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USING HEART RATE TO TAP INTO MOTIVATIONAL AND EMOTIONAL PROCESSES DURING TEACHING AND LEARNING

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Abstract

A current ambition of research into motivation and emotion in teaching and learning is to investigate motivation and emotion in more holistic ways and to dive deeper into the dynamics of motivation and emotion processes in the classroom setting. Physiological measures have the potential to reach these goals by moving beyond between-person comparisons of habitual, often self-reported, levels of motivation and emotion. For a long time, tracking physiology was only possible in lab settings, which is problematic for studying authentic processes as they occur during teaching and learning. But recent technological innovations have enabled physiological measurement in ambulatory settings, such as the classroom. For many educational researchers interested in motivation and emotion, dealing with these measures can be challenging. This chapter provides a basic introduction to physiological measures in general and heart rate in particular. We also discuss the conceptual meaning of heart rate in studies on motivation and emotion. Furthermore, we present concrete tips for collecting heart rate data (i.e. study preparation, data cleaning, and data analyses). An important conclusion is that physiological measures open up some new aspects of human functioning to educational researchers and can complement (but not replace) behavioural and self-report measures of motivation and emotion.

Research into motivation and emotion currently strives to investigate human functioning in more holistic ways, which means also including bodily functioning and physiology next to widely used measures relying on participant's introspection. Especially in the field of emotions, investigating the physiological component of emotion (next to cognitive, affective, and motivational components) is well aligned with both theoretical models and empirical

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measures (Pekrun et al., 2011; Scherer, 2009). Another, but related, ambition of research into motivation and emotion in learning and teaching is to move beyond between-person comparisons of habitual, often self-reported, levels of motivation and emotion. Physiological measures are a promising way to get insight into moment-to-moment changes associated with motivation and emotion, without solely relying on self-report.

For educational researchers, dealing with physiological measures can be challenging. This is not only because of the technicalities of collecting data in classrooms but also because of the different nature of data cleaning, data analysis, and the conceptual interpretation of the findings. The aim of this chapter is to provide the reader with a basic introduction to physiological measures in general, and heart rate in particular. We discuss the conceptual meaning of heart rate in studies on motivation and emotion, and share our personal experience with collecting heart rate data in the context of studying teacher-student interaction and emotions.

Studying the Dynamics of Motivational and Emotional Processes

Motivation and emotion have for a long time been studied with methods relying on self-report that compare differences between individuals, like questionnaires and interviews. Because research questions that involve emotions and motivation, however, often involve processes *within* rather than between individuals, such between-person approaches have received a fair amount of criticism. Between-person designs examine the relationships between variables based on individual differences and thereby fail to consider variation within an individual over time, or the relations between variables within individuals (Murayama et al., 2017). Conclusions drawn from research using a between-person design cannot easily be generalised to the within-person level and thus might inform both theory and practice inadequately (i.e. Simpson's paradox; for more information and a graphical representation, see Hamaker & Grasman, 2014). In order to test the validity of psychological and learning models and draw conclusions that apply to processes within an individual, it is therefore important to collect repeated measurements of motivation and emotion over time within persons.

With the ambition to dive deeper into the situatedness and context specificity of emotional and motivational processes – from moment to moment within persons – scholars have sought tools that allow them to study experiences in specific situations instead of differences in habitual emotions or motivation between persons. Many researchers have incorporated momentary focused self-report using repeated diaries or the experience sampling method (ESM; Csikszentmihalyi & Larson, 1987), also in the classroom setting (e.g. Roos et al., 2020). Notwithstanding its conceptual and psychological importance, such methods are still prone to biases affecting self-report in general, such as recall inaccuracies (Carson et al., 2010) and overestimation of own abilities (Podsakoff et al., 2003). Moreover, asking repeated questions about how you feel right now or about motivational states potentially disrupts the natural flow of behaviour, cognition, and emotions (Scollon et al., 2009), and it can be viewed as targeting only one component of human functioning.

To supplement or sometimes even to replace self-report, researchers have looked for directly observable correlates of motivation and emotion. Prominent examples are direct observations in classrooms (Van Braak et al., 2021) or the (automatic) coding of facial expressions to extract emotional states (D'Mello et al., 2017). Such approaches have in common that they are independent of volition and explicit influence of the individual who is studied (Mossink et al., 2015) and that they target objective behaviours (also referred to as motor expressions; Scherer, 2009) rather than subjective feelings. Thus, some of the problems connected to self-report can be circumvented with such measures. However, observations are often labour-intensive, and, although more objective, the perception of the observer might not match the actual feelings of the participants themselves (Donker et al., 2021).

Physiological measures could give a more direct insight in the appraisal, motivation, and emotion of a participant and thereby overcome some of the drawbacks of ESM and observational research. Examples are tracking eye movements (Wolff et al., 2015), brain activity (Dikker et al., 2017), skin conductance (Roos et al., 2020), and heart rate (Donker et al., 2020; Scrimin et al., 2018). These measures also offer the possibility to study within-person processes at high frequency, and thus to account for the situatedness and context specificity of emotion and motivation. While ESM often results in a maximum of ten to 50 measures within a person over the course of several days or weeks, physiological measures may result in several hundred or even a thousand data points within an hour of observation.

A More Holistic Approach to Motivation and Emotion

Incorporating physiological measures into educational psychology research has also a more substantial purpose. Some have argued that to fully understand human functioning, research on motivation, emotion, and learning must take into account the more implicit evaluations of the self and the environment (Blascovich, 2008; Cacioppo et al., 2017; Schultheiss & Wirth, 2018). The basic assumption, especially behind physiological measures, is that differences in physiological responding underlie differences in behaviours and psychological experiences. Currently, it is also acknowledged that a specific individual history in terms of social interactions and psychological experiences can shape an individual's physiology. The least that can be said is that psychological aspects as well as behaviour and physiology together form a single system that underlies human functioning. A well-known example that reflects this is Scherer's component process model of emotions (2009), where emotions are conceptualised as including subjective feelings, motor expressions, action tendencies, and physiological reactions. Also, in theoretical models as well as empirical measures of academic emotions, physiology is often seen as one of the components of emotions, next to cognitive, affective, and motivational components (Pekrun et al., 2011; Roos et al., 2020). Thus, it can be argued, if we want to fully understand emotion and motivation in educational settings, we also need to incorporate physiology in our theorising and empirical work.

Heart Rate as Measure of Physiological Arousal

This chapter focuses on heart rate as an example of a physiological measure that can complement behavioural measures and self-report of motivation and emotion, because heart rate is one of the most robust, sensitive, and most widely used physiological measures (Kreibig, 2010; Myrtek, 2004). Heart rate encompasses both the sympathetic and parasympathetic branches of the autonomic nervous system (ANS). While the sympathetic system is related to quick responses and mobilisation ("fight or flight"), the parasympathetic system is more slowly activated and is sometimes referred to as more concerned with dampening activation ("rest or digest"). Heart rate can easily be collected ambulatorily and in a very small temporal resolution because the ANS reacts faster to changes and stressors in the environment compared to the hypothalamic-pituitary-adrenal (HPA) axis, which makes it well-suited for within-person analyses of motivation and emotion dynamics.

The heart is first and foremost a pump, supplying the body with oxygen by sending blood into the lungs and then to the rest of the body. It has four chambers: two atria and two ventricles. The atria pump blood inside the ventricles, which pump blood to the outside of the heart. The right atrium and ventricle pump blood to the lungs to get oxygenised. The left part of the heart receives the blood from the lungs and pumps it via the arteries into the body. Each heartbeat cycle consists of two phases: systole, during which the ventricles contract and pump blood into the body, and diastole, during which the ventricles relax and get filled with blood again.

The pacemaker cells in the sinoatrial node produce an electrical impulse that causes the heart to contract. An electrocardiogram (ECG) is a way to record the electrical activity of the heart. It requires at least two electrodes on the participant's body, which sense the (changes in) electrical activity during the heartbeat cycle (see Figure 17.1; the well-known "heart rate graph"). The P wave reflects the contraction of the atria, which is followed by the QRS complex, representing ventricular systole, and the T wave representing ventricular diastole, after which the cycle is repeated. Heart rate is calculated based on the number of R-peaks in a minute. For example, a heart rate of

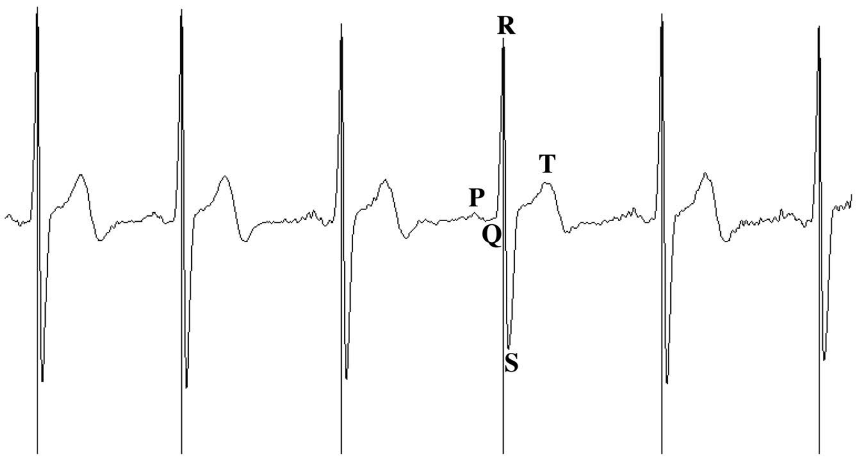

FIGURE 17.1 Graphical representation of five repeated heartbeat cycles

70 beats per minute means that there were 70 R-peaks and thus 70 heartbeat cycles during this minute.

Conceptual Meaning of Heart Rate in Studies on Motivation and Emotion

The basic idea behind using heart rate in psychological research is that, by controlling heart rate for physical activity levels (which ask for more oxygen being pumped to the muscles), the residual physiological activation can inform us about psychological or cognitive processes and "emotional arousal" (Myrtek, 2004). That is, when people evaluate their self or their environment, their motivational system automatically mobilises the physiological resources needed for anticipated action (i.e. increased sympathetic activation and an increased heart rate; Behnke & Kaczmarek, 2018; Blascovich, 2008). When an individual judges a situation as relevant and potentially harming their goals, their physiological system will get activated to support action. These action-oriented cognitive processes are in essence what influential scholars such as Lazarus and Folkman, Frijda, and Scherer have called primary appraisals (e.g. "this is important" or "not sure whether I can do this"). Appraisals, in turn, form the basis of emotions (e.g. anxiety or enthusiasm; Moors et al., 2013). As such appraisals are not easily accessed cognitively or verbalised, physiological measures might be well-suited to get insight in these processes (Scherer, 2009).

Efforts have been made to link specific patterns of physiological activation to specific motivational and emotional states. However, there is no clear one-to-one connection between physiological and emotional changes.

Although some (lab-based) studies have found a link between physiological arousal and some discrete emotions, it is hard to differentiate between positive versus negative emotions by physiology only (Kreibig, 2010). Kreibig (2010) concludes that, only if several advanced measures of the autonomic nervous system are combined with respiratory measures, some discrete emotions can be distinguished in the laboratory.

The Dynamics of Emotional Processes in Teachers (DEPTh) Project

Given this state of affairs, we concluded for our own research on teaching (see the DEPTh project; Donker, 2020) that it would be possible to infer changes in teachers' emotional arousal from ambulatory heart rate measures (i.e. in the classroom, during teaching), such as identifying moments of personal importance, but that it would be rather unlikely to infer more specific motivational states or even momentary, discrete emotions. The goal of our project was to better understand how teachers' and students' self-reported emotions arise from what happens during the classroom (i.e. teacher-student interaction and teachers' physiological arousal). We combined physiological measurement of teacher's heart rate with continuous coding of teachers' interpersonal behaviour based on a video recording of the lesson to add the interpretation of physiological changes. As a coding scheme, we used the interpersonal circle (Wubbels et al., 2006; see Figure 17.3). This circumplex model depicts how prototypical teacher behaviours (such as being directing or understanding) can be seen as a combination of certain levels of agency (i.e. social influence) and communion (i.e. friendliness).

Considerations during Data Collection

Collecting heart rate data in ambulatory settings has become more common since the 1990s, following the increased availability of ambulatory devices. Still, the field is in its infancy, and clear guidelines for using heart rate in research on motivation and emotion are hard to find. Below, we give an overview of issues to consider during the collection of heart rate data in the classroom setting (i.e. study preparation, data cleaning, and data analyses).

Study Preparation

Which Device?

When choosing a device for measuring heart rate, important considerations are how easy the device is to use in school settings as well as the quality and reliability of the data. There are two broad categories of ambulatory devices: devices using photoplethysmography (PPG) and devices using ECG measurement.

Examples of devices using PPG are Empatica E4, Fitbit, and other smartwatches. These devices use infrared light to measure changes in blood volume in tissue under the skin due to diastole and systole (for more details, see Moraes et al., 2018). Although these devices are easy to use, inexpensive, and non-invasive, our experience was that the resulting data are heavily affected by movement. When teachers moved their hands, the sensors lost contact with the skin and blood volume changes could not be tracked, resulting in huge amounts of missing data.

Data collected using ECG devices are generally more in line with the laboratory standard (Dobbs et al., 2019; Georgiou et al., 2018), but such devices are often also more invasive and expensive. Examples are the Movisens Ecg-Move 4, Imotions, Shimmer3, and the VU-Ambulatory Monitoring System (VU-AMS). In our study, we used the VU-AMS (www.vu-ams.nl), which has a seven-lead configuration and includes ECG, ICG (impedance cardiography), and physical activity measurements. The VU-AMS was specifically developed for research purposes and dedicated software and an extensive user manual are available. The data are stored on a CompactFlash card during the recording and can be uploaded onto a local computer. A drawback is that electrodes need to be placed on the participant's chest and back. Teachers or students might therefore be hesitant to participate as they are not familiar with the methodology and placing the electrodes could be experienced as invasive. It is important to provide clear information letters with a good balance between explaining the methodology and not making it too complex. Attaching the device in a separate room is also advised. Teachers who participated reported no problems fitting the device and teaching while wearing the VU-AMS. The device has also been used successfully with younger populations.

(What) Baseline?

Experimental studies in lab settings usually include a baseline measurement (e.g. Scrimin et al., 2018). After setting up the device, participants are often instructed to watch a relaxing video during a short period. The heart rate assessed during this period is then used to correct experimental data for differences in individuals' baseline in order to be able to compare group means.

In our study, we were mostly interested in within-teacher changes in physiological arousal (between situations) rather than in mean differences between (groups of) teachers. We therefore did not compare absolute heart rate values, but only within-person deviations from individual mean scores. As such, a teacher's average heart rate during a lesson served as a benchmark against which situational changes were evaluated.

Using a baseline can nonetheless be necessary or desired, but is at the same time challenging in the classroom. First, teachers often have a tight schedule with only short breaks in between lessons, which makes it hard to find a good moment for the baseline measurement. Also, teachers might be even more aroused just before or after the lesson than during teaching. Second, the question is how adequate a resting baseline would be for an activity such as teaching, as in our sample the average teacher heart rate resembled values commonly reported for vigorous exercise. As a solution, more differentiated baseline values could be calculated, such as separate averages for whole group lecturing or seatwork (cf., Junker et al., 2021).

Data Cleaning

Artefact Correction

Before the analysis, the raw data need to be checked for any irregularities caused by external influences, such as connection problems or a noisy signal. Most software programs use an algorithm to identify artefacts automatically, which can then be checked manually by the researcher. It is advised to not rely on the automatic corrections only, but to make any manual corrections with at least two trained assistants and to check their agreement in data adjustments. In our project, less than 1% of the heart rate data needed corrections (mainly moving the identification of the R-peak) and assistants discussed differences in corrections until agreement was reached. Please note that doing the artefact corrections can be time-intensive when the data collection period is long or when the signal is noisy.

Controlling for Physical Activity

To be able to tap into the emotional part of physiological arousal, heart rate changes due to actual movement need to be filtered out. We used the regression-based Additional Heart Rate approach described by Myrtek (2004). This approach is based on the idea that emotional arousal is the arousal that exceeds the arousal that could be expected based on the level of physical activity. A challenge in our case was that physical activity was related not only to heart rate but also to teachers' interpersonal behaviour (see Figure 17.2). For example, agency (i.e. being imposing or directing) was often associated with higher physical activity (e.g. standing in front of the classroom, walking around). Because we were interested in the association between interpersonal behaviour and heart rate, we did not want to take this substantive overlap already out in the regression analyses. Therefore, we first regressed physical activity on interpersonal behaviour and saved the residual physical activity (i.e. the variability not related to interpersonal behaviour). Second, we regressed heart rate on the residual physical activity score and saved the residuals as our emotional arousal score. Higher values indicated more arousal than could be expected based on physical activity.

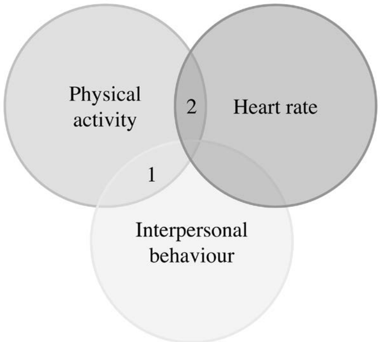

FIGURE 17.2 Graphical representation of the Additional Heart Rate approach (Donker et al., 2018; Myrtek, 2004)

We used five-second time intervals and did separate regression analyses for each teacher because the correlations between heart rate, interpersonal behaviour, and physical activity level are different per person.

Data Analyses

Physiological measurement often results in long time series, also referred to as intense longitudinal data. Such data enable researchers to analyse precisely how the heart rate of a teacher or student fluctuates over time and whether there are any associations with other variables. We present three approaches for data analyses that we used in our studies.

Univariate Analyses

Based on the physiological data, we calculated person-specific statistical indicators to characterise specific teachers, and to compare teachers by correlating the indicators with outcome variables, such as teacher or student emotions (Donker et al., 2020; Mainhard et al., 2022). The challenge here is to find a balance between finding overall patterns (which in the end reflect between-person differences) and using the intensive physiological data to its full potential. Lab studies often summarise physiological data into a mean heart rate value to compare groups. However, by using only the mean, information on the changes over time is lost. What could be interesting is to calculate mean levels for shorter time periods or specific teacher activities and compare these within persons to see what is most arousing for a specific teacher (e.g. Junker et al., 2021).

To get more insight in variability, we calculated the standard deviation, range, and autocorrelation of the heart rate time series (Donker et al., 2018, 2020). Standard deviations and range mainly tap into the extremeness of the heart rate values over the course of the lesson. Autocorrelations additionally give information on how well a value can be predicted by the previous score. Lower standard deviations, smaller ranges, and higher autocorrelations for heart rate represent less dynamic changes over time and might point towards lower reactivity to changing classroom situations and/or less recovery (Houben et al., 2015). It is important to note that for shorter time intervals, the autocorrelation might be automatically higher because data points are more closely connected. However, by using larger time-intervals we might lose the richness of the moment-to-moment data. See Donker et al. (2018) for a graphical representation of how aggregating heart rate data at 10-, 30-, and 60-second intervals fails to capture moment-to-moment changes in heart rate.

Stability or predictability measures combine the autocorrelation with the magnitude of the changes (i.e. standard deviation) and is usually calculated as the mean squared successive difference (MSSD; Jahng et al., 2008). Higher values represent more extreme moment-to-moment changes (i.e. instability) in heart rate. Such a pattern could be associated with more extreme emotional arousal at several times during a lesson and/or more demanding situations during the lesson (see *Identifying Situations*), and thus potentially more negative emotions after the lesson. It is important to note that not only the MSSD but also the standard deviation and range of heart rate are often higher in people with higher (uncorrected) average heart rates (see Donker et al., 2020).

Multivariate Analyses

Physiological data in itself is hard to interpret in relation to emotion and motivation. It is therefore advised to combine physiological measures with other measures, such as (video) observation, experience sampling, or eye tracking. In this way, the additional data help to make sense of the physiological arousal. In our case, we used behavioural observation of teacher's interpersonal behaviour during the lesson.

We quantified the strength and direction of the relationship between teacher's emotional arousal and interpersonal behaviour using cross-correlations. Cross-correlations can be seen as person-specific correlations, and thus as an indication of teachers' individual *action tendencies* (Mainhard et al., 2022; Scherer, 2009). Figure 17.3, for example illustrates the cross-correlations between agency, communion and heart rate for one specific teacher (i.e. Teacher A in Donker et al., 2018). The coloured dots represent the teacher's heart rate when showing a certain level of agency and communion in class, with darker colours indicating higher heart rates. In our total sample of 75 teachers, the cross-correlation between heart rate and teacher agency ranged from −.43 to .68 (M = .17, SD = .25). The

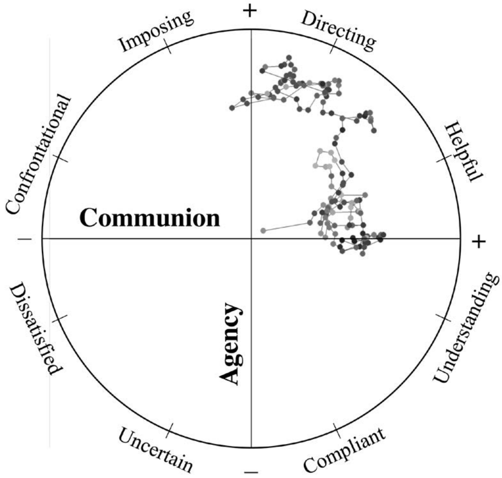

FIGURE 17.3 The Interpersonal Circle for Teachers combined with heart rate values

cross-correlation between heart rate and communion ranged from −.65 to .51 (M = −.08, SD = .21). Thus, overall teachers had a high heart rate when they showed relatively high agency and low communion, but there were large differences between teachers. Regarding the link with emotions, we found that especially teachers who had an increased heart rate while showing high levels of communion reported negative emotions after the lesson (e.g. anger; Donker et al., 2020).

Identifying Situations

Heart rate data could also be used to identify specific, potentially demanding, moments during a lesson. In one of our projects, we selected all moments during a lesson where the heart rate of the teacher was two standard deviations above their personal mean (Donker, 2020). The number of peak moments ranged from 0 to 26 per teacher. Interestingly, more experienced teachers had more of these high heart rate situations. All these situations were then coded in terms of the instructional setting. We found that teachers experienced the most extreme heart rate peaks during the lesson start and during teacher-centred activities.

Future Directions

Using heart rate in ambulatory classroom settings to get an insight into motivational and emotional processes is promising, but the field is in its early phases and rapidly evolving. Future studies should replicate earlier findings and include larger samples to improve the generalisability of the findings. Moreover, also student's emotional arousal should be included in future research to study for example emotional contagion in the classroom (Järvenoja et al., 2018; Pijeira-Díaz et al., 2018). Applying multilevel modelling is useful to separate between- and within-person associations of physiological measures with other variables such as interpersonal behaviour and emotional outcomes. Statistical methods such as Dynamic Structural Equation Modeling (DSEM; Hamaker et al., 2018) are promising in this regard, but high autocorrelations as we found in our behaviour coding may prevent an efficient use of such applications as yet.

Furthermore, it should be considered that there is no clear one-on-one link between physiological arousal and emotions or motivation. Especially in ambulatory settings, there are many variables that could affect the physiological arousal of participants, beyond motivational or emotional processes. Scrimin et al. (2018) for example linked heart rate (variability) to cognitive effort. Including more specific and advanced physiological indicators, such as cardiac output and total peripheral resistance, could help to clarify some of the ambiguity and to differentiate for example between challenge versus threat motivational states (Blascovich, 2008). More in general, we should not expect that it will be possible any time soon to use physiological measures *instead of* self-report of internal motivational or emotional processes. Instead, combining physiology with more (qualitative) data, such as teachers' perceptions of specific classroom situations and their self-reported motivation and emotion seems to be a more likely and fruitful path for future research. In our case, we showed that observing teachers' interpersonal behaviour was helpful in interpreting the physiological patterns. However, specific appraisals of situations cannot be discerned with observational data, beyond identifying potential episodes of personal relevance through heart rate peaks. Therefore, selecting and analysing specific classroom situations could, for example be used as a starting point for physiology-stimulated recall interviews with teachers. Such an approach could provide more information on the idiosyncratic way in which teachers interpret classroom situations and how physiological reactions affect their emotional experiences.

Conclusion

Research into motivation and emotion has recently moved from using mainly between-person self-reported data towards including more momentary, within-person measures. One promising avenue is the use of physiological measures, such as heart rate. Due to recent technological advancements, physiological measures can now be collected in ambulatory settings, such as the classroom, which increases the ecological validity of the findings. Using physiological measures can not only open up pathways to assessing within-person measures but they also enrich research into motivation and emotion in more substantive ways. For example, theorising on emotions often involves componential models that also include physiology next to cognitive, affective, and motivational components.

Before physiological data can be included in research designs and collected, however, choices about devices or baseline measurements need careful consideration and more insight into the conceptual meaning of heart rate is needed. We hope that this chapter is helpful for future researchers and encourages them to implement physiology in their studies on motivation and emotion in teaching and learning. Doing this will help us to better understand within-person processes as well as the situatedness and context specificity of emotion and motivation.

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References

Behnke, M., & Kaczmarek, L. D. (2018). Successful performance and cardiovascular markers of challenge and threat: A meta-analysis. *International Journal of Psychophysiology*, *130*, 73–79. https://doi.org/10.1016/j.ijpsycho.2018.04.007

Blascovich, J. (2008). Challenge and threat. In A. J. Elliot (Ed.), *Handbook of approach and avoidance motivation* (pp. 431–445). Psychology Press.

Cacioppo, J. T., Tassinary, L. G., & Berntson, G. G. (Eds.). (2017). *Handbook of psychophysiology* (4th ed.). Cambridge University Press.

Carson, R. L., Weiss, H. M., & Templin, T. J. (2010). Ecological momentary assessment: A research method for studying the daily lives of teachers. *International Journal of Research & Method in Education*, *33*, 165–182. https://doi.org/10.1080/1743727x.2010.484548

Csikszentmihalyi, M., & Larson, R. (1987). Validity and reliability of the Experience-Sampling Method. *Journal of Nervous and Mental Disease*, *175*, 526–536. https://doi.org/10.1007/978-94-017-9088-8

D'Mello, S., Dieterle, E., & Duckworth, A. (2017). Advanced, Analytic, Automated (AAA) measurement of engagement during learning. *Educational Psychologist*, *52*, 104–123. https://doi.org/10.1080/00461520.2017.1281747

Dikker, S., Wan, L., Davidesco, I., Kaggen, L., Oostrik, M., McClintock, J., Rowland, J., Michalareas, G., Van Bavel, J. J., Ding, M., & Poeppel, D. (2017). Brain-to-brain synchrony tracks real-world dynamic group interactions in the classroom. *Current Biology*, *27*, 1375–1380. https://doi.org/10.1016/j.cub.2017.04.002

Dobbs, W. C., Fedewa, M. V., MacDonald, H. V., Holmes, C. J., Cicone, Z. S., Plews, D. J., & Esco, M. R. (2019). The accuracy of acquiring Heart Rate Variability from portable devices: A systematic review and meta-analysis. *Sports Medicine*, *49*(3), 417–435. https://doi.org/10.1007/s40279-019-01061-5

Donker, M. H. (2020). *In DEPTh: Dynamics of emotional processes in teachers – An exploration of teachers' interpersonal behavior and physiological responses*. Utrecht University.

Donker, M. H., Van Gog, T., Goetz, T., Roos, A. L., & Mainhard, T. (2020). Associations between teachers' interpersonal behavior, physiological arousal, and lesson-focused emotions. *Contemporary Educational Psychology*, *63*, Article 101906. https://doi.org/10.1016/j.cedpsych.2020.101906

Donker, M. H., Van Gog, T., & Mainhard, M. T. (2018). A quantitative exploration of two teachers with contrasting emotions: Intra-individual process analyses of physiology and interpersonal behavior. *Frontline Learning Research*, *6*(3), 162–184. https://doi.org/10.14786/flr.v6i3.372

Donker, M. H., van Vemde, L., Hessen, D. J., van Gog, T., & Mainhard, T. (2021). Observational, student, and teacher perspectives on interpersonal teacher behavior: Shared and unique associations with teacher and student emotions. *Learning and Instruction*, *73*, Article 101414. https://doi.org/10.1016/j.learninstruc.2020.101414

Georgiou, K., Larentzakis, A. V., Khamis, N. N., Alsuhaibani, G. I., Alaska, Y. A., & Giallafos, E. J. (2018). Can wearable devices accurately measure Heart Rate Variability? A systematic review. *Folia Medica*, *60*(1), 7–20. https://doi.org/10.2478/folmed-2018-0012

Hamaker, E. L., Asparouhov, T., Brose, A., Schmiedek, F., & Muthén, B. (2018). At the frontiers of modeling intensive longitudinal data: Dynamic Structural Equation Models for the affective measurements from the COGITO study. *Multivariate Behavioral Research*, *53*, 820–841. https://doi.org/10.1080/00273171.2018.1446819

Hamaker, E. L., & Grasman, R. P. P. P. (2014). To center or not to center? Investigating inertia with a multilevel autoregressive model. *Frontiers in Psychology*, *5*, Article 1492. https://doi.org/10.3389/fpsyg.2014.01492

Houben, M., Van den Noortgate, W., & Kuppens, P. (2015). The relation between short-term emotion dynamics and psychological well-being: A meta-analysis. *Psychological Bulletin*, *141*, 901–930. https://doi.org/10.1037/a0038822

Jahng, S., Wood, P. K., & Trull, T. J. (2008). Analysis of affective instability in ecological momentary assessment: Indices using successive difference and group comparison via multilevel modeling. *Psychological Methods*, *13*, 354–375. https://doi.org/10.1037/a0014173

Järvenoja, H., Järvelä, S., Törmänen, T., Näykki, P., & Malmberg, J. (2018). Capturing motivation and emotion regulation during a learning process. *Frontline Learning Research*, *6*(3), 85–104. https://doi.org/10.14786/flr.v6i3.369

Junker, R., Donker, M. H., & Mainhard, T. (2021). Potential classroom stressors of teachers: An audiovisual and physiological approach. *Learning and Instruction*, *75*, Article 101495. https://doi.org/10.1016/j.learninstruc.2021.101495

Kreibig, S. D. (2010). Autonomic nervous system activity in emotion: A review. *Biological Psychology*, *84*, 394–421. https://doi.org/10.1016/j.biopsycho.2010.03.010

Mainhard, T., Donker, M. H., & Van Gog, T. (2022). When closeness is effortful: Teachers' physiological activation undermines positive effects of their closeness on student emotions. *British Journal of Educational Psychology*, *92*, 1384–1402. https://doi.org/10.1111/bjep.12506

Moraes, J. L., Rocha, M. X., Vasconcelos, G. G., Vasconcelos Filho, J. E., de Albuquerque, V. H. C., & Alexandria, A. R. (2018). Advances in photopletysmography signal analysis for biomedical applications. *Sensors*, *18*, Article 1894. https://doi.org/10.3390/s18061894

Mossink, J. C. L., Verkuil, B., Burger, A. M., Tollenaar, M. S., & Brosschot, J. F. (2015). Ambulatory assessed implicit affect is associated with salivary cortisol. *Frontiers in Psychology*, *6*, Article 111. https://doi.org/10.3389/fpsyg.2015.00111

Murayama, K., Goetz, T., Malmberg, L.-E., Pekrun, R., Tanaka, A., & Martin, A. J. (2017). Within-person analysis in educational psychology: Importance and illustrations. *British Journal of Educational Psychology Monograph Series II*, *12*, 71–87.

Myrtek, M. (2004). *Heart and emotion. Ambulatory monitoring studies in everyday life*. Hogrefe & Huber Publishers.

Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P., & Perry, R. P. (2011). Measuring emotions in students' learning and performance: The Achievement Emotions Questionnaire (AEQ). *Contemporary Educational Psychology*, *36*, 36–48. https://doi.org/10.1016/j.cedpsych.2010.10.002

Pijeira-Díaz, H. J., Drachsler, H., Järvelä, S., & Kirschner, P. A. (2018). Sympathetic arousal commonalities and arousal contagion during collaborative learning: How attuned are triad members? *Computers in Human Behavior*, *92*, 188–197. https://doi.org/10.1016/j.chb.2018.11.008

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*, 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Roos, A. L., Goetz, T., Krannich, M., Jarrell, A., Donker, M. H., & Mainhard, T. (2020). Test anxiety components: An intra-individual approach testing their control antecedents and effects on performance. *Anxiety, Stress and Coping*, *34*, 279–298. https://doi.org/10.1080/10615806.2020.1850700

Scherer, K. R. (2009). The dynamic architecture of emotion: Evidence for the component process model. *Cognition & Emotion*, *23*, 1307–1351. https://doi.org/10.1080/02699930902928969

Schultheiss, O. C., & Wirth, M. M. (2018). Biopsychological aspects of motivation. In J. Heckhausen & H. Heckhausen (Eds.), *Motivation and action* (3rd ed., pp. 407–451). Springer.

Scollon, C. N., Kim-Prieto, C., & Diener, E. (2009). Experience sampling: Promises and pitfalls, strengths and weaknesses. In E. Diener (Ed.), *Assessing well-being: The collected works of Ed Diener* (pp. 157–180). Social Indicators Research Series. https://doi.org/10.1007/978-90-481-2354-4

Scrimin, S., Patron, E., Ruli, E., Pagui, C. E. K., Altoè, G., & Mason, L. (2018). Dynamic psychophysiological correlates of a learning from text episode in relation to reading goals. *Learning and Instruction*, *54*, 1–10. https://doi.org/10.1016/j.learninstruc.2018.01.007

Van Braak, M., Van de Pol, J., Poorthuis, A. M. G., & Mainhard, T. (2021). A micro-perspective on students' behavioral engagement in the context of teachers' instructional support during seatwork: Sources of variability and the role of teacher adaptive support. *Contemporary Educational Psychology*, *64*, Article 101928. https://doi.org/10.1016/j.cedpsych.2020.101928

Wolff, C., Van den Bogert, E., Jarodzka, N., & Boshuizen, H., H. P. A. (2015). Keeping an eye on learning: Differences between expert and novice teachers' representations of classroom management events. *Journal of Teacher Education*, *66*, 68–85. https://doi.org/10.1177/0022487114549810

Wubbels, T., Brekelmans, M., Den Brok, P., & Van Tartwijk, J. (2006). An interpersonal perspective on classroom management in secondary classrooms in the Netherlands. In C. M. Evertson & C. S. Weinstein (Eds.), *Handbook of classroom management: Research, practice, and contemporary issues* (pp. 1161–1191). Lawrence Erlbaum Associates.