Establishing a Link between Electrodermal Activity and Classroom Engagement

Leslie Potter  
_Iowa State University_, potter@iastate.edu

J. Scallon  
_Iowa State University_

Daniel Swegle  
_Iowa State University_, dswegle@iastate.edu

Trevor Gould  
_Iowa State University_, tggould@iastate.edu

Güç E. Okudan Kremer  
_Iowa State University_, gkremer@iastate.edu

Follow this and additional works at: https://lib.dr.iastate.edu/imse_conf

Part of the Engineering Education Commons, and the Operations Research, Systems Engineering and Industrial Engineering Commons

Recommended Citation  
https://lib.dr.iastate.edu/imse_conf/201

This Conference Proceeding is brought to you for free and open access by the Industrial and Manufacturing Systems Engineering at Iowa State University Digital Repository. It has been accepted for inclusion in Industrial and Manufacturing Systems Engineering Conference Proceedings and Posters by an authorized administrator of Iowa State University Digital Repository. For more information, please contact digirep@iastate.edu.
Establishing a Link between Electrodermal Activity and Classroom Engagement

Abstract
Technological and pedagogical advancements over the last three decades have significantly changed how students are taught in the industrial engineering classroom. However, changes in teaching do not necessarily equate to increased learning. How can we determine if classroom teaching methods and activities increase the engagement of students, which then may increase the amount of learning that is taking place? Research indicates that electrodermal activity (EDA) can predict engagement in a classroom setting. Assuming that students learn both better and more when they are engaged, we can use EDA to determine which classroom methods and activities are most effective. We measured students' EDA in two different industrial engineering courses. Preliminary results indicate that we can correlate classroom activities and methods with student engagement. This paper describes our first steps for establishing a connection between EDA and classroom pedagogy, methods of data collection, results, and lessons learned. We compare our results to previously published literature and identify similarities and differences. This work provides a foundation for using EDA measurements to inform industrial engineering educators about increasing engagement, and consequently learning, in the classroom.

Keywords
Electrodermal Activity (EDA), engagement, pedagogy, learning

Disciplines
Engineering Education | Operations Research, Systems Engineering and Industrial Engineering

Comments
Establishing a Link between Electrodermal Activity and Classroom Engagement

Abstract ID: 583574

Potter, L., Scallon, J., Swegle, D., Gould, T., Okudan Kremer, G.
Industrial and Manufacturing Systems Engineering, Iowa State University
Ames, Iowa, 50011 USA

Abstract

Technological and pedagogical advancements over the last three decades have significantly changed how students are taught in the industrial engineering classroom. However, changes in teaching do not necessarily equate to increased learning. How can we determine if classroom teaching methods and activities increase the engagement of students, which then may increase the amount of learning that is taking place? Research indicates that electrodermal activity (EDA) can predict engagement in a classroom setting. Assuming that students learn both better and more when they are engaged, we can use EDA to determine which classroom methods and activities are most effective. We measured students’ EDA in two different industrial engineering courses. Preliminary results indicate that we can correlate classroom activities and methods with student engagement. This paper describes our first steps for establishing a connection between EDA and classroom pedagogy, methods of data collection, results, and lessons learned. We compare our results to previously published literature and identify similarities and differences. This work provides a foundation for using EDA measurements to inform industrial engineering educators about increasing engagement, and consequently learning, in the classroom.

Keywords
Electrodermal Activity (EDA), engagement, pedagogy, learning

1. Introduction

For the past three decades, technological and pedagogical advancements have significantly changed how students are taught, and consequently learn, in the classroom. The fast-paced evolution of social media and technological tools (e.g., Facebook, Twitter, Top Hat, etc.) has in recent years allowed professors to communicate with students in ways that are more relatable to younger generations. According to Purdue University, “Social media is now being recognized as an accepted form of instruction in some instances, and groups such as Scholastic Teachers provide excellent support and tips for instructors” [1]. Since 1998, online learning management systems like BlackBoard and Canvas have become increasingly prevalent in higher education [2]. By 2009, the increased availability of computers has made it easier for students to access the internet, with 97% of classrooms having computers, and 93% of those having Internet access [1].

The concept of active learning and its place in pedagogical history is summarized by Bishop and Verleger [3]. Significantly increased use of active learning classroom techniques since the early 1990s include project-based learning and flipped classrooms, both of which often include technology [3, 4]. However, an increase in the sophistication of classroom technology and changes in classroom pedagogies do not necessarily equate to increased academic student success. To remain globally competitive, it is critical to reform the educational system, as quickly and effectively as possible, to sustain a well-educated population. According to Serdyukov, “the actual pace of educational innovations and their implementation is too slow as shown by the learning outcomes of both school and college graduates, which are far from what is needed in today’s world” [5]. To assess the effectiveness of teaching methods that will allow industrial engineering faculty to make informed adjustments in real time, we must develop real-time measures.

Many theories of learning have engagement (i.e., paying attention) as a central component, where the base assumption is that students learn better when paying attention [6]. Although engagement is seen as an indicator of successful instruction, there is no consensus on how engagement is defined, nor is there a definitive link between engagement...
and learning. One definition of engagement is a student’s willingness, need, desire, and compulsion to participate in, and be successful in the learning process [7]. Fredricks and colleagues identified behavioral, emotional, and cognitive dimensions to engagement [6]. Student engagement has also been defined as “the quality of effort students themselves devote to educationally purposeful activities that contribute directly to desired outcomes” [8]. Appleton and coworkers defined engagement as “a multi-dimensional construct comprised of four subtypes: academic, behavioral, cognitive, and psychological” [9]. Given the wide-ranging understanding of engagement, there is considerable interest in establishing effective methods for its measurement to evaluate cognition and learning. Measuring student engagement and understanding its implications on STEM learning is a critical need for improving engineering education.

We define engagement as the measurable/observable behavior of a person attentively and actively participating in learning, which correlates with self-reported levels of engagement. Although the duration of student engagement might be captured through video recording, for instance, such collected data may not fully represent the level of engagement. The subject matter, physical comfort, and stress level, in addition to many other influences, may affect a student’s interest in learning and thus, their engagement. Finally, delivery mediums may be unintentionally distracting or disinteresting, varying due to a student’s prior affinity to technology and preferred ways of information intake.

Given the importance of engagement and potential complexities surrounding its measurement as explained above, our team designed pilot experiments to measure and interpret engagement results in various learning settings. This paper describes these pilot experiments and plans for follow-up experimentation. Results from this stream of work are applicable to engagement and cognitive task performance settings, including learning.

2. Literature Review
Several studies have attempted to quantify engagement using physiological measures, for example, electroencephalogram (EEG) used by Dockree et al. [10]; EEG, Electrocardiography (ECG), Electrooculography (EOG) and skin conductance level (SCL) used by Fairclough and Venables [11]; EEG used by Gevins et al. [12]; Cerebral Blood Flow Velocity (CBFV) by Matthews et al. [13]; EEG by Tops and Boksem [14]; and eye tracking used by Beatty [15]. This stream of research has found that changes in attention, arousal, cognitive function, and the autonomic nervous system relate to engagement. However, the use of EEG and eye-tracking equipment is not practical and is costly for out-of-laboratory study (e.g., classroom experimentation).

Electrodermal activity (EDA), or skin conductance level (SLC), has also been studied for decades and used in many different applications. For example, it has been used to study how detrimental interruptions in a working environment are to job performance [16]. EDA is also an important index of attentional engagement, or arousal. Varied arousal levels can be captured using an EDA sensor that measures the “neurally mediated effects on sweat gland permeability, observed as changes in the resistance of the skin to a small electrical current, or as differences in the electrical potential between different parts of the skin” [17]. Enhanced electrodermal activity is associated with increases in the anterior cingulate cortex during motivational and anticipatory processing [18], an area of the brain that plays a major role in motivation, conflict monitoring, and focused attention [19]. EDA readings have been useful in observing a person’s engagement with the immediate task/information at hand (e.g., Peccchinenda) [20]. Others have shown that electrodermal activity is suppressed for traumatic brain injury patients compared to controls and that electrodermal activity can reliably predict poorer performance on a Sustained Attention to Response Task [21]. Hernandez et al. further showed that electrodermal activity is a reliable predictor of engagement during playful interactions between children and adults [22]. These studies suggest that electrodermal activity is a reliable predictor of attentional engagement and that it could be a very useful tool with which we can measure engagement during learning.

Basic behavior information, such as if a person is being lively or quiet, can be obtained fairly easily using heart rate and skin conductance data [23]. People exhibit unique readings for EDA, so obtaining individual baselines and maximums for experimental participants is an important aspect of any study [24]. Boucsein details in Electrodermal Activity how researchers surprised subjects by popping balloons to obtain their maximum EDA values [24]. He also notes that for reasons thus far unknown, there is a small portion of the population who do not exhibit good EDA data, and such data must be excluded from results. Zuger et al. note that there isn’t necessarily a correlation between the emotions that EDA predicts and the facial expressions of participants. This could be due partly to subjects trying, consciously or subconsciously, to hide their emotions and is important because it indicates that subject observation alone is insufficient to assess engagement; one study estimates a 60.1% correlation between facial expressions and EDA [16]. EDA varies by age group, so confining a study to one age group limits experimental data complications [24]. Seasonal change is another cause of EDA variation [24], and women tend to have lower EDA than men [24]. It has been noted that there are genetic similarities in EDA, especially with twins, and more so with monozygotic twins.
than dizygotic twins [24]. A possible indicator of inaccurate data (artifacts) are large spikes in EDA [24], which can be caused by a variety of different reasons that have nothing to do with engagement, such as sneezing, laughing, or rapid movement. While not all data spikes are artifacts, it is important to evaluate them for inclusion.

Based upon the EDA related engagement measurements described herein, we assert that EDA measurement enabled by modern sensor technologies is a practical alternative for engagement measurement. However, discerning which data to include/exclude from experimental results is pivotal to successful classroom engagement prediction. Quantitative and qualitative analysis of data collected from equipment and classroom observations must be combined and scrutinized for correlations. Our pilot experimentation below presents our investments in this direction.

2. Methods

2.1 Preliminary Work

After reviewing the literature related to biosensors and measuring engagement, we investigated different types of commercially available biometric data collection equipment, including wristbands, finger transducers, headbands, and eye trackers. Based on the criteria of price, comfort, feasibility, user-friendliness, durability, and use cost, along with considerations for software support and scalability via cost, we identified three viable product options for measuring student engagement, including Empatica E4, BIOPAC EDA Finger Transducers, and Bio Signals Flux EDA Sensors. Using the weighted criteria matrix shown in Figure 1, we chose to test the Empatica E4 wristband. Empatica’s E4 wristbands are unobtrusive in classroom environments. The E4 is worn on the wrist similarly to a watch or fitness tracker, and is battery powered (no wires anchor the subject to any equipment). It records electrodermal activity, blood volume pulse, acceleration (movement in the x, y, and z direction), heart rate, and body temperature.

<table>
<thead>
<tr>
<th>Product</th>
<th>Price</th>
<th>Comfort</th>
<th>Feasibility</th>
<th>User-Friendliness</th>
<th>Durability</th>
<th>Use Cost</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Empatica E4</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>240</td>
</tr>
<tr>
<td>BIOPAC EDA Finger Transducer</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>220</td>
</tr>
<tr>
<td>Bio Signals Flux EDA Sensor</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>170</td>
</tr>
</tbody>
</table>

Figure 1. Weighted criteria matrix for biosensor equipment assessment

Using three E4 units, we performed preliminary observations of the data collected under specific conditions and developed an initial data collection protocol. Because rapid movement can cause spikes in EDA readings with the E4, potentially leading to inaccurate measurements, the unit is worn on a subject’s non-dominant wrist to minimize extraneous movement. Once the impact of movement was understood, the impact of subjects’ emotional states on EDA was tested by having them listen to different types of music, and by suddenly startling them. We observed (and confirmed) that different emotions caused changes in EDA levels, and that spontaneous events that cause immediate emotional changes (like being startled) result in EDA spikes. Additionally, because of observations that body temperature is affected by a subject walking to class in cold weather, our developed protocol requires subjects to be in their learning climate (i.e., indoors) for an hour before data collection begins to establish a baseline temperature.

2.2 Initial Data Collection

After establishing a baseline understanding of E4 usage and interpretation of its output, preliminary experiments with four undergraduate research assistants, all male industrial engineering students between the ages of 18 and 21 years, were conducted during colder months at a large, midwestern university. During each class period of data collection, one research assistant wore an E4 device while others documented what happened. Data was collected in a freshman engineering programming course (IE148) and in a sophomore engineering drawing and machining course (IE248). IE148 is a first-year industrial engineering course comprised of approximately 50% programming and 50% professional skill development (e.g., problem-solving, communication, and teamwork). The course is taught by an experienced instructor using partially flipped and team-based learning pedagogies. Students watch pre-recorded technical lectures prior to taking individual and team quizzes. They work on assignments during class time so that they can ask for help in person, in real time. Professional skills instruction includes hands-on activities, videos, traditional lectures/discussion, and student presentations. Classes of up to 40 students are personalized; the instructor knows the students’ names and interacts with individual students. Capturing student arousal in a classroom environment where students interact with the instructor, teaching assistants, and other students, as well as with different types of technology ensures testing a range of potential engagement situations, as opposed to students sitting in a large lecture hall with no interactions during a class taught using passive learning via traditional lecture. By
comparison, IE248 is a second-year course that focuses on engineering drawing by hand, machining, calculations related to machining, and computer numeric controlled programming. While active learning for IE248 takes place in weekly smaller enrollment, hands-on drawing and machining labs, the course lecture time includes approximately 80 students in the classroom, with more traditional passive learning. The instructors do, however, include thought-provoking questions that cause students to engage in deep thinking, providing a contrasting model for data collection.

For each classroom experiment, one student wore an E4 device while another student monitored the wearer of the device and the classroom activities. An E4 is shown in Figure 2A on a student’s non-dominant hand during a typical lecture class. The monitor recorded classroom and subject activities at one-minute intervals, as shown in Figure 2B.

![Figure 2A. Wearing an E4](image)

![Figure 2B. Time stamp observations of student activities during learning](image)

We note that similar to Boucein’s observations, one student’s EDA data remained fairly constant regardless of the situation, and was thus excluded from our analysis. Initially, raw data was plotted in Excel and compared to Empatica-generated graphs. Because the data appeared to be graphed accurately by the Empatica software, Empatica graphs were used for further analysis. Each class period’s data was uploaded to Empatica and processed using its support software. Figure 3 shows an example of the data collected for one subject during one class period. While the data shown must still be normalized, the visualization of the delivery environment (lecture, videos, and group collaboration) indicates a correlation between the amount of engagement and the employed learning platforms. The top data track is EDA, followed by blood volume pulse, acceleration, heart rate, and temperature.

![Figure 3. Example of biometric engagement data collection from IE148 (first year IE course)](image)

After data was captured from students for given class periods, they were surveyed about their sense of engagement during their class, along with physical and mental states of being (hunger level, rested/tiredness level, enjoyment of the course subject, etc.). Survey responses were based on a 1-6 Likert scale, with responses of 1 being not very interested, and 6 being very interested. Students were also asked to indicate how much they generally enjoy different types of class activities like lecture, group work, videos, etc., again using a Likert scale of 1 to 6 (1 = dislike very much; 6 = like very much). Open ended questions about student preferences and perceptions during the class were also asked. The data collected was used as a protocol testing experiment.

3. Results and Discussion

In capturing these initial data streams, many observations inform the data collection process, and ensure an ability to capture true responses and not just noise. We are encouraged by the correlation of student survey answers with the data we are capturing. For example, one instance observed a spike in heart rate when the instructor walked close to
the student in the classroom. Another showed electrodermal activity increasing during laughter. A third instance showed electrodermal activity increasing when a student checked their phone.

The major goal of this project is to establish how to practically measure student engagement during learning settings. Building on the initial experimentations and results described in this paper, we will investigate the connections between arousal level and heart rate as captured by the Empatica E4 sensor, exploring the effects of gender and personality in various learning conditions in laboratory and classroom settings. Specifically, three measures of skin conductance, which were successfully used in other experiments [20], will be computed. First, the number of spontaneous responses greater than 0.05 μSiemens initiated within the observation interval will be counted and expressed as a rate per minute (SCR-rate). The amplitude of the largest response will be recorded as maximum amplitude. The slope of change in skin conductance level during the observation interval (SCL-slope, expressed in μSiemens per minute) will be computed by removing all points corresponding to spontaneous responses, and regressing the remaining points on time.

However, we note that Yoshida et al. [25] argued that physiological measures fall short in conveying the state of engagement and recommended using the concept of “flow” to fill this gap. Flow is defined as “the holistic experience that people feel when they act with total involvement” [26]. It is expected to occur when the perceived challenge and skill levels are balanced at a high degree of difficulty. If the challenge level exceeds the skill level, it may be a source of anxiety (and impede learning), while the converse may lead to boredom and disengagement. When the challenge-skill balance is appropriate at a high degree of difficulty, it induces concentration on a task and disengages the resources spent on receiving and interpreting information unrelated to the task. A person in flow displays maximum capacity at a controllable level of performance and feels an intrinsic reward [27]. We hypothesize that higher levels of engagement will be associated to higher levels of learning (i.e., higher accuracy on learning task) and shorter task completion times. In future experiments, we will use a validated flow scale by Yoshida et al. [25], the Flow State Scale for Occupational Tasks. Our next tasks will include answering the following research questions:

i. Can the Empatica E4 sensor be used to reliably capture engagement in learning settings? For this research question, we will collect data from a large sample of students under same learning conditions.

ii. What are the implications of heart rate, gender, and personality on engagement measures? Regression models will isolate the effects of these factors.

iii. How can EDA be used to contribute to the measurement of flow? Our initial thoughts in answering this question are to do correlation studies between EDA data and other forms of flow measures.

4. Conclusions
As per our initial EDA readings, we confirmed previous findings regarding how EDA is affected by extraneous movement, seasonal temperature, and sudden mood changes. We also observed that not all subjects have EDA that shows dramatic change over time. We developed a scalable data collection protocol that can include all students in a course so that we can capture and compare data across a large sample size. Our next step is to monitor multiple students simultaneously during the same class and look for similarities and differences between students’ EDA changes related to classroom pedagogy. We will also look at specific measures of skin conductance, allowing us to make informed comparisons of gender and personality. Ultimately, we would like to create an EDA app that could alert both students and instructors when students are no longer in a flow state. It would encourage students to re-engage and instructors to change their pedagogy in real time. Our initial work provides a foundation for using EDA measurements to inform industrial engineering educators about increasing engagement, and consequently learning, in the classroom.

References


