# An Initial Exploration of Engineering Students' Emotive Responses to Spatial and Engineering Statics Problems

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# An initial exploration of engineering students' emotive responses to spatial and engineering statics problems

Work in Progress

## Abstract

The goal of this Work-in-Progress study is to explore the emotive responses of seven engineering students as they worked on spatial and engineering statics problems. The research team used multi-modal approaches that combined the validated Positive Affect Negative Affect Scale (PANAS) scale with an electrodermal wrist sensor that students wore as they solved the problems.

The electrodermal sensor measured participants' electrical skin conductivity and events were timestamped and normalized to participants' baseline electrodermal readings. These values were correlated to self-reported emotion before and after participants solved each problem set. Also, using the PANAS scale, emotion and its potential correlation to performance in rotations (Purdue Spatial Visualization Tool Revised-PSVT: R) and sectioned surface visualization (Mental Cutting Test-MCT) were explored. Preliminary findings suggest that the time spent as well as the difficulty of the problems influenced the magnitude of physiological arousal students experienced in the exam. Recording and analyzing such physiological arousal opens a door to an alternative method of investigating student performance to different engineering problems-sets. Extensions of this work in the future can help inform engineering educators on how certain problem-types can be more or less conducive to emotional responses that may deter or encourage student learning and performance.

## Introduction

### *Academic emotions*

Students' academic learning, performance, and persistence has been an ongoing topic of discussion among motivational researchers, educational researchers and psychologists [1]. In particular, *academic emotions* have been a key focal point of discussion [1]. Academic emotions occur when students attend a class or participate in class-related tasks (e.g., exams) [2]. These emotions entail coordinated and multi-component processes that integrate emotive, cognitive, motivational, expressive, and peripheral physiological subsystems [2]-[5]. For example, a student may experience anxiety about taking an exam. This emotion is manifested as thoughts of worry about failing (cognitive), a nervous feeling (affective), an increase in heart rate (physiological), an urge to escape the exam (motivational), and a display of facial expressions of anxiety (expressive) [1]. However, there are still gaps in our understanding of the mechanisms that make up students' academic emotions and how these may influence performance as literature suggest that both emotions and cognition are intertwined [1]. Those that have attempted to understand these mechanisms have seldom attempted to explore them in authentic classroom settings and tasks or with multi-modal approaches [6]-[8].

Academic emotions consist of two factors that characterize two dimensions: (a) *valence dimension* (positive or negative factors) and (b) *activation dimension* (focused or unfocused energy factors). Academic emotions differentially influence student performance. For example, positive emotions (e.g., joy) may increase engagement and nurture creative learning strategies, while negative emotions (e.g., boredom) may have an opposite effect, diminishing engagement and supporting superficial cognitive processing [2]. In other instances, negative emotions (e.g., anger) may increase an individual's desire to prevent future failure [2] and serve to improve performance.

***Multi-componential measure of academic emotions***

Traditionally, academic emotions are measured with self-reports [9], [10]. However, self-reports pose high risks of subjectivities during data collection and analysis of their items [9]-[11]. Self-reports also limit a more granular understanding of the emotive events that transpire during a classroom activity [7] and its influence to student performance on a task. To this end, more and more researchers are relying on multi-modal approaches that use more than one method to explore constructs representative of the coordinated and multi-component processes underlying emotions [6]-[8], [12]. Today, many researchers combine self-reports with tools such as physiological electrodermal sensors, facial expression analysis software, and encephalogram monitors [6], [7], [13]-[15]. In particular, electrodermal sensors based on electrodermal activity (EDA), are of interest due to their portability, non-intrusive nature, and ability to help researchers understand arousal responses (or engagement) due to specified events in a closer-to-real-time manner [14].

Depending on the goals of the research study, the choice of these multi-modal methods may vary [16]. For example, Sprangler and colleagues [17] used biological markers of stress (cortisol in saliva) to study 40 teacher-students over a 3-month examination period. The researchers collected saliva from the participants immediately before, five, and fifteen minutes into the exam. They found that cortisol was highest during anticipation of the exam, which correlated to higher levels of negative emotions, but did not appear to be maintained after the exam finished. Harley and colleagues [7] sampled math, engineering, social science, business, and art majors that were randomly assigned to a MetaTutor program (a multi-agent, intelligent tutoring hypermedia system) teaching about biology. They collected facial expressions, electrodermal activity, and self-reports and showed a 75.6% agreement between facial expressions and emotion self-reports, a 60.1% agreement rate between facial expressions and electrodermal activity (EDA), and 41.3% agreement between emotion self-reports and electrodermal activity. The last study suggests that depending on the context, multi-modal tools may be used to understand potential correlations between academic emotional processes and its related performance outcomes.

***Academic emotions in authentic engineering education***

The study of academic emotions in engineering education with the intent of informing classroom practices, assessment, and instructional interventions is limited. In 2015, Husman and colleagues [18] explored the emotions of engineering students enrolled in an ethics course. The researchers used self-reports and salivary cortisol at the beginning and end of class and found a negative correlation between class-related positive emotions (i.e., enjoyment) and students' cortisol levels. The more enjoyment students self-reported, the less psychological stress they experienced and the better they performed.

Villanueva and colleagues have reported using self-reports with electrodermal activity sensors [19], [20] while Goodridge, Call, and colleagues have used electroencephalogram monitors [21], [22] to study performance in an engineering statics course. Each study has developed methods to identify how the type of exam problem could influence the activation of students' pre-frontal cortex and EDA arousal [19]-[22], which influence student performance and learning of different engineering problems. Some electroencephalography (EEG) research and theory such as that found in the n*eural efficiency hypothesis* seek to identify periods of focus in study participants and when considered in context with academic emotion data collection [23] may yield important information about a student's performance on an exam in real-time. In other words, a student's use of their cognitive resources to perform work on a problem may associate with their exam-related emotions.

This Work-In-Progress paper represents the combined efforts of Villanueva, Goodridge, and Call to develop a pilot study where an emotions self-report was combined with an electrodermal sensor and an electroencephalogram monitor. Work around performance and EEG results has been published recently [22]. The present analysis aims to explore student performance data as it correlates with self-reported emotions and EDA. The ultimate goal of this work will be to inform testing designs and guide engineering educators on the influence that problem-set sequencing and selection could have on engineering student performance.

For this study, three authentic engineering problem-sets were selected from: (a) the Mental Cutting Test (MCT) problem-set (measures plane cutting in a 3-D space; referred to as *MCT* from this point forward), (b) the Purdue Spatial Visualization Test: Visualization of Rotations (PSVT:R) problem-set (measures rotational movement in a 3-D space; referred to as *PSVT:R* from this point forward), and (c) problems representative of 3-D force equilibrium concepts in an engineering statics course (referred to as *Statics* from this point forward).

**Research Hypothesis**

This pilot study aimed to explore the following hypotheses:

**$H_o$:** No difference in student performance or electrodermal activity will be found as students completed the engineering problem-sets
**$H_1$:** A change in student performance will be linearly correlated to a change in electrodermal activity and self-reported emotions (either positive or negative) as students completed the engineering problem-sets
**$H_2$:** A change in student performance will not correlate to a change in electrodermal activity and self-reported emotions (either positive or negative) as students completed the engineering problem-sets

The aims for this study were to:

1. Understand if the self-reported academic emotions from the students correlated with their recorded electrodermal activity

2. Understand if the recorded electrodermal activity correlated with any of the three engineering problem-sets, in terms of performance

## Method

### Participants

For this Work-In-Progress study, seven participants, all Mechanical engineering students, were recruited through convenience sampling at a rural western research university in the U.S.. The student composition was 6 male and 1 female and all were sophomore/junior engineering students. Participants were at the time enrolled in a Statics class and performance in the course was not considered when recruiting students. For all participants, this was the first time they had taken the Statics course, which is a pre-requisite course for subsequent professional courses in Mechanical, Civil, Environmental, and Biological Engineering. Statics is also considered a gateway course in engineering [24].

### Engineering Problem-Sets

The selected problem-sets were identified based on the nature and expected skill sets that students were expected to develop in this Statics course (Figure 1). Five representative PSVT:R, MCT, and Statics problems were chosen. MCT is an occupationally designed, valid, and reliable instrument used to measure how an individual mentally maps a two-dimensional sectioned surface when referencing a two-dimensional trimetric drawing of an object and a cutting plane passing through it [25]. Solutions show a variety of configurations but a correct solution often requires the learner to engage in mental rotation of a solution as well as visualizing the proportion of the sides of the object as they are cut with the plane. PSVT:R problems require a student to mentally rotate an object represented with a 2-D drawing and to then select the proper solution orientation for that object [26]. These spatial problems were chosen due to their capability to represent two fundamental components of force addition, direction and magnitude, that are proposed to correlate with orientation (rotation) and proportion and that are represented with vector mathematics in a Statics course [27]. The Statics problem-set represents a traditional introductory Statics problem where a student must identify the resultant force consequential to two or three component forces. To solve such problems, an engineering student must know how to mentally rotate and reference a two-dimensional drawing.

Problem formats varied for the problem-sets. Both PSVT-R and MCT problems relied on multiple choice selection items where participants were asked to identify the answer that most closely associated with the manipulated object. The Statics problems required participants to hand-write their work and provided a final response on paper. The computer program simply presented the problem and enabled participants to move on to the next question. The Statics problem-set paralleled material covered for these students in class within the same semester they were involved in the study to ensure the problems were authentic to the context of their learning.

### Multi-Modal Approaches

#### *Experimental Layout*

Following protocols established by Villanueva and colleagues [19], [20] and Goodridge, Call, and colleagues [21], [22], participants were asked to wear a sports band on their non-dominant wrist one hour before the study started and to not consume (e.g., caffeine) or wear (e.g., hair spray, hair gel, topical medications) any products that may have interfered with the readings. The sports band allowed for accumulation of baseline sweat formation in order for the sensor to collect skin conductance readings [19].

(a) (b) (c)

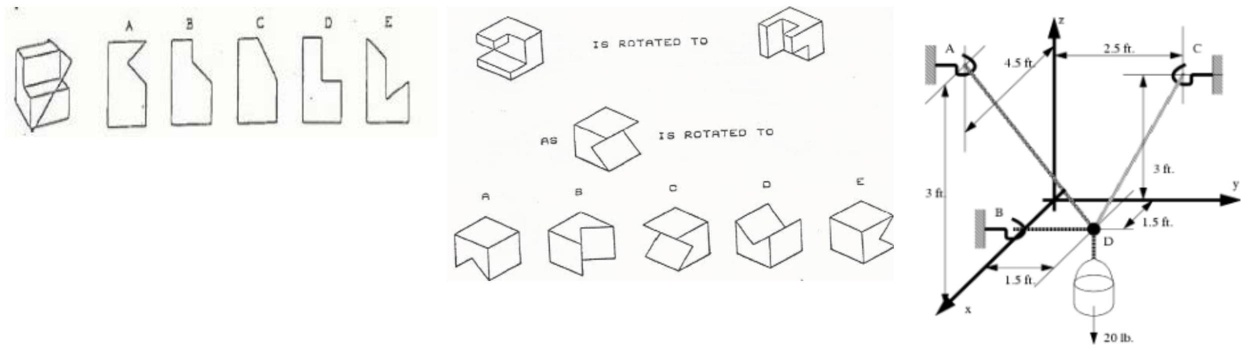


**Figure 1**. Three representative problem-set types: (a) MCT, (b) PSVT:R, (c) Statics. The images in (b) and (c) are presented with permission from the Purdue Research Foundation (© Copyright Purdue Research Foundation, 1976) [26] and the instructor that designed the Statics problem, respectively. The MCT problem image in (a) does not require permission due to the longevity in its use from inception and because there is no records of renewing of the copyright prior to 1976 [25]. The Statics problems were developed by Goodridge due to his expertise in engineering statics and mechanics [27].

The participants were asked to sit down on a pre-designed research layout (Figure 2) where a computer containing a slide show with the problem sets were presented under the platform of an E-Prime psychological timestamping software program (E-Prime Professional, Version 2, Psychology Software Tools). Upon start of the session, the cleaned electrodes of an electrodermal sensor were placed on top of the median neve of the non-dominant wrist of the participant as described by Villanueva and colleagues [19], [20]. A video camera and secondary camera were used to record participants' facial expressions and verbalizations of the problem-sets for triangulation purposes. Students were provided with blank sheets of paper and were asked to bring their graphing calculators and pencils as they solved the Statics problem-sets. The electroencephalogram monitor was placed on the participants' heads and was linked to the E-Prime program following procedures illustrated by Call et al., [21]. Events indicated by the E-Prime timestamps were identified in the EDA and video records during post-processing. The experimental schematic diagram is shown in Figure 2.

*Electrodermal activity data collection*

An electrodermal sensor (Empatica E3, Boston, MA) was placed on the participants' non-dominant wrist to prevent compounding factors such as signal-to-noise ratio exuded from excessive hand movements [14], [19], [20]. Accelerometers that are embedded in the sensors were used to identify any additional movements by the participants and were used as criteria to determine potential outliers in the data as described by others [28].

Each electrodermal sensor recorded the electrical conductivity of the skin (in microSiemens, µS) at a frequency of 4Hz (period is 1/4 of a second) at a low electrical current of 1100mAh (Empatica, Boston, MA) during the laboratory session. Each participant was in the session for an average span of two hours, which yielded approximately 28,800 data points per participant. All EDA datasets were normalized via range-correction that considers an individual's autonomic (baseline) response as it relates to the maximum and minimum levels of the amplitudes of the EDA response [14], [19], [20], [29].

The mean for the range-corrected EDA was then calculated and was further filtered if participants' EDA levels contained a range-corrected maximum less than 0.05 (5% of maximal EDA) as it could have been indicative of sensor malfunction, data transfer issues, or hypo-responsiveness of the participant [14], [19], [20], [30]. Also, to avoid any potential distortions in the analysis [14], responses by participants, problem-sets, and surveys were averaged.

*PANAS self-report data collection*

The Positive Affect Negative Affect Scale (PANAS) [31] was used as the embedded pre- and post-survey instrument for this pilot study. PANAS is a validated scale to explore individuals' state (in-the-moment) or momentary (after a short period; e.g., a week) emotions due to an intervention or task. The survey consists of 20 items using a 5-point Likert scale ranging from very slightly or not at all (1) to extremely (5). Cronbach's alpha coefficient for the positive emotion scale ranges between 0.86 to 0.90 and between 0.84 to 0.87 for the negative emotion scales, suggesting a reliable and validated instrument.

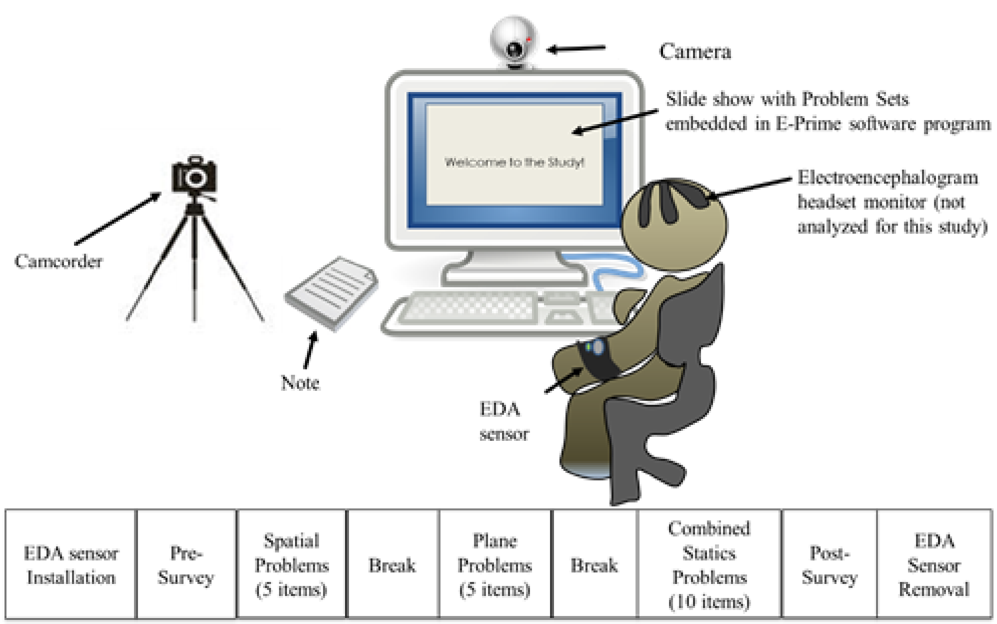


**Figure 2.** Layout of experimental design. A participant is sitting in front of a computer that has a slide show in an E-Prime software program with a slide show containing the three types of problem sets along with a PANAS pre- and post-survey. The participants wore an electroencephalogram monitor as well for this pilot study but these results will not be discussed in this Work-In-Progress paper as it has been previously published elsewhere [22].

*Student Performance data collection*

For the student performance data, scores were determined based on whether the student got the correct final answer or not. Positive points (+1) were attributed if the students performed steps of the problems correctly and negative points (-1) were assigned if the student did not perform the problems correctly. A score of zero (0) was assigned if students skipped a step or a problem. For the purpose of this study, the performance scores were compared against the mean range-EDA measured from the participants.

*Statistical analysis*

All values were compared in a constant comparative manner by each type of problem-set or survey (considered as the *events* for this study). All values were calculated as the mean and standard deviation per participant. A Pearson correlation analysis was conducted for the electrodermal data in comparison to the PANAS self-reported emotions and student performance data for each problem set; p-values under 0.05 were considered statistically significant, p-values under 0.10 were considered marginally significant.

## Results

*Electrodermal Activity*

The mean range-corrected EDA values for each event by participant and the mean time expended by the participants per event are summarized in Figure 3. As expected, the Statics problems required a greater amount of time to complete the problem-sets. No significant changes were found between the PSVT:R and MCT problem-sets or the pre- and post- surveys. A t-test analysis (Table 1) was conducted for the mean range-corrected EDA values per event. Both PSVT:R and MCT problem sets showed an approximately two-fold decrease in EDA response when compared to the Statics problem set ($p<0.001$ for both cases). Pre- and post- survey EDA values revealed no significant differences ($t=1.12$; $p=0.13$).

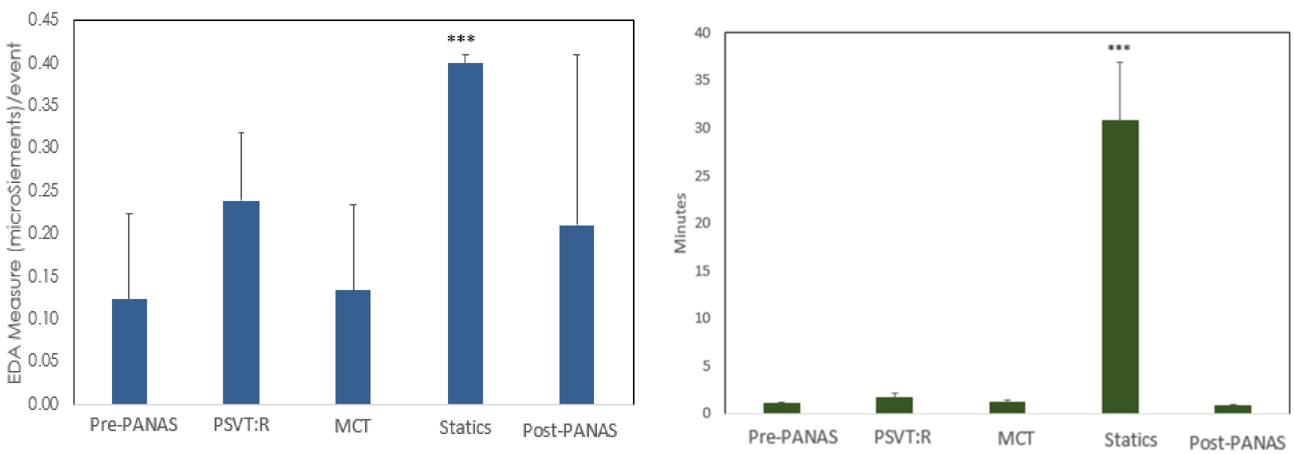


**Figure 3.** Mean range-corrected EDA values for each event (left graph) and mean time expended for each event (right graph). For both instances, the Statics problem sets resulted in the highest EDA response and time expended by the participants; *** represents statistical significant ($p<0.001$) differences compared to the other problem-sets.

*PANAS Self-Report*

Factor analysis was used to measure potential relationships between the latent variables of valence (positive, negative) for the emotions self-report. Factor loadings with an absolute value of an Eigen score of 0.40 or greater [32], [33] denoted a predominant presence of this emotion. Before the laboratory session, students experienced primarily negative emotions (e.g., distress, upset, irritation, shame, nervousness), which were mitigated by the end of the session. Positive emotions (e.g., enthusiastic, excited, strong) were maintained until the end of the session.

**Table 1**. T-test analysis of the mean range-corrected EDA and standard deviation (in parenthesis) for the three problem sets (PSVT:R, MCT, and Statics problems); *** represents statistical significance ($p<0.001$).

| Mean Range-Corrected EDA (SD) | | | p-values |
|---|---|---|---|
| **PSVT:R** | **MCT** | **Statics** | |
| 0.75 (0.57) | 0.95 (1.12) | | 0.842 |
| 0.75 (0.57) | | 0.18 (0.17) | **<0.001** *** |
| | 0.95 (1.12) | 0.18 (0.17) | **<0.001** *** |

**Table 2**. Representative factor analysis of the pre- and post- survey administrations of the negative and positive emotions items on the PANAS Scale and mean (standard deviation) self-reported values; $^{+}$represents a marginally significant value via t-test analysis of the means of each post-survey item compared to the pre-survey ($p < 0.10$).

| | Pre-Survey | | | Post-Survey | | |
|---|---|---|---|---|---|---|
| **Emotion** | Negative | Positive | Mean (SD) | Negative | Positive | Mean (SD) |
| Distressed | **-0.684** | **0.650** | 1.0 (0.5) | 0.121 | **0.875** | 2.0 (1.0) |
| Upset | **-0.987** | -0.078 | 1.0 (0.8) | -0.338 | **0.868** | 1.0 (0.4) |
| Scared | 0.049 | **0.864** | 1.0 (0.5) | **0.625** | 0.073 | 1.0 (0.5) |
| Hostile | 0.265 | **0.834** | 1.0 (0.8) | -0.228 | **0.498** | 1.0 (0.4) |
| Irritable | **-0.987** | -0.078 | 2.0 (1.4) | **-0.618** | **-0.401** | 1.0 (0.5) |
| Ashamed | **-0.644** | -0.162 | 2.0 (1.1) | **-0.757** | 0.225 | 1.0 (0.4) |
| Nervous | **-0.950** | -0.136 | 2.0 (1.1) | -0.338 | **0.868** | 1.0 (0.5)$^{+}$ |
| Jittery | -0.344 | 0.018 | 2.0 (1.0) | 0.162 | **0.911** | 2.0 (0.9) |
| Afraid | -0.330 | **0.619** | 1.0 (0.4) | -0.301 | **-0.459** | 1.0 (0.5) |
| Interested | 0.024 | **0.905** | 4.0 (1.3) | -0.228 | **0.498** | 4.0 (0.8) |
| Excited | **0.915** | -0.079 | 3.0 (1.1) | **0.848** | -0.200 | 3.0 (0.9) |
| Strong | **0.748** | **0.584** | 3.0 (1.3) | **0.830** | -0.235 | 3.0 (1.0) |
| Enthusiastic | **0.773** | **-0.463** | 3.0 (1.3) | **0.618** | **-0.632** | 3.0 (0.8) |
| Proud | **0.445** | **0.791** | 3.0 (0.8) | **0.968** | -0.189 | 3.0 (0.8) |
| Alert | **0.987** | 0.078 | 3.0 (1.1) | **0.734** | -0.436 | 4.0 (0.4) |
| Inspired | **0.901** | 0.188 | 3.0 (1.1) | 0.115 | 0.149 | 3.0 (1.1) |
| Determine | **0.723** | **0.470** | 4.0 (0.5) | **0.529** | 0.044 | 4.0 (0.6) |
| Attentive | -0.229 | -0.346 | 4.0 (1.1) | **0.454** | -0.064 | 4.0 (0.7) |
| Active | **0.825** | 0.149 | 3.0 (1.3) | **0.960** | 0.251 | 3.0 (0.5) |
| Guilty | **0.492** | 0.249 | 1.0 (0.0) | **0.488** | -0.367 | 1.0 (0.0) |

*Student Performance*

For the PSVT:R problem-set, the majority of students had at least 4 out of 5 problems correct. The average performance for this problem set was 69% of correct responses. For the MCT problem-set, the majority of student had at least 3 out of the 5 problems correct. The average performance was 54%. For the Statics problem-set, the average performance was 66%. MCT and PSVT:R correct responses paralleled previous findings reported by Wood et al., [27].

*Correlational Analysis*

Pearson correlational analysis was conducted between the mean range-corrected EDA responses and the mean of the items for each event (Table 3). Potential positive moderate correlations were found between the Pre-PANAS with EDA and MCT with EDA. However, only the Pre-PANAS condition was statistically significant ($p<0.05$).

**Table 3**. Pearson correlation coefficients of the EDA data with the PANAS survey responses and performance data on each problem-set; absolute values of 0.1 to 0.39 signify a weak correlation, 0.40 to 0.59 signifies a moderate correlation, and 0.6 to 1.0 imply a strong correlation; the sign represents the direction of the correlation; * represents a moderate correlation; p-values under 0.05 are considered statistically significant.

| | Pearson's *r* | p-value |
|---|---|---|
| Pre-PANAS | 0.44* | **0.03** |
| PSVT-R (Rotational Performance) | 0.26 | 0.29 |
| MCT (Cutting Plane Performance) | 0.43* | 0.17 |
| Statics (Statics Performance) | 0.29 | 0.21 |
| Post-PANAS | 0.14 | 0.29 |

## Discussion

Our study used multi-modal approaches to explore engineering students' examination experiences to various types of problem sets. We found that many emotions demonstrated a loading on the positive and negative scales before and after the experimental session. One interesting example was 'nervous', which remained high and loaded on the positive valence dimension. This emotion may have served to stimulate a student's impulse to want to meet the goals of these tasks [1], [2].

Self-reported emotions such as 'shame' increased whereas other emotions such as 'afraid' decreased and 'enthusiastic' increased. It is likely that the valence loaded for these types of emotions was used to mediate negative emotions and propel the students to continue to engage with the problem and task at hand [1], [2], [33]. Mediation may occur when one or more emotions may load into positive and negative scales of a self-report. It is also possible that since the responses in this study were represented by a mean response from a collective group of individuals, that some emotions took precedence for certain individuals over others. More work is needed to compare an individual's emotion in these types of problem-solving experiences and how these can influence learning and performance.

When exploring the different problem-sets, in terms of EDA response, we found that for both cases, no changes in arousal were found between the PSVT:R and MCT problem-sets but a significant difference was found between each type of traditional spatial problem-set when compared to the Statics problems. The multiple-choice nature of the MCT and PSVT:R versus the hand-written format of the Statics problems may have attributed to this difference. Additional work is needed to explore this finding further.

When assessing the correlations between the surveys and the different types of problem-sets with EDA, we found that for the pre-survey a moderate positive correlation was found but not in the post-survey event. Prior work by other researchers has found that prior to commencing a task or an experimental session, participants have anticipatory responses that may influence their emotional reactions to a task [17], [18]. In terms of performance on PSVT:R problems, we found that there was no correlation with EDA ($r$=0.26; p=0.29). In terms of performance on MCT problems, we found a moderate correlation although it was not statistically significant ($r$=0.43; p=0.17). For the Statics problems, we did not find a significant correlation with EDA ($r$=0.29; p=0.21). These results tie to previous work by Reusch et al., [22] indicating that MCT problems typically results in lower performance averages by students compared to PSVT:R problems for this population. It is expected, based on Reusch et al.'s results [22], that there is a higher difficulty level on the MCT problems used. This, in turn, may have been reflected by the moderate increase in EDA when we consider dividing this value by the time expended on the MCT problem-set as can be estimated from the two Figure 3 graphs (e.g., 0.05 microSiemens/minute for MCT). The preliminary results of this pilot study corroborate these findings by suggesting a higher normalized arousal (or mean range-corrected EDA/timed event) found in these types of problems compared to PSVT:R (0.13 microSiemens/minute) and Statics problems (0.01 microSiemens/minute) (Figure 3).

Parallel findings to this study conducted by Ruesch and colleagues [22], found that for these seven participants, neural efficiencies (indicative of knowledge and expertise on a problem) are positively correlated to PSVT:R problems performance but negatively correlated with MCT problems proposing the difficulty that students experienced in this problem-set. It is possible that like Reusch and colleagues suggested, "the neural efficiency hypothesis may not be supported by engineering students solving MCT problems, but may be supported by students solving PSVT:R problems" [22, p.6]. With greater participant numbers, we may develop more definitive conclusions related to performance in these types of problems due to multi-componential processes based on academic emotions [2].

## Limitations

Our work, although in its preliminary stages, represents one of the first studies to explore academic emotions when comparing different types of engineering problem-sets using a combination of self-reports and physiological tools (e.g., electrodermal activity). As a result, there are a couple of limitations to the study. The first one is the sample size. While we have a small number of participants, the types of constructs we are exploring (e.g., performance, self-reports) and the extensive data processing (EDA; ~28,800 data points/participants) needed to saturate the data for a more rigorous statistical analysis pose a distinct challenge. Given the complex nature of these types of experimental designs and the moderate correlations found for certain events, we are encouraged that studies of this nature that include additional participants may help unveil important emotional mechanisms that engineering students experience when solving different types of engineering problem-sets.

Also, we recognize that engineering problem-sets may be primarily cognitive in nature. While we did not expand upon the EEG section of the work, Ruesch and colleagues [22] have indicated that neural efficiencies may be positively correlated to rotation problems such as those on PSVT:R problems but negatively correlated with problems that require proportion and envisioning internal details cut with a cutting plane as seen on the MCT. This may imply that some problems are more cognitively focused in nature and may require more regulation of emotional processes during problem-solving tasks. Future work is needed to better understand both cognitive and emotional processes that engineering students undergo when solving different types of problems.

**Implications for Practice**

Literature suggests that emotion and cognition are intertwined [1] and are processes that cannot be separated when considering student learning and performance [1] –[5]. In engineering courses where new concepts (e.g., mechanics) are introduced to early engineering students, understanding how students experience learning and performance for particular problem-sets can help educators develop good practices for exam preparation and design. While the authors understand that there are many variables that could influence students' reactions to an engineering problem-set that are out of reach (e.g., a bad day), there are other variables that engineering educators can control (e.g., exam design) to optimize student performance and success. This work represents a first step towards assisting educators and students to benefit from future evidence-based practices that could stem from future studies.

**Conclusion**

The work from this pilot study is one of the first to explore the emotive responses of engineering students to different types of Mechanical Engineering problem-sets via self-reported emotions and electrodermal arousal and explore if they associated with performance. We found that the students carry with them an anticipatory emotional reaction that may influence their performance on different types of problems. We also found that the problem-set types (e.g., MCT versus Statics) influenced physiological responses from the students. Together, these preliminary findings point to the need to better understand students' emotional processes as they solve engineering problems as these may influence their performance.

**Acknowledgements**

This work could not have occurred without the assistance of the following research assistants: Sarah Lopez, Jorge Espinoza, and Maria Valladares. We are indebted to their assistance in data collection and initial analysis. This work was also partially supported by a seed grant awarded to the Villanueva and a Presidential Doctoral Research Fellowship to the Call at the home institution of these authors.

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