Exploring Fitness Trackers as a Research Method for Developing Personas of Stress during Classroom Problem Solving

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In this report, I examine the capacity of fitness trackers to assist in differentiating students' experiences of stress during classroom problem solving. I cluster $N = 26$ students' heart rate variability plots based on categories of description created using a phenomenographic analysis of their reported emotional experiences during a scripted lesson on roots of polynomial functions. My results reveal that fitness tracker data can be a valuable indicator of when a student will report classroom distress. However, the tracker data can give both "false-positive" and "false-negative" indications a student will report distress, reinforcing that biometric data cannot be treated as a proxy for students reported experiences of stress. Nonetheless, my results do support the use of fitness tracker data to guide deeper inquiry into student experiences. For example, fitness tracker data can assist in identifying classroom moments to discuss in a video stimulated recall interview.

Keywords: math anxiety, academic distress, problem solving, fitness trackers, heart rate

Although active learning may generally have a positive impact on students' performances in science and mathematics courses (Freeman et al., 2014), not all groups have equal access to these benefits; for example, because student participation is essential to most styles of active learning, there is a higher frequency of peer-peer interaction, creating more opportunities for students with minoritized social identities to experience a marginalizing event (Reinholz et al., 2022). Classroom stressors can foster academic distress, or anxiety caused by university course environments. Academic distress has other known correlates: coursework demands, assessment pressures, instructor teaching style, and a student's sense of belonging (Larcombe et al., 2022). Additionally considering the high prevalence of math anxiety among undergraduate students in the United States (Lanius et al., 2022; Lanius, 2022; Hopko et al., 2003; Hopko, Crittendon, Grant, & Wilson, 2005; Hopko, Hunt, & Armento, 2005; Isiksal et al., 2009; Rancer et al., 2013), studies concerning psychological stress during classroom problem solving are particularly timely and important. Wearable technologies capable of collecting heart rate data, more succinctly called fitness trackers, provide an alluring prospective tool for *in situ* indication of student anxiety or distress during classroom problem solving (Singh et al., 2018; Kim et al., 2018). To explore the research potential and pitfalls of fitness trackers, this report compares clusters of student's fitness-tracker data plots to categories of description created using a phenomenographic analysis of their reported emotional experiences during a lesson on roots of polynomial functions.

Heart Rate Fitness Trackers & Distress Indication

A meta-analysis of 37 studies concluded that current evidence supports the use of Heart rate variability (HRV) for the indication of psychological stress in a particular situation (Kim et al., 2018)—for example, job-strain (De Bacquer et al., 2011) or computer-work stress (Hjortskov et al., 2004). Additionally, HRV has been shown to be a statistically significant indicator of junior high students reporting math anxiety while performing an arithmetic task such as $7 + 2$ (Tang et al., 2021). Heart rate variability (HRV) is a summative measurement of the variation in length of time between heart beats during a window of time. Slight variations in length of time between heart beats is normal in healthy individuals and is caused by the autonomic nervous system receiving conflicting feedback from the parasympathetic nervous system (informally, the rest-and-digest-system) and the sympathetic nervous system (or the fight-or-flight-system) (Singh et al., 2018). When the sympathetic and parasympathetic nervous systems are in balance, there is greater variation in the length of time between heart beats. On the other hand, when the body needs to react to an external stimulus, such as stress, messages from the sympathetic nervous system overpower messages from the parasympathetic nervous system, and there is less variation in the length of time between heart beats. Ultra short term HRV, which uses heart rate data from a couple of minutes, can be reliably computed for monitoring mental stress (Salahuddin et al., 2007), thus allowing us to synchronize changes in a student's HRV to tasks and stimuli they experience in their undergraduate math course.

Research Questions

What are the stress-related emotional experiences of undergraduate students during classroom problem solving? How does an undergraduate student's heart rate variability change if they report experiencing math anxiety or academic distress during classroom problem solving?

Theoretical Perspectives

Concerning Methodology. I utilized phenomenography (Marton, 1986). To clarify how phenomenography differs from the more familiar phenomenology, in a phenomenological study the phenomenon itself is investigated; in a phenomenographic study the variation in how people experience the phenomenon is investigated (Larsson & Holmström, 2007). Phenomenographic research is an iterative process where the researcher familiarizes themselves with the descriptions of experience, identifies distinctive or structurally significant characteristics, groups and classifies similar answers, and builds named categories; see Table 1 of Han & Ellis (2019). The final product of my analysis is categories of description that explain the variations of experience present in the data. Phenomenography can then be used to build personas, lifelike characters to assist in student-centered design in educational contexts (Huynh et al., 2021).

Concerning Fitness Tracker Data. I must avoid data-essentialism, or the position that students can be reduced to their biometric data or that the data collected by fitness trackers is "objective" reality (Svensson & Poveda Guillen, 2020). Research data are produced through a laborious and time-intensive process involving the decisions of a variety of people. Further, fitness tracker data is limited by the capacity of our locations and technologies (Ribes & Jackson, 2013). Consequently, I view biometric data as a human artifact that must be situated in its context.

Methods

Fitness Trackers & Heart Rate Variability

Photoplethysmography (PPG) uses light-emitting diodes (LED) and photodiodes to detect blood volume changes directly under the surface of the skin, with each peak in blood volume corresponding to a beat of the heart (Singh et al., 2018); see Figure 1. The PPG sensor records the length of time between successive peaks of blood volume, providing an accurate approximation of the length of time between heart beats. To process the collected heart rate data, I partitioned each students PP interval data into 3 time windows and utilized the HRV variable root mean square of successive differences (RMSSD) to compute an HRV value for each student in each time window of the lesson; see Figure 1 for the RMSSD formula. The most common cause of inaccuracy with PPG measurement is motion artifacts (Fine et al., 2021), for example rapid arm movement, which occurs during certain types of intense physical exercise, where the optical sensor loses contact with the skin. Although I used a procedure for detecting and cleaning optical-coupling-based errors within the heart rate data, I sought to avoid the issue entirely and encouraged research participants to secure the watch snugly to the forearm of their non-dominant hand. Further, participants remained sitting during the experiment, which minimized the amount of arm movement.

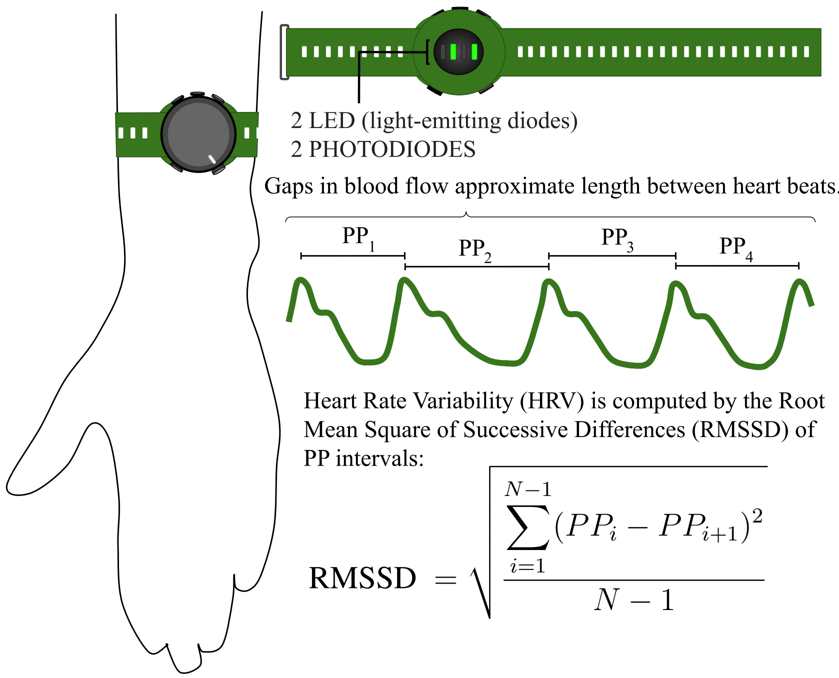

Figure 1. Photoplethysmography (PPG) sensor data to compute heart rate variability (HRV)

Scripted Math Lesson & Reflection Survey

After securing institutional review board approval from Auburn University's Office of Research Compliance, I invited undergraduate students enrolled in a lower-level math course to participate in my study. Students wore a fitness tracker during a 15 minute scripted math lesson. The lesson has a purposefully placed stressor called Cardano's formula (Harris & Stocker, 1998): Any cubic polynomial of the form $s(x) = x^3 + ax + b$ such that $4a^3 + 27b^2 > 0$ has real root

$$x = \sqrt[3]{-\frac{b}{2} + \sqrt{\frac{b^2}{4} + \frac{a^3}{27}}} + \sqrt[3]{-\frac{b}{2} - \sqrt{\frac{b^2}{4} + \frac{a^3}{27}}}.$$

Lesson Window 0. The lesson began with an instructor introducing the topic *Section 3.1 Roots of Polynomials* on a chalkboard. After seeing a notation-heavy definition of polynomial function, the instructor presented an example of a linear and a quadratic polynomial. The students were then assigned *Problem 1. True or False: The function $s(x) = 4$ is a polynomial* to complete on a provided handout. Window 0 will be treated as an acclimation period for the study and will not be included within participant's heart rate variability plots below.

Lesson Window 1. After waiting for visual cues that all students had completed problem 1, the instructor provided the correct answer and reviewed the definition of root and provided an example. Students were then instructed to complete *Problem 2. Find the root of* $p(x) = 3x + 1$.

Lesson Window 2. Again, after the instructor received visual cues that it was time to continue the lesson, they provided the answer to problem 2 and presented the quadratic formula, using it to find the roots of an example.

Lesson Window 3. Following a presentation of Cardano's formula, the instructor assigned *Problem 3. Use Cardano's formula to find a root of* $p(x) = x^3 - 1$ stating "Don't forget to check that Cardano's formula applies by verifying $4a^3 + 27b^2 > 0$." After waiting 2 - 3 minutes, the instructor revealed that the correct answer was $x = 1$ and concluded the lesson.

Note that the partition of events into windows 0 - 4 is done to guarantee each window has sufficient time for an accurate and reliable HRV computation and is not based on the composition of events. Immediately following the lesson, students completed a reflection survey to report when they had experienced anxiety and to describe their experience in their own words. Many students also chose to contemporaneously report their emotional experience by writing on the provided lesson handout.

Results

The 29 participants included 18 women and 11 men. Five students were enrolled in College Algebra, Finite Math, or Pre-Calculus. Twelve students were enrolled in Calculus I or Calculus II. Eight were enrolled in Calculus III, Differential Equations, or Linear Algebra. One student was enrolled in an elementary math content course for pre-service teachers and three participants did not specify a current math course.

Clusters of Fitness-Tracker Data Plots

I clustered participants HRV plots together based on the categories of description created from my phenomenographic analysis of students' reflection data and lesson handouts. Note that there is great individual variation in the typical ranges one might see for HRV-RMSSD values, which can be as low as 21 ms and as great as 103 ms (Umetani et al., 1998). To make the HRV plots comparable between individuals, I normalized every plot by dividing a student's three RMSSD values by their maximum RMSSD value. Within each normalized HRV plot, a dashed line is given as a visual indicator of values that suggest the student will report feeling distressed while attempting an assigned problem. The placement of this dashed line was determined using a logistic regression model that estimates the probability a student will report distress given their HRV value is below this line is greater than 50%, with the odds increasing the further the value moves below the line. This statistical analysis is not the focus of this report and thus is omitted here, but will appear in other work. I provide the line here as a visual aid to assist readers in interpreting the plots. For each cluster of plots, I constructed an average normalized HRV plot by averaging the normalized HRV values of students in that cluster. Of the $N = 29$ profiles to analyze, there were 5 categories of description that were common to at least 3 students. Categories with fewer than 3 participants will be excluded from this discussion because there were too few data points to meaningfully cluster the normalized HRV plots and take an average.

Categories of Description

Labels. I utilize the word distressed in labeling the categories to signify disruptive unpleasant feelings or emotions that interrupted or inhibited the student's ability to adapt or cope with a lesson stressor. The other key label is abstaining, which indicates that these students chose not to attempt an assigned problem.

Category 1: Distressed. These 5 students first reported distress in Lesson Window 3 where Cardano's formula was introduced and they were instructed to use the formula to find the root of a cubic polynomial. One participant wrote that they felt overwhelmed *"by the sudden barrage of variables and unfamiliar terms"* with another explaining, *"Not having enough examples before having to try by myself gave anxiety."* One participant experienced academic distress because they were not able to finish the problem before the instructor moved on; they wanted to be sure that they could get the right answer on their own. The normalized HRV plots of the five students in this cluster can be found in Figure 2. All but one students normalized HRV values remained above the distress indicator line until the third window, where all HRV values lie below.

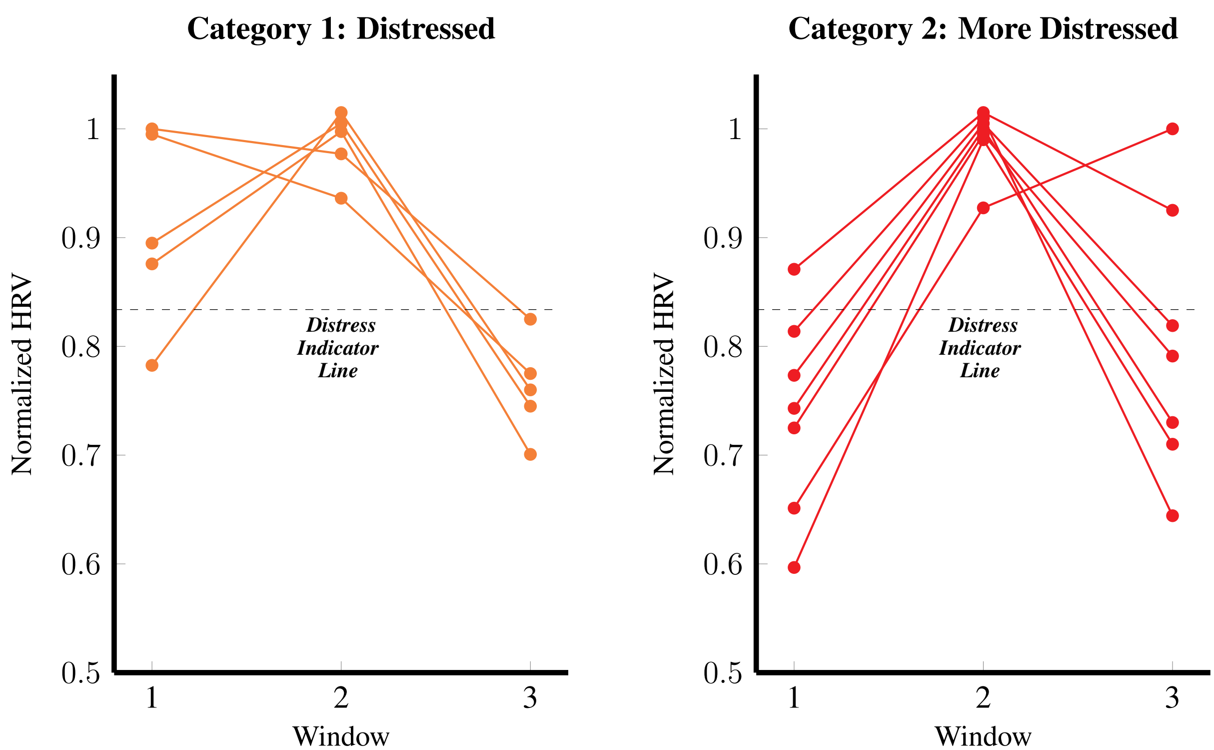

Figure 2. Clustered normalized HRV plots for Category 1 and Category 2

Category 2: More Distressed. For the 7 students in this cluster, the source of distress in Lesson Window 1 was the instructor announcing that problem 1 was true. Six students expressed that they felt bad or disappointed that they had gotten the answer wrong, with one student writing *"I felt like it was a trick question and felt badly that I didn't know it"*. Several students indicated that they did not understand why their answer was wrong, with one student explaining that their source of distress was that they thought the instructor lied or misspoke and that problem 1 was in fact false. Note that the lesson script does provide a brief explanation as to why problem 1 is true, but students were not given the opportunity to ask any questions of clarification during the lesson. None of these students reported distress during Lesson Window 2, which started with them receiving feedback that they answered problem 2 correctly. This group reported distress in Lesson Window 3, conveying feelings similar to those reported by the Category 1 group: anxiety, panic, overload, and “blanking out”. The normalized HRV plots of the 7 students can be found in Figure 2. Note although one students plot makes the same inverted V shape as the majority of the other plots, their window 1 and window 2 values do not lie below the distress indicator line. Also note one participant’s HRV lies well above the distress indicator line in window 3.

Category 3: Distressed & Abstaining. These 3 students first reported distress in Lesson Window 3, however - unlike the participants in the previous two categories - they chose not to attempt problem 3. One participant, rather than copying the problem from the board onto their handout, wrote *“I genuinely don’t know how to do this one at all”* and another reflected after the lesson *“I simply did not know how to solve it.”* Their 3 plots can be found in Figure 3.

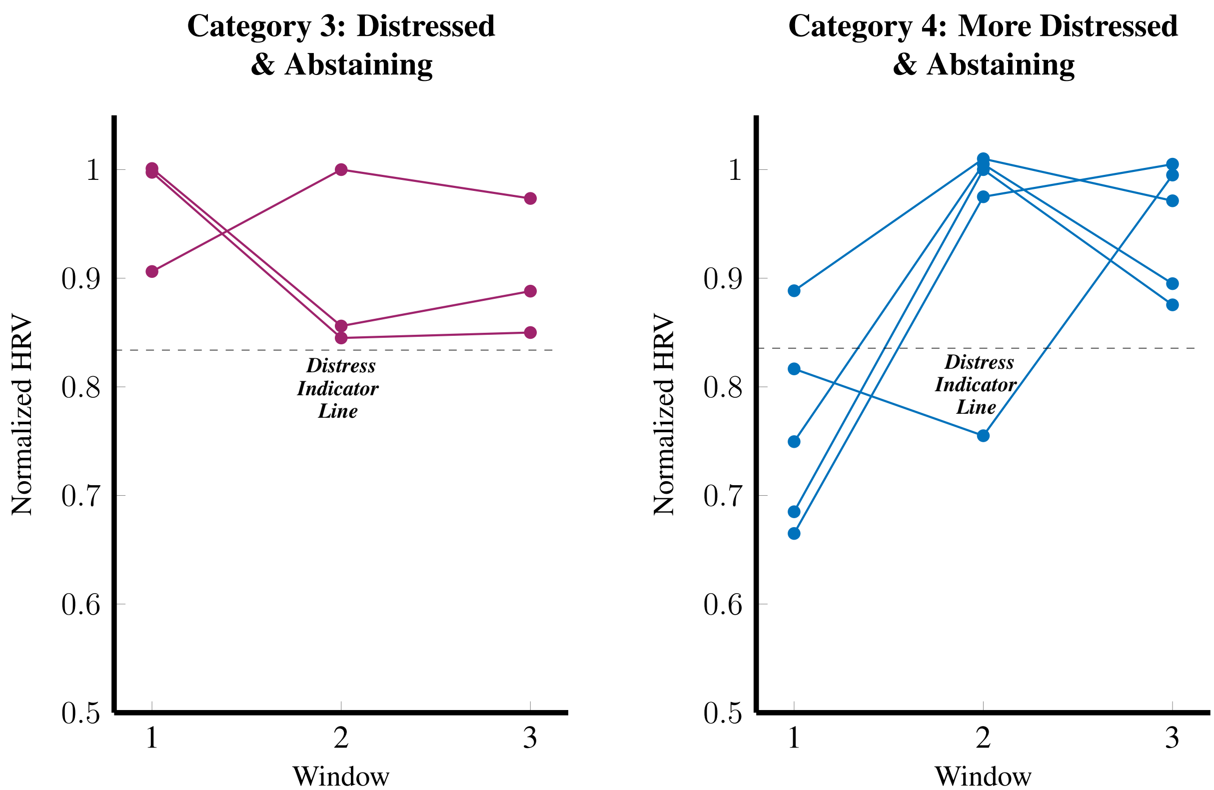

Figure 3. Clustered normalized HRV plots for Category 3 and Category 4

Category 4: More Distressed & Abstaining. For the 5 students in this cluster, Lesson Window 1 caused distress when the instructor provided the solution to Problem 1. One student wrote, *“I got it wrong, wasn’t sure about my answer in the first place.”* This group felt less stressed during Lesson Window 2, with one student explaining *“during the second problem I regained my confidence because I knew what to do”*. In Lesson Window 3, these students reported distress and chose not to attempt problem 3. One student wrote *“I literally would not know where to start”* in the space provided to copy the problem and do scratch work. Their normalized HRV plots are in Figure 3.

Category 5: Undistressed. The final category contains the 6 students who did not report feeling distressed during the lesson. Their normalized HRV plots appear in Figure 4. Note that at various times, participants normalized HRV values dropped below the distress indicator line.

Category Averages. The cluster average for each category of description appears in Figure 4. Note that, on average, student's normalized HRV values dropped below the distress indicator line if and only if they reported feeling distressed while actively attempting an assigned problem.

Discussion & Implications

Within the normalized HRV plots, there are 4 instances of a "false-negative", where the HRV plot suggests the student will not report feeling distressed while attempting to solve a problem and the student did report distress. There are 6 instances of a "false positive", or instance where the HRV plot suggests the student will report feeling distressed while attempting to solve a problem and the student did not report distress. Thus, the *overall alignment rate* across these 26 profiles was 87%. These results suggest that fitness tracker data can be valuable to guide deeper inquiry into the student experience; however, low HRV does not guarantee a student is distressed and high HRV does not guarantee a student is undistressed. Further, HRV cannot provide a direct measure of the *amount* of distress or give an instantaneous indication a person is experiencing distress.

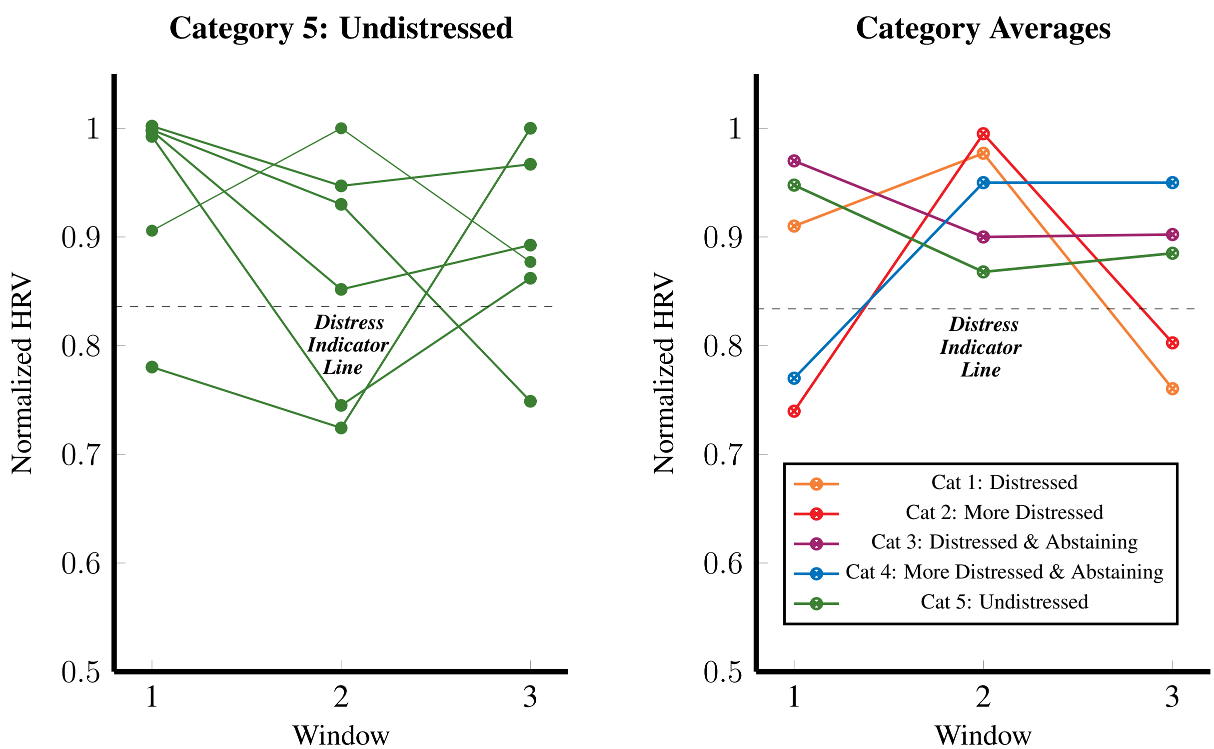

Figure 4. Clustered normalized HRV plots for Category 5 and Category Average plots

The role of HRV in Education Research

In Figure 4, we see that the plot average for Category 3: Distressed & Abstaining has the same overall shape and structure as the plot average for Category 5: Undistressed. This suggests that HRV can only discern when a student may report feeling distressed if the student is actively problem solving. I recommend that fitness tracker data primarily be used for triangulation, as a way to identify moments during classroom problem solving for video stimulated recall interview with research participants. With deliberate and careful use, fitness trackers provide an innovative research design tool that can integrate qualitative and quantitative measures in the study of psychological stress during classroom problem solving.

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