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# Differences in perceived stress levels and measured stress while solving spatial tests

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# Differences in Perceived Stress Levels and Measured Stress while Solving Spatial Tests

## Abstract

Many events, including tests, personal conflicts, and hard deadlines, may result in a high level of stress for both students and educational practitioners. For example, taking a test is particularly stressful for students who are less prepared and who may have limited knowledge of the subject. There is a dearth of literature regarding the stress levels, real or perceived, experienced by students while solving spatial tests. Advancements in micro-electromechanical systems have helped researchers in collecting physiological data with smart devices such as wristbands, chest bands, and armbands. In particular, wristbands have been widely recommended by researchers because they are easy to wear, easy to use, and "non-invasive," since they are similar to watches or exercise tracking devices.

This paper aims to explore the differences in self-reported stress levels perceived by engineering students and their stress levels recorded by a wristband while solving spatial tasks. An Empatica E4 wristband sensor was used to collect multiple body signals including 3-axis acceleration signals, Electrodermal Activity (EDA) signal, heart rate, and body temperature. In particular, recorded EDA signals reveal information on emotional and cognitive state by measuring the electrical resistance of the skin. If a person is under stress or experiencing increased cognitive load, the skin conductance increases. To measure the perceived stress levels by the participants, a perceived cognitive load instrument scale was used.

This study involved 143 undergraduate engineering students at two large public research universities. The study was conducted over two sessions. The first phase of the study was online with participants completing three spatial tests including the Mental Cutting Test (MCT), the Paper Folding Test (PFT), and the Surface Development Test (SDT). The perceived cognitive load instrument was administered after each spatial test. During the second phase of the study, 35 participants were selected based on their performance on the spatial tests to come in person and wear the wristband device while completing spatial and verbal analogy tests and solving six engineering mechanics problems. The same perceived stress scale was administered at the end of each of these tests/tasks. Data was analyzed and evaluated to determine how stress level, both perceived and measured, varied for high and low spatial visualizers while solving spatial tests. The result highlights that engineering students experience stress while solving spatial problems. Analysis indicated that there were no statistically significant differences between the high and low spatial visualizers. Limitations of the study are discussed at the end.

## Background

Academic stress can be described as the student's interaction with environmental stressors, the student's cognitive judgment in coping with those academic-related stressors and involves the psychological or physiological response to these stressors [1-3]. Engineering students must undergo a substantial and comprehensive curriculum during their undergraduate years—aspects of the curriculum are often described as being stressful. Progression through the engineering curriculum can be stressful because the students are expected to perform well with a significant workload in the form of projects and other required homework. Consequently, to meet such demands, students may not be able to enjoy their campus life [4]. Excessive stress can lower work efficiency and prolonged stress among students can cause health-related problems and have a major negative impact on students' well-being and productivity [5 - 6].

Academic stressors also include the students' perception of the extensive knowledge base required to solve problems with a sense of inadequate time to develop solutions [7]. Many researchers have documented that students report experiencing academic stress at predictable times each semester with the greatest sources of stress resulting from taking and studying for exams and a large amount of content to master in a small amount of time [3] [8]. If we could detect these academic stressors and detect them in time, students might perform better [9]. Further, identifying high stress situations could help students maintain the appropriate working cognitive state to better achieve their academic goals.

A physiological response to stress corresponds to psychological change and these measurements can't be manipulated by the individual. The mechanism that maintains the body under a stable condition is achieved by the autonomic nervous system (ANS), which maintains the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). From medical research literature, it is known that stress can activate the SNS [10] and the PNS can bring stress levels back to a rest state. Intuitively, SNS triggers increases in heart rate, Heart Rate Variability (HRV), blood pressure, etc. Electrodermal Activity (EDA) can be used for assessing both ANS and SNS responses. The EDA physiological response is strongly related to SNS because skin conductivity is mainly a result of the sweat glands solely controlled by SNS. EDA remains one of the most direct methods of measuring stress related to ANS responses [11, 12]. In comparison to HRV, EDA is relatively easy to measure and potentially suitable for long-term continuous data collection purposes.

In earlier studies, EDA has been used in the classification of mental stress when measured with another simultaneous physiological measurement [11, 13, 14]. Only limited papers have been reported that have separated EDA classification rates for identifying stress responses. Even though literature has identified stress as an expected response to test conditions, only limited studies have reported stress levels that have been verified by other metrics or techniques [15-17]. In most research studies, authors have only used one instrument to measure stress, but we identified only limited studies which use comprehensive analysis of survey instruments with ANS-based mental state assessment (Wristbands) [17]. This study adds to the literature by conducting a comprehensive analysis of responses to the self-report stress instruments in conjunction with the biosensor that records the EDA levels measured while solving spatial tests. The biosensor used in the study was the Empatica E4 wristband.

## Purpose and Hypothesis

The main objective of this study is to explore the differences in self-reported stress levels perceived by a participant vs the stress recorded by a wrist band (in terms of EDA levels) while solving spatial visualization tests. The hypothesis tested in this research is: The stress levels experienced by low visualizers will be higher (based on EDA measurements and the self-reported scale) than those experienced by high visualizers when solving spatial tasks.

## Method

### *Setting and Participants*

The current study took place at the University of Cincinnati and the University of Nebraska-Lincoln and their respective Colleges of Engineering. In the first phase of the study, 143 undergraduate engineering participants completed three widely accepted tests of spatial cognition and provided researchers with demographic data. All phase 1 testing was accomplished online. In the second phase of the study, a purposeful sample of 22 Male and 13 Female participants of varying spatial skill levels were invited individually to a classroom to take a fourth spatial test as well as some additional tests that will not be reported on here. The room had standard ambient light. All mandatory COVID protocols were followed during the Phase 2 testing.

### *Data collection*

When measuring a cognitive factor such as spatial ability, it is common practice to administer multiple tests to obtain a precise measure of the factor [18]. These individual scores on each test are then converted to a single composite z-score to determine an individual's level of spatial ability within the sample. The three spatial tests used in this study were the Mental Cutting Test (MCT), Paper Folding Test (PFT), and Surface Development Test (SDT).

During the second phase of the study, the students wore a wristband that recorded EDA levels while solving a spatial reasoning test. Participants completed a self-reported stress scale instrument after the test. The second session of the research study was held individually and was administered in a neutral location outside of the students' typical schedule, allowing for every student to take the test at a time of their convenience.

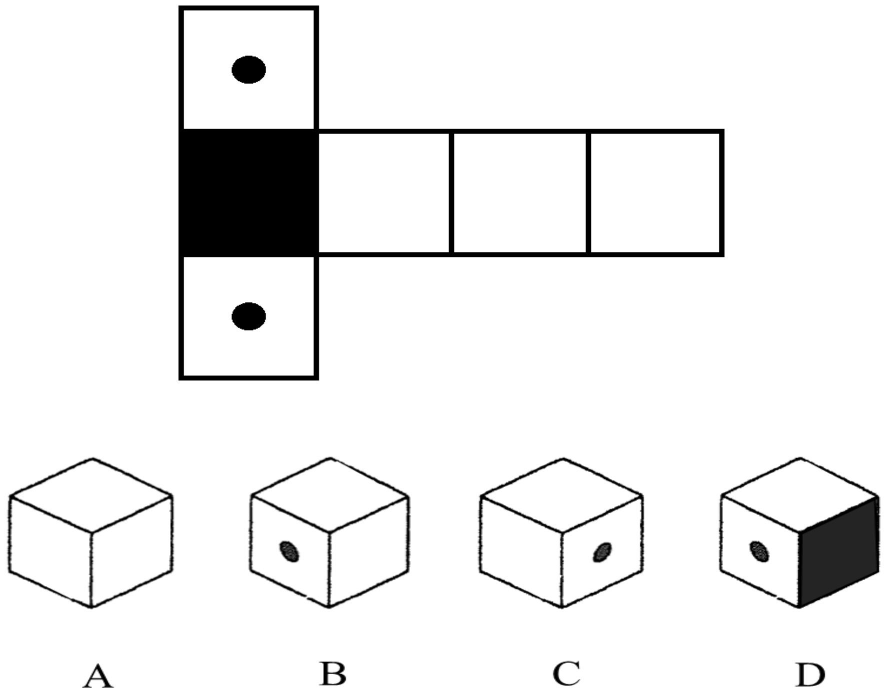



**Figure 1: Spatial Reasoning Test - Example Question (Correct response A)**

*Spatial reasoning test*

Spatial reasoning tests are tests that are intended to determine a participant's ability to manipulate 2D shapes or 3D objects, visualize movements and change between shapes, and spot patterns between those shapes.

The spatial assessment students completed during the Phase 2 testing consisted of 10 questions designed to see how well they could visualize the folding of a pattern to form a three-dimensional object. The assessment comprises patterns with shading or designs on them. These patterns can be folded to make a cube. Figure 1 shows an example problem from the spatial task. For this test, students must select the object that *cannot* be formed by folding up the pattern.

*Physiological Response*

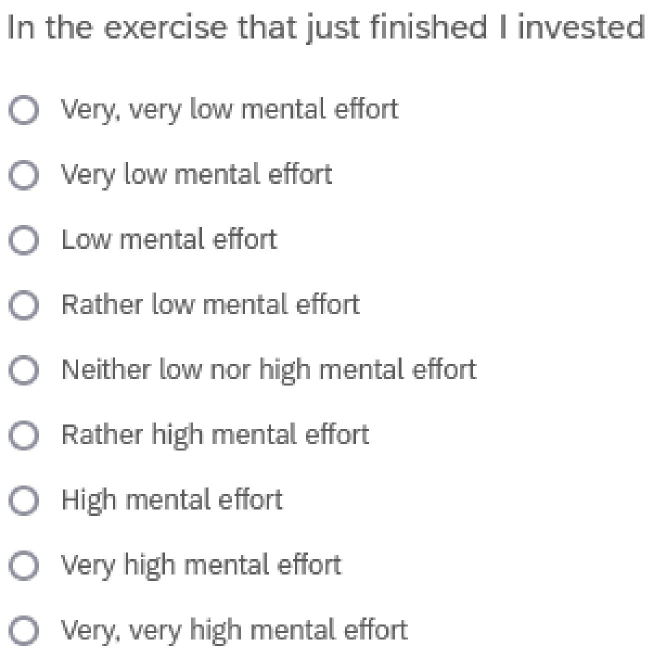
The Empatica E4 was the device selected for this study because it provides an easy-to-use means of continuously collecting time-stamped biometric data. Data collected by the device includes accelerometer readings for identifying significant physical movements, skin temperature, blood volume pressure, heart rate, heartbeat inter-beat interval, and EDA. The device also incorporates an event mark button which allows participants to tag events that can later be linked to different experiences. This can support investigators in determining whether there is an association between physiological responses and engagement with test material. In this research study, EDA signals were extracted for participants completing the spatial reasoning test. These signals are an indication of the emotional or mental stress of the participants engaged with the test material reflected in electrical skin resistance. While taking the spatial reasoning test, each participant was alone inside the room and observed by a researcher from outside the room through glass panes in the walls and the door. The researcher observed from outside the room to minimize additional emotional stress that may be experienced from direct close observation which could distort the sensor readings. This was also an important component of the COVID protocol for in-person testing.

*Perceived Cognitive Load Instrument*

In past years, self-rating scales have been used widely to obtain measurements of cognitive load. Self-rating scale techniques assume that people can evaluate their own cognitive processes and honestly report the amount of mental effort they spent. Although questions remain, it has been frequently shown that people are capable of providing a numerical indication of their perceived mental burden. Paas was the first person to demonstrate this finding in the context of cognitive load theory [19]. The instruments used in the present study were demonstrated to be valid and reliable measures of overall cognitive load experienced by an individual [19 - 24]. These measures were multidimensional and used a 9-point scale for measuring perceived stress when performing a cognitively challenging task. The scales assess a group of associated variables such as level of difficulty, mental effort, stress, and concentration. These variables are connected to cognitive load [25 - 28]and were counted towards the self-reported stress scale that were used in this analysis. Figure 1 shows an example item from the instrument measuring of the perceived level of difficulty was measured after taking the test.

***Data Analysis***

To answer a research question exploring the differences in self-reported stress levels perceived by a participant versus the EDA levels recorded by the wrist band while solving spatial visualization tests, a Spearman correlation coefficient was calculated between the self-reported scale scores (individually) and the measured EDA values.



In the exercise that just finished I invested

- Very, very low mental effort
- Very low mental effort
- Low mental effort
- Rather low mental effort
- Neither low nor high mental effort
- Rather high mental effort
- High mental effort
- Very high mental effort
- Very, very high mental effort

**Figure 2: Subjective Measure – Level of Mental Effort**

**Results**

Out of the selected 35 participants, 7 participants were removed due to incomplete data points and EDA recording errors. These errors could have been the result of a loss of connectivity between skin and the Empatica E4 sensors which resulted in no data being recorded at these times. Inclusion of these instances would distort results, therefore, the data for these participants was removed before analysis. Survey data was collected in relation to participants' self-reported level of difficulty, mental effort, stress, and concentration after completing the spatial reasoning test. Table 1 shows the correlations between the four constructs on the instrument. Level of Difficulty and Mental Effort were found to be strongly positively correlated, $r(27) = 0.830$, $p<0.001$. Level of Difficulty and Concentration was also found to be strongly positively correlated, $r(27) = 0.744$, $p<0.001$. All other factors were found to be moderately positively correlated with $r(27)$ in the range of 0.44 – 0.62. From this correlation matrix, it was clear that the level of difficulty had a mutual relationship with mental effort, stress, and concentration. It was also indicated from the analysis that mental effort had a relationship with stress and concentration. This indicates that an increase in item difficulty may create overall stress and require more attention in solving difficult problems such as those found on the spatial reasoning test.

**Table 1: Correlation matrix for Self-reported Scores (Spearman Correlation)**

| | **Level of Difficulty** | **Mental Effort** | **Stress** |
|---|---|---|---|
| **Level of Difficulty** | | | |
| **Mental Effort** | .830** | | |
| **Stress** | .565** | .621** | |
| **Concentration** | .744** | .723** | .439* |

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

The correlation between measured EDA levels and self-reported scores was also calculated. EDA values were the readings from the wristband. Del EDA is the EDA value that is subtracted from the averaged EDA values during the spatial reasoning test. The overall score was the average score of the self-reported scores. It is inferred that Del EDA and overall score were found to be weakly correlated with $r(27) = 0.204$, $p=0.298$. Here, we have P-value which is greater than the significance level ($\alpha = 0.05$), thus the null hypothesis is rejected. We conclude that the correlation is not statistically significant i.e., that there is not a significant linear correlation between the Del EDA and Overall Score on the self-reported instrument for this population.

The participants were grouped into two groups of high and low spatial visualizers based on their average score (Mean) of all the participants. The standard Deviation (SD) was also calculated. High spatial visualizers were identified as those scoring one SD above the Mean (>Mean + S.D) and Low spatial visualizers were identified as those scoring one SD below the mean (<Mean – SD).

An Independent Samples t-test was also performed to investigate whether the differences in high and low spatial visualizers was statistically significant for Del EDA. Results are tabulated in Table 2. From this analysis, there was not a significant effect on Del EDA values at the $p<0.05$ level for the spatial levels (high and low) [$t_{7.288} = -1.916$, $p = 0.301$]; however, the effect size was low to medium.

**Table 2: Independent Sample t- test – Del EDA and Level of Spatial Skills**

| | High | Low | F-value | p-value | Cohen's d effect size |
|---|---|---|---|---|---|
| Del EDA | .068 | -.122 | 1.225 | .301 | 0.217 |

We correlated spatial scores with the reported stress levels. Results are tabulated in Table 3. It is inferred from the analysis that the students' spatial score is negatively correlated with self-reported scores, which indicates that relationship between the two variables move in opposite directions. In other words, students with lower levels of spatial skills reported higher levels of stress when completing the spatial tasks. You can also see the consistent strongly positively correlated relationships between the constructs from the self-reported instrument.

**Table 3: Correlation matrix for Self-reported scores with Spatial Scores (Spearman Correlation)**

| | Spatial Score | Level of Difficulty | Mental Effort | Stress |
|---|---|---|---|---|
| **Spatial Score** | | | | |
| **Level of Difficulty** | -.328 | | | |
| **Mental Effort** | -.176 | .933** | | |
| **Stress** | -.429 | .921** | .885** | |
| **Concentration** | -.133 | .792** | .909** | .752* |

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Additionally, we also correlated Del EDA values with self-reported scores using Spearman's coefficient (level of difficulty, mental effort, stress, concentration). It was found that Del EDA was weakly positively correlated with the self-reported scores in the range of 0.089 to 0.199 with no statistical significance at the $p < 0.05$ level. Also, 61% of participants had a negative score in the Del EDA indicating that the baseline EDA was very high. Baseline used in this study was the initial stress level before taking this test and getting to know how the spatial reasoning test is framed and they experienced lower stress while completing the spatial test.

## Discussion and Limitations

There has been significant research supporting the importance of spatial visualizations skills in engineering, but there is a lack of research work that focuses on exploring the stress experienced by individuals while solving spatial skills tests. It is clearly known from various research studies that high levels of stress can interfere with attention and reduce working memory, leading to lower performance on the task at hand. Solving problems with spatial components is common in an engineer's workplace. It is important to understand how stress can impact a person's work. If a person finds it stressful to solve spatial problems, this stress might spill over into other aspects of their work. The results from this study highlight that engineering students experience stress while solving spatial problems. There was clear evidence that while solving the spatial test a) there is a relationship between level of difficulty and mental effort, and concentration; b) there is relationship between mental effort with stress and concentration. It was also shown that the level of spatial skills had no significant effect on measured EDA values or self-reported measures of cognitive load. This could be due to the relatively small sample size for each group or due to problems associated with the collection of baseline data. The study was conducted during COVID which may have resulted in higher stress levels throughout for the students participating in the study limiting the predictive ability of the current stressor [29] and contributing to producing no statistical significance between groups. The other challenge during this study was scheduling the in-person participation for the second phase of the study. Most of the participants were not around campus because almost all of their classes were offered online, meaning they had to make a special trip to campus to participate in the study. A larger sample size might have shown differences in EDA between students from low and high spatial skill levels. Also, some data points from the wristband were invalid, so greater care might have been taken in collecting the biosensor data.

## Conclusions

In this work, we have used wearable sensor as stress detection system along with a self-reported scale of perceived stress. Higher levels of perceived stress influences student anxiety, and likely influences student performance on tests and other high stakes assessments. This study has been conducted with a limited number of participants. Students reported higher levels of stress that was not observed in their physiological response. The Independent Sample t-test analysis indicated that there were no statistically significant differences between the levels (high and low) of spatial skill and the measured EDA.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