristband and start the mobile transmission application. If a specific time interval is requested by the pedagogical agent, the suitable NN heartbeat intervals will be selected based on the time stamp and the RMSSD of these values will be determined. After the learning phase, the performance of the learner is evaluated and the final score is reported to the user (Figure 5).

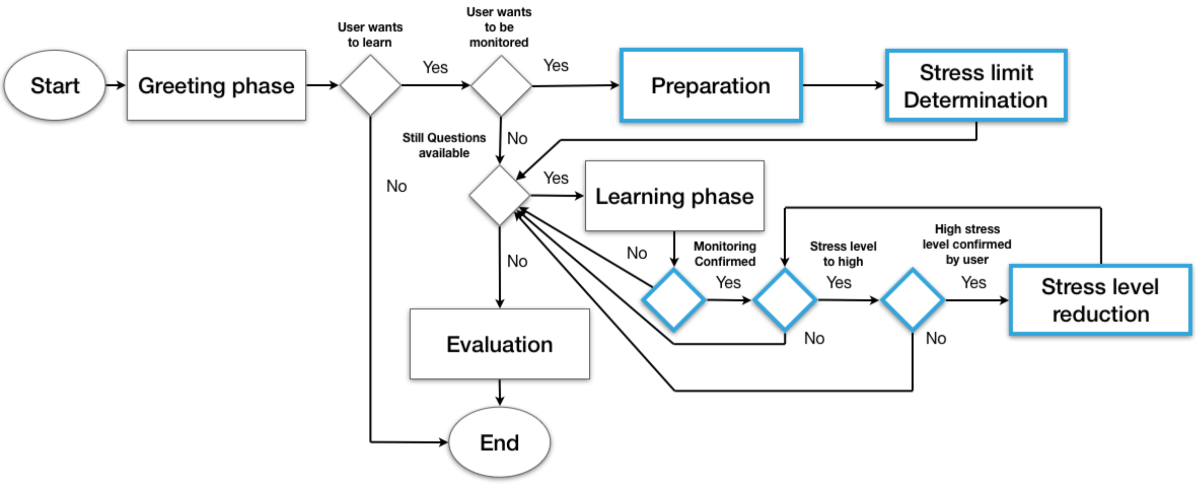


*Figure 5.* A Dialogue-based Intervention Process.

## 3. Evaluation

The goal of the evaluation study is to determine the effectiveness and benefits of the pedagogical agent LIZA that was extended with the capability of measuring HRV and detecting the critical stress level of learners. Amongst others, the following hypotheses are examined:

1. The RMSSD is a suitable indicator for determining the learner’s critical stress threshold.
2. The proposed stress reduction strategies lead to the relaxation of learners.

### *3.1 Design*

For the evaluation study, 34 participants (10 males, 24 females) aged between 21 and 59 (mean 31 ± 11 years) were acquired and assigned to a test or a control condition by random. The control condition was required to evaluate the effect of the proposed stress reduction strategies (which is Hypothesis 2). The study was conducted in a quiet environment under the supervision of the project leader. In both conditions, each participant was asked to use the pedagogical agent to perform two stress tests, each with a different level of difficulty, to determine the learner's stress threshold (cf. Section 2.3).

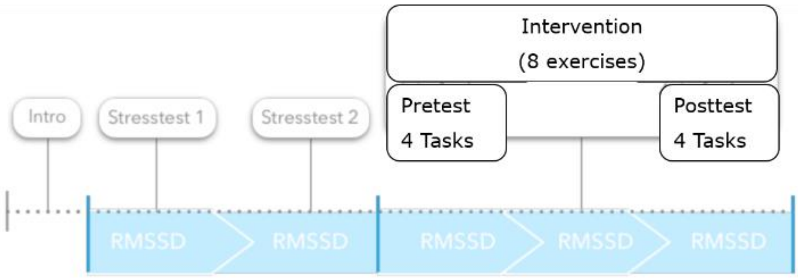


*Figure **6***. Experiment Procedure.

Figure 6 summarizes the experiment procedure. In the first phase, each participant is invited to take a seat in front of a notebook. He/she is informed and explained about the procedure of the experiment by a study supervisor. After signing a consent form and answering the demographic form (gender, age, profession, medical-relevant aspects including heart disease, depression, alcohol addiction), an Empatica E4 wristband is put on the wrist of the participant. Data transfer between the wristband and the server is activated and calibrated.

Next, in the second phase, each participant is asked to use the developed pedagogical agent to carry out the two stress tests. The individual stress threshold is determined in this phase.

In the third phase, in which learning should take place, participants can start to solve reasoning tasks provided by the pedagogical agent. The tasks are grouped into two blocks: a pretest and a posttest, each is composed of four tasks. The experiment is designed with a pretest and a posttest to determine any learning effect. After the first block, RMSSD is calculated. Only the test condition has a stress-coping phase between the two task blocks if the current RMSSD exceeds the threshold. After the stress-coping phase, participants are asked to solve again 4 tasks. The reasoning task categories of the pretest and posttest are the same, but the tasks are different. In the end, each participant gets an evaluation of how successful the tasks have been solved. For every phase of the experiment procedure (pretest, stress-coping phase, posttest), RMSSD is calculated so that the development of the indicator can be followed. In addition, the participants are required to self-report their current state of mental load after each measurement cycle using a short questionnaire KAB (Berth, 2003). The self-report is required to carry out a concurrent validity for proving that RMSSD is a relevant instrument for measuring stress (Adams et al., 2014). There exist different stress self-report instruments for different purposes, e.g., Aerospace (Draycott & Kline, 1996). To measure stress in the context of learning, a suitable self-report is required. The KAB questionnaire has six adjective-pairs representing six questions: 1) tense-calm, 2) anxious-unconcerned, 3) worried-carefree, 4) restless-relaxed, 5) skeptical-trusting, 6) uncomfortable-comfortable. The rating for each question varies on a scale between 1 (the left adjective) and 6 (the right adjective). The average KAB index is calculated by the sum of ratings for all questions divided by six. If $KAB_{index} \leq 3$, that means, the subjective perception of cognitive load is in the stressful state, otherwise if $KAB_{index} > 3$, the subject is in the non-stressful state, i.e., comfortable state. The experiment procedure of the control condition does not include the stress-coping phase.

## 3.2 Results

**Hypothesis 1**

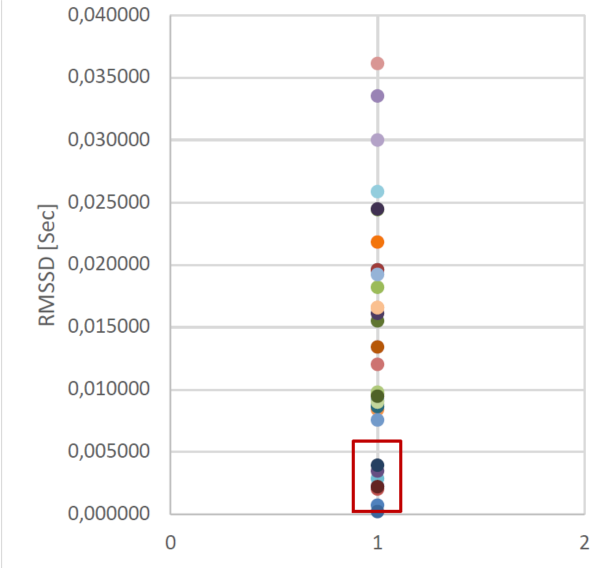


*Figure 7*. RMSSD Differences between Two Stress Tests.

Figure 7 shows the difference between the RMSSD values of the two stress tests. On the Y-axis, the absolute difference between the RMSSD values of each participant is displayed. The design of the stress tests assumes that through the difficulty of the test, each participant may have a range between normal cognitive load and stressful cognitive load and this range can be determined using RMSSD as a stress indicator. Statistical results show that the absolute difference between RMSSD values of two stress tests is 0.0136 seconds (=13.6 milliseconds) on average over all participants and the difference is significant (p= 0.0079) at a significance level of 0.05. That is, RMSSD can be used to determine individual stress thresholds in real-time, although the RMSSD difference between the stress tests is small. Such a small RMSSD difference could be explained by two possible reasons. The first case could be that both tests induce a small cognitive load. As a result, the stress-coping strategy was introduced in a state with a small cognitive load. The second case could be that both stress tests induce a high cognitive load. This case, ideally, would not influence the stress-coping phase. However, for individual learners, a high cognitive load could last a long time.

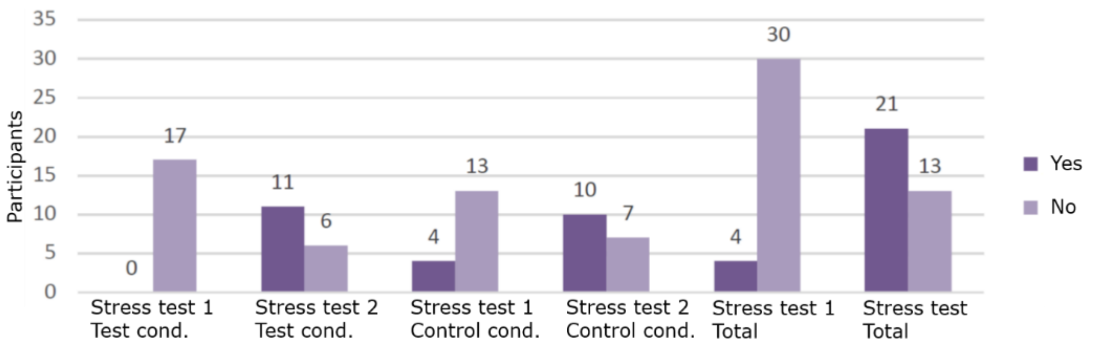


*Figure 8*. Participants who rated the Tests with $KAB_{index} \leq 3$ (i.e. stressful).

Self-reports can be used to concurrently validate the results of RMSSD. For this purpose, the KAB index has been considered as an instrument to measure subjective stress state. Only four of thirty-four participants self-report a KAB index less than 3 after the first stress test, i.e. they felt stressed. After the second stress test, twenty-one of thirty-four participants rated their KAB index less than 3, i.e., the second stress test induces stress (see Figure 8). The KAB index difference between the first and the second stress tests is significant (p=4.08199 E-10). This result corresponds to the significant RDSSM difference between the two stress tests. Therefore, Hypothesis 1 can be confirmed.

### Hypothesis 2

Table 1. *Results after Pretest, the 1st Stress Coping and the 2nd Stress Coping Phases*

| | **After Pretest** | | | | **After 1st Stress Coping** | | | | | **After 2nd Stress Coping** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Nr. | RDSSM threshold exceeded | Stress confirmed | KAB≤3 | KAB≤4 | Tendency RDSSM | Tendency KAB | KAB>3 | KAB>4 | RDSSM threshold exceeded | Stress confirmed | Tendency RDSSM | Tendency KAB | KAB>3 | RDSSM threshold exceeded |
| 01 | Y | Y | Y | Y | ↓ | ↑ | Y | Y | Y | Y | ↓ | | Y | Y |
| 02 | Y | Y | Y | Y | ↑ | ↑ | Y | Y | | | | | | |
| 04 | Y | Y | Y | Y | ↓ | ↑ | | | Y | Y | ↓ | ↑ | Y | Y |
| 07 | Y | Y | Y | Y | ↑ | ↑ | Y | | | | | | | |
| 08 | Y | Y | | Y | ↑ | ↑ | Y | Y | | | | | | |
| 09 | Y | Y | | Y | ↑ | ↑ | Y | Y | | | | | | |
| 12 | Y | | | | | | | | | | | | | |
| 13 | Y | Y | | Y | ↑ | ↑ | Y | Y | Y | | | | | |
| 14 | Y | Y | | | ↑ | ↑ | Y | Y | Y | | | | | |
| 16 | Y | Y | Y | Y | ↓ | ↑ | Y | | Y | | | | | |
| 17 | Y | Y | | Y | ↓ | ↑ | Y | | Y | Y | ↑ | ↑ | Y | Y |

To test Hypothesis 2, RDSSM values and KAB indexes before and after the stress-coping phase are compared. Table 1 summarizes results after the pretest, after the first and the second stress-coping phases. In each phase (represented by each bound column), the participants whose RDSSM exceeded the RDSSM threshold are listed and they had the opportunity to confirm their stress state subjectively upon a question asked by the pedagogical agent. After solving four reasoning tasks of the pretest, there were eleven participants in the test condition whose RDSSM exceeds the stress threshold after solving the four tasks of the pretest, and ten of them confirmed their stress state subjectively. Thus, the determination of the stress threshold based on RDSSM was reasonable. Among those ten participants, five of them had a KAB index less equal to 3. If the KAB threshold for stress were defined at scale 4, there would be nine participants exceeding the threshold. In the stress-coping phase, each participant whose RDSSM exceeded the threshold has two chances to apply a stress-coping strategy. After applying the first stress-coping strategy, ten participants (who have confirmed their stress state subjectively) rated higher KAB index than after the pretest. That means these ten participants could reduce their stress. The difference of KAB indexes between the first stress-coping strategy and the pretest is significant with $p=0.0034$. Among these ten participants, nine of them had a KAB index greater than 3, i.e. they achieved a relaxed state (see Table 1, 2nd bound column). Considering the change of RMSSD of these ten participants, we can learn from statistics that only six participants had an increase of RMSSD which is an indicator of stress recovery. Four of these six participants had RMSSD values below their stress threshold and thus could finish their stress-coping phase. Analyzing individual participants, we can learn that participant #16 has opposite tendencies of RMSSD ( ↓ ) and KAB ( ↑ ). It is noted that the RMSSD value of participant #16 lies on the threshold, thus, the opposed tendencies of RMSSD and KAB can be accepted. Also, participant #17 showed at the end of the stress-coping phase increasing KAB and RMSSD. Thus, this could be assumed that a longer application of stress-coping strategy results in better stress recovery. Especially, this tendency is visible after applying the second stress-coping strategy. It is also worth investigating individual participants (#01, #04, #17) whose RMSSD still exceeds the stress threshold even after the second stress-coping strategy was applied. The reason is that the range of RMSSD between the two stress tests of these participants was too small, and thus the calculated stress threshold could be very sensitive. Also, participant #13 had this problem. The RMSSD difference between the two stress tests of this participant was 7.5 milliseconds which is the smallest range among other participants.

The second hypothesis, whether the stress reduction phase leads to the relaxation of the learner, could be partially confirmed. 90% of the participants stated in a self-assessment a recovery, which indicates the effect of the applied stress reduction strategies. But only in nearly 50% of the cases, the RMSSD also falls below the threshold. Possible reasons for that could be deficits in stress threshold determination, insufficient choice of strategies, or insufficient application time. Taking t-test analysis of RMSSD, the RMSSD difference between the stress-coping phase and the pretest is 5.9 milliseconds and is not statistically significant (p= 0.2903).

## 4. Conclusions and Future Work

This paper has demonstrated the integration of physiological factors in technology-enhanced learning environments using wearable sensors. The contribution of the study presented in this paper is two-fold. It helps researchers to choose RMSSD as a relevant metric for determining the individual stress threshold level of learners in computer-supported learning environments. Second, it suggests embedding feasible relaxation strategies into learning systems. Due to the limit of this paper, data regarding pretest and posttest have not been analyzed. In near future, the impact of stress-coping strategies in the context of learning needs to be analyzed.

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