Physiological synchrony in the classroom

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Background

Physiological synchrony (PS) refers to the degree to which physiological measures of multiple individuals uniformly change (Palumbo et al., 2017). In a controlled laboratory study, we found that physiological synchrony reflects selective attention: The electroencephalogram (EEG), heart rate and electrodermal activity (EDA) of participants showed similar changes when they paid attention to similar aspects of an auditory stimulus (Stuldreher et al., 2020).

PS may also be informative of attentional engagement in educational settings. Dikker et al. (2017) found that students' EEG was more synchronized with each other when they were more, rather than less engaged during a semi-regular biology class. However, lessons were adapted specifically to the study and EEG sensors are still considered to be rather obtrusive.

In the current work, we use data of two earlier conducted studies to assess PS in EDA and heart rate among students during regular classes. As a first step in probing whether PS in peripheral measures might be used for monitoring attention in secondary school education, we compared PS between students in the same versus different classrooms, and aimed to distinguish students attending the same class from students attending different classes.

Methods

Study 1 (Thammasan et al., 2020) was conducted at two schools in the Netherlands. The study was approved by the institutional ethics research board of Tilburg University. Data of 86 adolescents (14.9 $\pm$ 0.5 years) coming from 17 different classes were collected during a regular school day. EDA (palm-based) and heart rate were monitored using the Movisens EdaMove 4 (Movisens GmbH, Karlsruhe, Germany) and Wahoo Tickr (Wahoo Fitness, Atlanta, GA, USA), respectively.

Study 2 was conducted at one secondary school in the Netherlands. The study was approved by the Scientific and Ethical Review Board of the Faculty of Behavior & Movement Sciences, VU University Amsterdam. Data of 29 adolescents (13.8$\pm$0.4 years) coming from 21 different classes were collected for 24 hours, including a regular school day. EDA (palm-based) and electrocardiogram (ECG) were recorded using the VU University Ambulatory Monitoring System (VU-AMS). ECG peaks were detected following Pan and Tompkins (1985) and transformed into heart rate time-series.

Data from both studies were epoched to the on- and offset of lessons. We further refer to each epoch as a 'student', where one such epoch represents one unique combination of one lesson (or classroom) and one student. Statistics of the number of students in both studies are in Table 1. For each student, we computed PS using inter-subject correlations with all other students from that study, following Stuldreher et al. (2020). For each student, PS toward students attending the same lesson was computed by averaging over synchrony scores with all other students in the same classroom. PS toward students not attending the same lesson was computed by averaging over synchrony scores with all other students not in the same classroom. Figure 1AB depicts this processing pipeline.

Using paired sample t-tests, we tested for each study and each physiological measure whether physiological synchrony was higher for students when paired with others attending the same classroom than when paired with others not attending the same classroom. In addition, we examined for each student whether classification into 'same' or 'different' classroom based on PS worked out correctly.

Results

Figure 1CD summarizes the results.

For study 1, PS for students was significantly higher when paired with students attending the same class than when paired with students attending other classes, both for heart rate ($t(74)=5.36$, $p< .001$) and EDA ($t(58)=1.89$, $p=.032$). Classifying an individual to the group to which they showed a higher PS resulted in classification accuracies of 77.3% (heart rate) and 61.0% (EDA).

For study 2, PS for students was not significantly higher when paired with students attending the same class than when paired with students attending other classes, both for HR ($t(10)=0.48$, $p=.322$) and EDA ($t(12)=0.53$, $p=.303$). Classification accuracies were 36.4% (heart rate) and 38.5% (EDA).

The null-finding in study 2 may be explained by the lower amount of data compared to study 1 (both in terms of number of shared lessons and non-shared lessons; see Table 1). Indeed, when re-examining data from study 1 using the same characteristics as for study 2, by randomly sampling 1000 times from the complete dataset, PS is no longer significantly larger for students attending the same class compared to students attending different classes for both heart rate ($t(10)=1.64$, $p=.066$) and EDA ($t(7)=0.91$, $p=.196$). Classification accuracies in this case are 54.7 +- 12.8% for heart rate and 60.7% +- 17.0% for EDA.

Discussion

We here showed that PS in heart rate and EDA can be picked up using wearables in the classroom – students following the same lesson in the same classroom show stronger PS for both measures compared to students in other classrooms. This reached significance in data from one of the two studies that we analyzed, and the same trend is visible in the other study. We suspect that the main cause of the null result in one of the studies is the low number of participants, particularly those in the same classroom (on average only 1.02 classmate rather than 4.72 for heart rate and 1.23 rather than 1.78 for EDA) - see spread in 'same class' PS values for study 2 in Figure 1C. Heart rate seems to be a more robust measure than EDA. This was not specifically expected on the basis of our earlier work, using the same wearables as in Study 1 in a controlled, laboratory setting (van Beers et al., 2020) where both measures performed about equally well, or EDA somewhat better. EDA might be relatively sensitive to noise in real life environments. Note that this study does not yet look into PS yet as a measure of attention and PS may have (partly) been caused by similar patterns in students' physical activity. The next step in examining and validating PS in heart rate and EDA as potential markers of selective attention in the real classroom environment, would be to register an independent, alternative measure of selective attention.

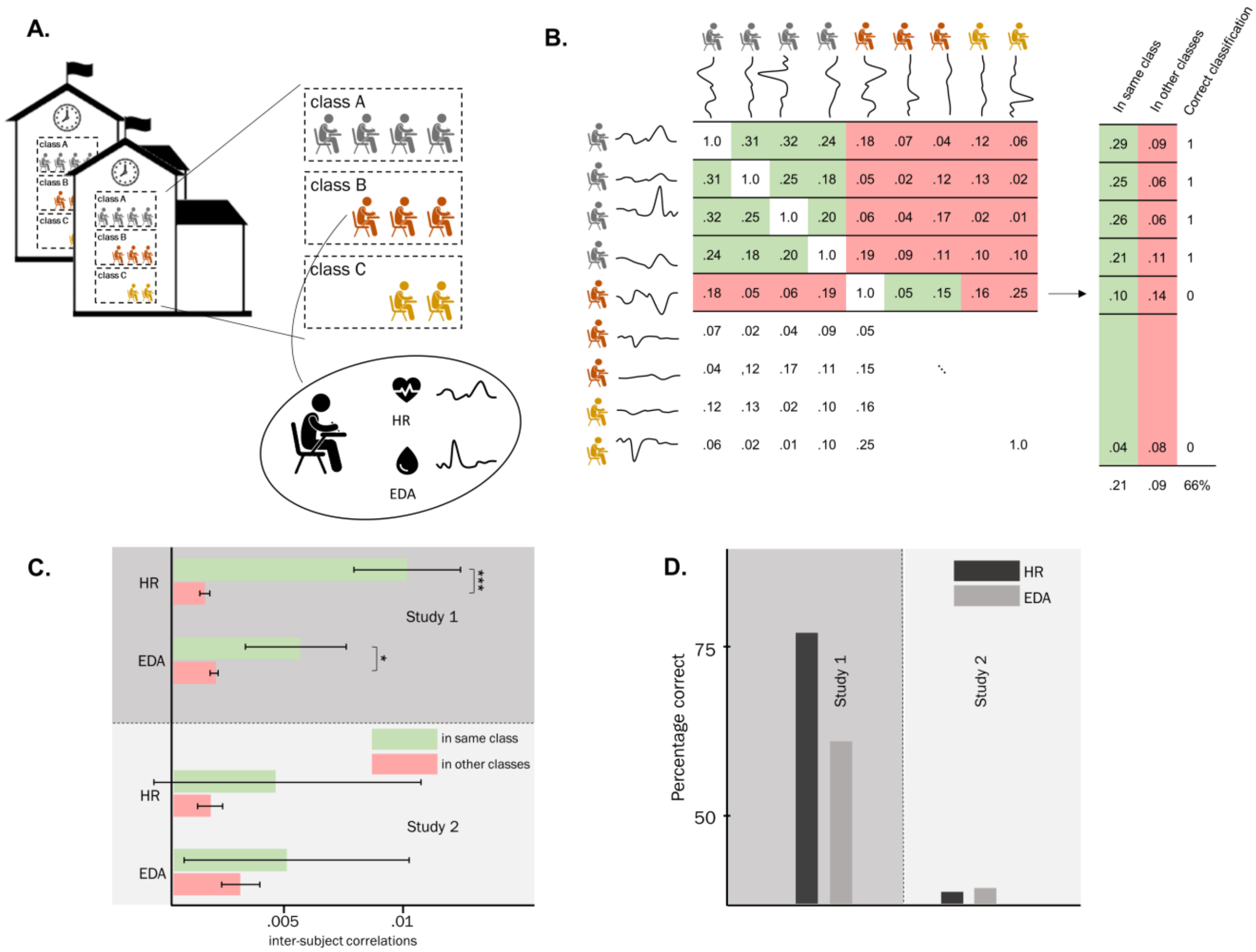

Figure 1. Overview of the processing pipeline and results. A. depicts that data were collected in two different studies in multiple groups of students per school. In each classroom, a varying number of volunteering students was equipped with heart rate (HR) and EDA sensors. B. shows how physiological synchrony (PS) was determined. For both HR and EDA, PS was computed using inter-subject correlations for all possible pairs of students from that study, resulting in a $N \times N$ matrix, were N refers to the number of collected datasets (= number of actual students × number of lessons) in the study. For each student, an average synchrony toward students attending the same lesson was computed by row-wise averaging over synchrony values with all other students in the same classroom (green cells) and an average synchrony toward students not attending the same lesson (red cells). C. shows the inter-subject correlations to students attending the lesson and attending other lessons for HR and EDA for studies 1 and 2. Error bars depict standard error of the mean. D. shows the percentage of correctly identified groups, when classifying the student to the group (same class/other class) that he or she showed highest synchrony with.

Table 2. Number of students (included data sets) for the two studies. Note that due to (partially) failed recordings, the number of included data sets differ between heart rate and EDA.

	Study 1		Study 2	
	Heart rate	EDA	Heart rate	EDA
Total number	75	59	11	13
Same lesson (mean $\pm$ SD per lesson)	4.71 $\pm$ 1.94	1.78 $\pm$ 1.65	1.02 $\pm$ 0.55	1.23 $\pm$ 0.44
Different lesson (mean $\pm$ SD per lesson)	333.28 $\pm$ 1.94	99.09 $\pm$ 74.58	115.17 $\pm$ 35.35	135.77 $\pm$ 0.44

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