frontiers | Frontiers in Education

TYPE Original Research
PUBLISHED 29 December 2025
DOI 10.3389/feduc.2025.1668861

OPEN ACCESS

EDITED BY
Kim Koh,
University of Calgary, Canada

REVIEWED BY
Robet L. Drury,
ReThink Health, United States
Paschalina Lialiou,
University of Piraeus, Greece

*CORRESPONDENCE
Mandy Klatt
✉ mandy.klatt@uni-leipzig.de

RECEIVED 18 July 2025
REVISED 10 November 2025
ACCEPTED 30 November 2025
PUBLISHED 29 December 2025

CITATION
Klatt M, Lotz C, Keßler P, Kachel G and Deiglmayr A (2025) From heartbeat to data—using wearable fitness trackers as an affordable approach to assess teachers' stress.
Front. Educ. 10:1668861.
doi: 10.3389/feduc.2025.1668861

From heartbeat to data—using wearable fitness trackers as an affordable approach to assess teachers' stress

Mandy Klatt[1]*, Christin Lotz[1], Peer Keßler[2], Gregor Kachel[1,3] and Anne Deiglmayr[1]

[1]Empirical School and Classroom Research, Institute of Educational Sciences, Leipzig University, Leipzig, Germany, [2]Department of Health and Prevention, Institute of Psychology, Greifswald University, Greifswald, Germany, [3]Developmental Psychology, Institute of Psychology in Education, Leuphana University, Lüneburg, Germany

Introduction: Past research on physiological indicators of teacher stress often had to rely on expensive and obtrusive assessment methods. Modern fitness trackers represent a non-invasive and convenient alternative.

Methods: This study investigated the use of wrist-worn fitness trackers to assess teachers' heart rate (HR) as an indicator of stress during teaching. In a laboratory study, we used a Fitbit® fitness tracker to assess teachers' HR before, during, and after a potentially stressful micro-teaching unit.

Results: Our results demonstrated that the fitness tracker was useful for mapping teachers' stress, with the data showing how teachers' HR increased before, peaked during, and progressively decreased after the micro-teaching unit. Moreover, we related the fitness tracker data to retrospective teacher self-reports and found that teachers' subjective stress appraisals and their teaching experience explained only small amounts of variance in HR data.

Discussion: We discuss the potential of fitness trackers as an affordable and ubiquitous assessment tool for research on teacher stress in the classroom and provide advice for practical implementation.

KEYWORDS

teacher stress, fitness tracker, heart rate, classroom disruptions, wearable technology, physiological stress measurement

Introduction

The teaching profession is one of the most stressful professions, with teachers facing a variety of stressors during their everyday work (Herman et al., 2020; Schult et al., 2014; Smith, 2000). To better understand mechanisms in teacher stress, there is a growing research interest in physiological measures such as heart rate (HR) as online measures of teachers' stress during teaching (Kärner and Höning, 2021; Wettstein et al., 2020). It has been shown that teacher-centered activities and typical classroom-related stressors increase teacher HR during teaching activities (Donker et al., 2018; Huang et al., 2022; Junker et al., 2021; Scheuch and Knothe, 1997; Sperka and Kittler, 1995). However, previous studies have often relied on expensive and obtrusive electrocardiographs (ECGs). Modern fitness trackers might represent a non-invasive and convenient alternative to assess teaching-related stress (Ferguson et al., 2015).

In teachers' daily work, classroom disruptions are a major stressor (Aloe et al., 2014; Boyle et al., 1995), and dealing with them is an important aspect of professional expertise (Wolff et al., 2015). According to Lazarus (1990) transactional model of stress and coping, the experience of stress in response to stressors such as classroom disruptions depends on the teacher's subjective appraisals, which, in turn, depend on their coping resources, such as their professional knowledge. The resulting stress response has a psychological, physiological, or behavioral dimension (Kyriacou and Sutcliffe, 1978). To comprehensively understand how classroom stressors impact teachers' stress responses across these dimensions, it is crucial to complement subjective self-reports with objective physiological measures (Wettstein et al., 2021). Teachers' use of wrist-worn fitness trackers in educational research provides fine-grained, *in vivo* data, allowing researchers as well as teachers themselves to continuously monitor their physiological stress response during teaching, across settings, and at low costs. Being able to monitor and eventually counteract teacher stress levels appears particularly relevant given the profession's generally high stress levels and associated negative health effects (Johnson et al., 2005; Montgomery and Rupp, 2005). To harness this potential, the present study explored the use of wrist-based fitness trackers as a tool to assess teachers' HR, as an indicator of stress, before, during, and after a teaching unit during which typical, potentially stressful, classroom disruptions occurred. Further, we explored to what extent teachers' subjective appraisals of classroom disruptions and their teaching experience predicted teacher stress as assessed by the fitness tracker.

Fitness trackers as a ubiquitous, low-cost tool for assessing physiological stress responses

Fitness trackers provide data on cardiovascular parameters such as HR, supporting personalized fitness goals (Nuss et al., 2021) and stress management (Hao et al., 2017). They can be used as ubiquitous, low-cost, and unintrusive data collection instruments (Godfrey et al., 2018), and their widespread use and everyday availability align with the increasing popularity and acceptance of so-called wearables among the general population (Peng et al., 2022). In contrast to self-reported questionnaires on stress (Chaplain, 2008; Liu and Yan, 2020) that are prone to biases like social desirability (Razavi, 2001) or recall errors (Van den Bergh and Walentynowicz, 2016), fitness trackers, as ambulatory assessment methods (Trull and Ebner-Priemer, 2013; Wettstein et al., 2020), offer more objective insights into teachers' stress levels by monitoring teachers' physiological stress responses without disrupting teaching (Donker et al., 2018; Runge et al., 2020).

One important health parameter assessed by nearly all wrist-worn fitness trackers is heart rate (HR) (Scalise and Cosoli, 2018). HR indicates the number of heartbeats within 1 min and is typically expressed as beats per minute (BPM) (Berntson et al., 2007; Hottenrot, 2007). HR can be detected and measured in different ways using sensors, such as electrocardiography (ECG) or photoplethysmography (PPG) (Mukhopadhyay and Islam, 2017). While ECG sensors offer precise measurements by detecting the heart's electrical activity, their intrusive nature and requirement of direct skin contact may limit their suitability (Kranjec et al., 2014), particularly in educational settings. In contrast, photoplethysmography (PPG) is a rather uncomplicated and inexpensive technique to measure HR, commonly found in commercially available fitness trackers (Castaneda et al., 2018). This optical method assesses HR by flashing green or red lights to measure changes in blood volume in the capillaries of the skin (Allen, 2007).

Physiologically, HR is regulated by the sympathetic and parasympathetic nervous systems (Pham et al., 2021). At rest, the average HR of adults typically ranges between 60 and 80 BPM (Sammito et al., 2024). An increase in sympathetic activity results in HR being sped up ("fight or flight" response; Taelman et al., 2009), whereas an increase in parasympathetic activity results in HR being slowed down ("rest and digest" response; Battipaglia and Lanza, 2015). Stress or mental and physical strain directly increases HR (Custodis et al., 2014; Sachs, 2014). Therefore, an increase in HR can be regarded as an indicator of increasing stress, and a decrease as an indicator of relaxation and ease (Kyriacou and Sutcliffe, 1978). Assessing these changes in HR, fitness trackers offer low-cost and unobtrusive access to psychological stress data.

HR in teaching-learning contexts

Prior research, typically using intrusive and labor-intensive data collection via ECG methods, has shown that changes in teachers' HR can be mapped onto stressors they had experienced during teaching. For example, teachers' HR tends to increase when teachers take an exposed position in student-teacher interactions (Donker et al., 2018; Junker et al., 2021; Scheuch and Knothe, 1997; Sperka and Kittler, 1995). Sperka and Kittler (1995), for example, recorded the HR of 16 pre-service teachers during their first lesson and showed that teachers' HR increased significantly during teaching. The activation was particularly prominent at the beginning of the lesson and gradually decreased over its course. The authors suggested that pre-service teachers' proactive coping strategies, such as actively managing student interactions, helped lower their HR levels. Other ECG studies identified typical stressors predicting increases in HR, such as class size (Huang et al., 2022) or low student engagement and motivation (Junker et al., 2021). Exemplarily, Junker et al. (2021) recorded the HR of 40 teachers during a real classroom lesson. Again, teacher stress, induced by factors such as low student engagement (e.g., lack of motivation or interest in tasks) or teacher-centered activities (e.g., teacher-focused classroom activities), resulted in elevated HR.

More recent studies used wrist-worn fitness trackers to investigate HR trends in instructional settings (Chalmers et al., 2021; Darnell and Krieg, 2019), but on learners rather than teachers. Darnell and Krieg (2019) measured the HR of 15 medical college students listening to lectures, using wrist-worn devices. The analysis revealed a constant HR decrease throughout the lecture, with HR peaks during more interactive learning phases. Chalmers et al. (2021) used HR data from a fitness tracker to identify physiological changes in 60 participants during stress-inducing tasks (i.e., the Trier Social Stress Test) (Kirschbaum et al., 1993). Average HR increased significantly from the resting to the stress-inducing phases. Even though the participants of these previous

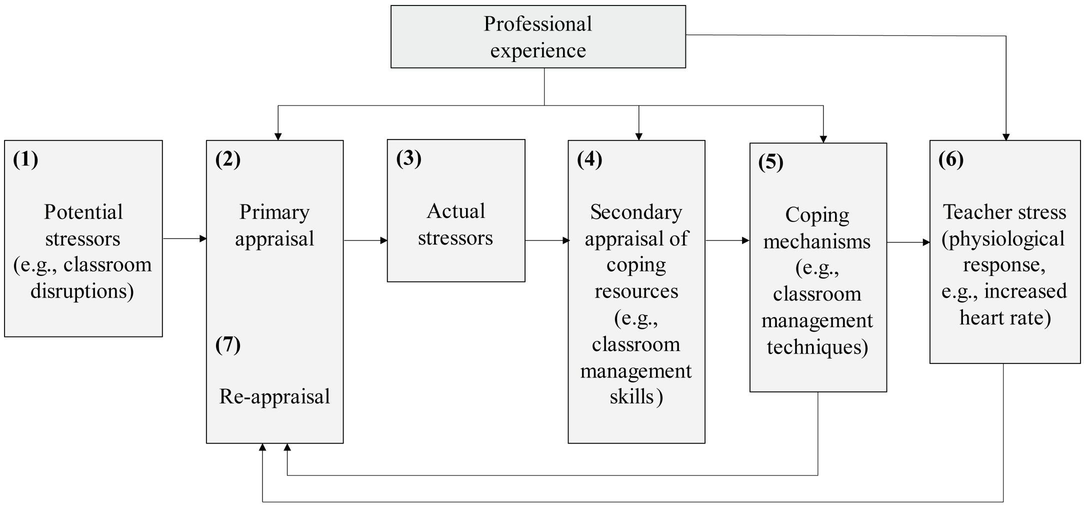

FIGURE 1
A model of teacher stress. The model was adapted from van Dick (2006, p. 37) and modified by the authors to specifically illustrate the appraisal and coping processes involved in responding to classroom disruptions.

studies (Chalmers et al., 2021; Darnell and Krieg, 2019) were not teachers but learners, they demonstrated that HR can be effectively recorded using fitness trackers over the course of a whole learning unit, as HR changes are in line with the occurrence of activating or stress-inducing tasks.

To the best of our knowledge, only one study has directly assessed teachers' HR during teaching using a wrist-worn fitness tracker: Runge et al. (2020) assessed HR as an indicator of stress in four in-service teachers during authentic lessons. They used fitness tracker recordings to create a profile for each teacher, in order to differentiate between teachers reporting higher vs. lower levels of stress. It was found that a high HR in combination with a high number of steps and short sleep duration was characteristic of teachers reporting high stress levels. However, it should be noted that the generalizability of these results is limited due to the small sample size.

In summary, previous studies have revealed that teachers' (and students') HR changes depend on their activities and the stressors they have experienced, with an increase in HR before the expected stressors occur, and with peaks in activating phases (Chalmers et al., 2021; Darnell and Krieg, 2019). For teachers, teacher-centered phases led to an increase in HR (Donker et al., 2018; Junker et al., 2021; Scheuch and Knothe, 1997; Sperka and Kittler, 1995). However, there is a lack of studies using teacher-worn fitness trackers in larger samples, exploring the feasibility of this convenient tool for researching links between teachers' HR and stress as a response to stress-inducing events.

A model of teacher stress

According to Kyriacou and Sutcliffe (1978), teacher stress can be defined as a negative affective response, typically accompanied by physiological changes such as increased HR, triggered by job-related demands, and perceived as threatening to one's self-esteem or wellbeing. Coping mechanisms help to reduce the perceived threat. Kyriacou's definition of teacher stress (see Kyriacou and Sutcliffe, 1978; and, for a more recent adaptation, van Dick, 2006) is based on the transactional stress model (Lazarus, 1966, 1990), which highlights the interaction between a person and the environment in the emergence of stress, whereby stress refers to a person's subjective reaction to an event (a stressor) that exceeds the person's adaptive resources.

Figure 1 illustrates, in a simplified way, how classroom events, particularly classroom disruptions, affect teachers' stress levels, based on van Dick's (2006) adaptation of Lazarus' transactional stress model. When a potentially disruptive classroom event occurs (1), teachers intuitively judge how disruptive or demanding the situation is (primary appraisal; 2). If the situation is appraised as threatening or overwhelming (3), teachers assess whether they possess sufficient resources, such as classroom management strategies and emotional regulation skills, to cope with the disruption (secondary appraisal; 4). Teachers then employ coping strategies, such as addressing the misbehavior or redirecting students' attention (5). If coping attempts are unsuccessful, stress results, often accompanied by physiological activation such as increased HR (6). Following the event, teachers re-evaluate both the situation and the effectiveness of their response (re-appraisal; 7), which may inform future coping efforts and emotional responses.

As shown in Figure 1, teachers' primary and secondary appraisals, as well as coping attempts, are influenced by professional experience. As professional experience grows, teachers develop cognitive scripts for managing classroom events, resulting in more complex and problem-focused classroom management skills (Wolff et al., 2021) and, in turn, more effective coping and less stress. Empirically, classroom management skills and problem-focused coping styles are linked to fewer instances of emotional exhaustion (Clunies-Ross et al., 2008; Maslach et al., 2001). Novices in the teaching profession, on the other hand, face considerable stress and often feel overwhelmed by the demands of teaching (Klusmann et al., 2012; Ophardt and Thiel, 2017; Wolff et al., 2015), with many leaving the profession within the first 5 years (Ingersoll and Smith, 2003). Accordingly, when resources are lacking and coping fails, negative consequences for health (e.g., burnout) and for work (e.g., high turnover rates) can arise (Aloe et al., 2014; Jalongo and Heider, 2006; Unterbrink et al., 2007), highlighting the importance of professional expertise for managing teacher stress (Fisher, 2011).

According to this transactional view, stress perception does not only depend on the objective occurrence of stressors but is also shaped by personal and contextual factors that influence appraisal processes. For example, Griffith et al. (1999) demonstrated that coping strategies such as disengagement or suppression of competing activities, as well as social support at work, significantly affect how teachers perceive and respond to job-related stressors. These findings underline that stress perception is highly individualized and depends on the interplay of external demands and available personal and social resources. An important factor with regards to teacher stress is teaching experience, as more experienced teachers typically possess more established classroom management routines and cognitive scripts that may help them appraise disruptions as less threatening and respond more confidently. Conversely, novice teachers often lack such routines and may therefore perceive disruptive events as more stressful and demanding (Klusmann et al., 2012; Ophardt and Thiel, 2017; Wolff et al., 2015). While our study primarily focused on teachers' physiological stress responses, acknowledging these multiple determinants of stress perception is essential for interpreting variation in how teachers experience and appraise classroom events.

Present study

The present study aimed to explore teachers' HR responses to potentially stressful events during a micro-teaching unit and to relate their physiological stress responses to their self-reported stress appraisals and teaching experience. We analyzed data from in-service and pre-service teachers who participated in a laboratory study as part of a larger project targeting the development of classroom management skills. Participants came to the lab individually and taught a short lesson to a class of three actors (i.e., trained student assistants) who performed several typical and possibly disruptive (i.e., stressful) classroom events.

Research questions and hypotheses

The present study addressed two overarching research questions: The first research question (RQ 1) was to investigate whether HR measures assessed by a wrist-based fitness tracker were a suitable and effective method for mapping teachers' HR over the course of the lab study, with a total duration of approximately 2 h, including phases before, during, and after a potentially stressful micro-teaching unit. Building on this research question, we specified the following methodological assumptions and hypotheses:

Methodological assumption 1a: Teachers' HR responses follow a global temporal pattern, with an initial increase, a peak during the micro-teaching unit, and a decrease during subsequent recovery phases.

Methodological assumption 1b: Z-standardization of HR values adequately accounts for inter-individual differences in baseline HR while preserving the same temporal dynamics as non-standardized values.

> *H1c*: Regarding HR levels, teachers' HR are highest during the micro-teaching unit, compared to all other phases.

> *H1d*: Regarding HR slopes, teachers' HR increases while they are preparing for teaching (*pre-teaching interval*), but decreases in all of the following intervals, while teachers are habituating to and recovering from the stressful micro-teaching unit.

The second research question (RQ 2) asked whether teaching experience made a difference in how classroom disruptions affected teachers' HR levels. Building on this research question, we formulated the following hypotheses and exploratory analyses:

> *H2a*: More experienced teachers exhibit lower HR levels than less experienced teachers.

> *H2b*: Teachers who perceive classroom events as more disruptive (disruption appraisal) show higher HR levels, irrespective of teaching experience.

> *H2c*: Teachers who feel more confident in dealing with classroom events (confidence appraisal) show lower HR levels, irrespective of teaching experience.

> *H2d*: Teaching experience, disruption appraisal, and confidence appraisal uniquely contribute to explaining variance in teachers' HR levels.

Exploratory analyses 2e: We explored whether teaching experience, disruption appraisal, and confidence appraisal were associated also with *changes* in HR slopes across study intervals.

Materials and methods

Participants

The sample consisted of $N = 84$ pre- and in-service teachers from Germany, who were recruited via personal contacts, email lists, and flyers. The data of three participants was lost due to failed data transmission, yielding an analysis sample of $n_{total} = 81$ ($n_{total} = 52$ women, $n_{total} = 29$ men), including 40 pre-service and 41 in-service teachers. Participants had a mean age of 30.95 years ($SD = 10.90$; range: 19–60) and an average teaching experience of 5.64 years ($SD = 9.46$; range: 0–37).

Ethics

The study was conducted in accordance with the ethical standards of the University's Institutional Review Board. All participants were informed about the study's aims before testing. Participation was voluntary, not incentivized, and only took place after written informed consent had been obtained. Given that physiological data constitute highly sensitive personal data, particular care was taken to ensure data protection and participant confidentiality. HR recordings were pseudonymized immediately upon collection and stored on secure university servers in compliance with General Data Protection Regulation [Regulation (EU) 2016/679; European Union, 2016], which classifies physiological recordings as special-category personal data requiring heightened protection (Art. 9). Only research staff had access to the data. No individual-level physiological results were disclosed to participants to avoid unintended psychological or evaluative consequences. All procedures adhered to institutional and international guidelines for research involving psychophysiological measures.

Setting and procedure

Each participant came to the lab for a period of approximately 2 h in total, and each participant underwent the same phases (see Figure 2).

In the *pre-teaching phase*, the experimenter welcomed the participants and helped them put on the fitness tracker. This was followed by a warm-up session to familiarize the participants with the laboratory setting and the class. This phase took about 10–15 min, and participants spent this time mostly standing or slowly walking around. During the *teaching phase*, the participants held their self-prepared micro-teaching unit to a class of three trained actors who performed nine, potentially disruptive, classroom events (e.g., chatting with a neighbor, heckling, looking at the phone; see Supplementary Table 1 for an overview and categorization of all events; and Supplementary Material Images 1, 2 for a depiction of the laboratory setting of the micro-teaching unit). Teachers freely chose the topic and class level of the teaching unit, with the only requirement that the unit had to be an introductory lesson and had to consist of supervised individual work and/or frontal teaching. The micro-teaching unit lasted about 15–20 min. Participants spent this time mostly standing or slowly walking around. While teaching, participants wore eye-tracking glasses, and their lesson was video-recorded. After having completed the micro-teaching unit, in the *post-teaching phase*, participants filled in questionnaires for approximately 10–15 min: a brief computer-based survey of sociodemographic data (e.g., teaching experience, gender, studied school type, studied school subjects, extracurricular teaching activities), and a short knowledge test that was irrelevant to the present study. In the *interview phase*, participants engaged in a Stimulated Recall Interview (SRI). During the SRI, participants sat in front of a computer monitor and watched the video of their own lesson from the ego perspective, as recorded through the eye-tracking glasses. The experimenter stopped the video each time one of the nine classroom events happened, and asked five open-ended and three rating questions per event. Two of the rating questions are relevant to the present study: the disruption and the confidence appraisal ratings (see Measures). The interview lasted about 45–60 min. Finally, in the *end phase*, participants filled in another questionnaire irrelevant to the present study, which lasted about 10–15 min.

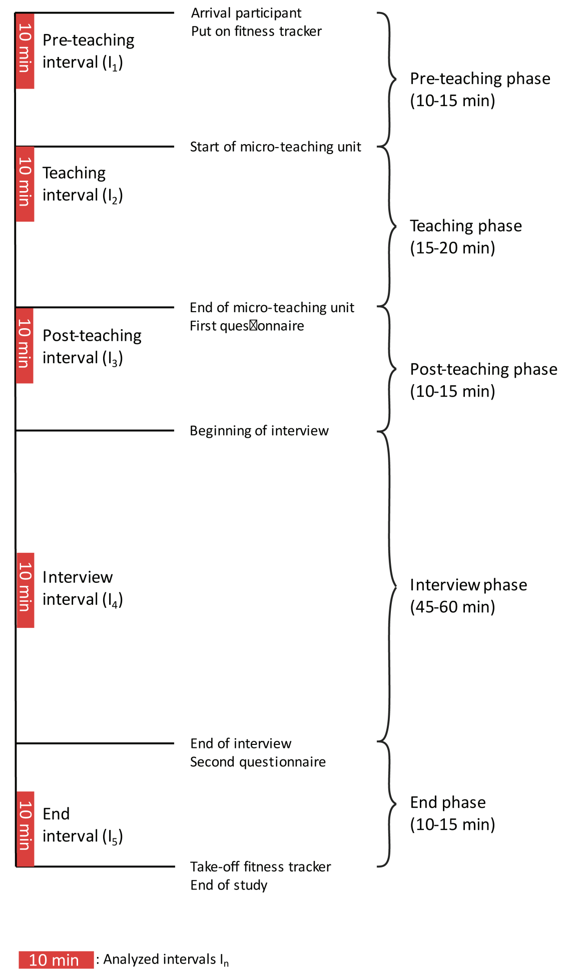

FIGURE 2
Procedure of the 2-h study, consisting of five phases with five representative 10-min intervals as the basis of our analysis.

Measures

Heart rate data and heart rate intervals

To measure teachers' HR, we used the wrist-based fitness tracker Fitbit® Charge 4. In line with the manufacturer's instructions (Fitbit Inc, 2020), the device was attached to the participants' non-dominant hand, a finger's width above the wrist bone. The tracker works by flashing green LEDs hundreds of times per second, using light-sensitive photodiodes to catch the reflected light, to calculate the volume changes in the capillaries. From this, the tracker calculated the heart beats per minute. HR measurements were generated at least every 15 s. The raw data contained the estimated HR in BPM for each time stamp. To account for individual differences in the baseline HR, we also

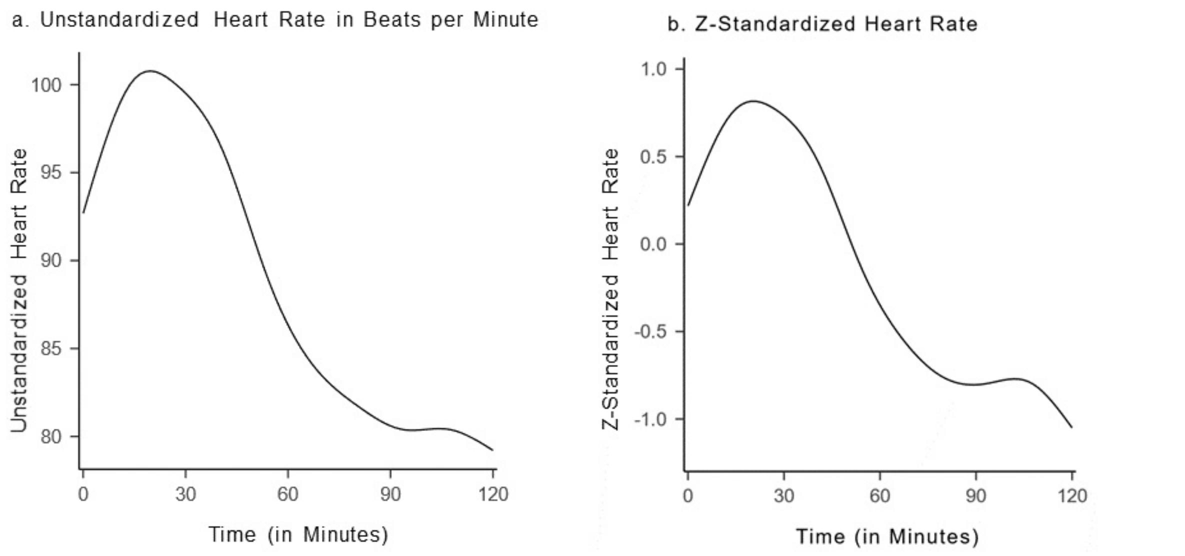

FIGURE 3
Overall Course of the HR with the unstandardized HR in BPM shown in **(a)**. And the Z-standardized HR shown in **(b)**. Over the course of the 2-h study.

calculated z-standardized HR values based on individual means, i.e., at the subject level of $n = 81$ participants (standardized HR).

Since we aimed to keep measurement intervals comparable between study phases, we aggregated HR over a representative 10-min interval within each phase (see Figure 2). Previous research has indicated that 10-min intervals are a useful duration for analyzing PPG data (Lu et al., 2008). The intervals were selected based on the following rules: The *pre-teaching interval (I_1)* comprised the first 10 min after the fitness tracker had been put on. The *teaching interval (I_2)* started 2 min after the lesson had started. This interval was of the highest relevance to our study. We explicitly chose an early 10-min interval within the *teaching phase*, as previous studies revealed that the beginning of a lesson is most demanding and potentially stressful with regard to teacher-student interaction (Claessens et al., 2017; Donker et al., 2018). The *post-teaching interval (I_3)* started immediately after the end of the teaching unit. The *interview interval (I_4)* was defined as the mid-10 min between the end of the teaching unit and the time point when the fitness tracker was taken off. All participants were being interviewed during this interval. The *end interval (I_5)* comprised the last 10 min before the fitness tracker was taken off.

Teaching experience

Participants' teaching experience was assessed as part of their sociodemographic data. Participants stated their work experience in years.

Subjective appraisal of the classroom events and coping processes

The subjective disruption and confidence appraisals were assessed during the SRI on an 11-point rating scale, ranging from 0 (*not at all disrupting/confident*) to 10 (*extremely disrupting/confident*). Ratings were averaged across the nine classroom events for each participant, as we were interested in the general stressfulness of the teaching phase for each participant.

Data analysis

To address the methodological assumptions, we first displayed smoothed HR trends over the entire 2-h recording period and visually inspected changes across phases before, during, and after the micro-teaching unit (methodological assumptions 1a).[1] In addition, we visually compared unstandardized and standardized HR trends over the 2-h recording period (methodological assumptions 1b).[2] For all further analyses, we used standardized instead of unstandardized HR values.

To test Hypothesis 1c, we averaged each person's standardized HR over each of the five selected intervals[3], resulting in one HR *level* measure per person per interval. We conducted a one-way Analysis of Variance with repeated measures as an omnibus test for HR level as the dependent variable and the five intervals as the repeated measures factor. Subsequently, we tested the mean differences between the *teaching interval (I_2)* and the other four intervals by planned contrasts and computed the effect size d (Cohen, 1988).

For testing Hypothesis 1d, concerning HR *changes* within each interval, we first conducted a linear estimation of the increase or decrease in standardized HR values over time for each participant. To this end, we used fixed intercept fixed slope regression models

1 The curve was smoothed using the geom_smooth() function from the ggplot2 package in R (Wickham, 2016) based on the smoothing method LOESS (Locally Estimated Scatterplot Smoothing). This method fits a polynomial surface determined by one or more numerical predictors, using local fitting.

2 Note that the study exceeded the planned duration of 2 for a few participants. To avoid distortions when mapping the HR over the course of the study (see Figure 3), the endpoint was set at 2 h for all participants, even though data from later time points was used in the end interval for a few participants.

3 We used the mean standardized HR instead of the mean intercept as we wanted to explain the mean HR of the entire intervals and not the HR at the very beginning of the interval (x = 0).

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(Gelman and Hill, 2006) for each interval to estimate intercepts and linear slopes for each individual, which were then averaged across individuals.[4] We tested Hypothesis 1d based on the unstandardized estimates of mean slopes (one estimate per participant per interval).

Addressing our second research question, we ran linear regression analysis with teaching experience and subjective appraisals as predictors of HR level and changes. To test Hypothesis 2a, we examined the effect of teaching experience on participants' HR levels (i.e., mean standardized HR) for each of the five intervals, using linear regression models with teaching experience as the sole predictor. To test Hypotheses 2b and 2c, we separately augmented the model by either teachers' disruption appraisal (Hypothesis 2b) or confidence appraisal (Hypothesis 2c) as predictors, while controlling for teaching experience. To test Hypothesis 2d, we examined the effects of all three predictors in one regression model. Furthermore, we repeated these steps to explore the effects of teaching experience and subjective appraisals on *changes* in teachers' HR (i.e., mean slopes). Please note: HR levels and changes were not regressed on the disruption and confidence appraisals in the *pre-teaching interval* (I_1), because the appraised classroom events had not yet taken place in that phase.

Results

Research question 1: mapping teachers' HR over the course of the study phases

Means, standard deviations, and range of teachers' unstandardized and standardized HR for the entire study period, and for the five intervals, are shown in Table 1. The unstandardized and standardized HR trends over the entire study period are displayed in Figures 3a, b, respectively. Results showed that HR initially increased, peaked, and then decreased (methodological assumption 1a), with the unstandardized and standardized HR graphs showing high similarity (methodological assumption 1b). Thus, for all further analyses, we used participants' standardized HR values.

4 Although this procedure does not account for non-monotonic progressions in individual HR, a graphical evaluation revealed that the linear estimates corresponded fairly well to the majority of the cases (see Supplementary Material Images 3–7).

To test Hypothesis 1c, we examined whether teachers' mean standardized HR *levels* were highest during the teaching phase compared to all other intervals. Consistent with our expectations, teachers showed the strongest physiological activation while teaching, followed by lower HR levels before and after the lesson, and the lowest levels during the interview and end intervals (see Figure 4). Repeated measures ANOVA revealed significant differences in mean standardized HR between intervals, $F(4, 400) = 260.62$, $p < 0.05$, $f = 1.60$ (large effect). Planned contrasts indicated that, as hypothesized (Hypothesis 1c), mean standardized HR was significantly higher in the *teaching interval* (I_2) than in all other intervals, specifically, the *pre-teaching interval* [I_1; $t(400) = -10.08$, $p < 0.05$, $d = 1.03$; large effect], the *post-teaching interval* [I_3; $t(400) = -6.94$, $p < 0.05$, $d = 1.37$; large effect], the *interview interval* [I_4; $t(400) = 15.00$, $p < 0.05$, $d = 3.29$; large effect], and the *end interval* [I_5; $t(400) = 22.54$, $p < 0.05$, $d = 4.64$; large effect].

Next, we examined HR *changes* (i.e., mean slopes) within each interval to test the hypothesis that HR increased during the *pre-teaching phase* and decreased during all other phases (Hypothesis 1d). The mean intercepts and mean slopes, complemented by their standard deviations for each interval, are shown in Table 2. The mean slope of the *pre-teaching interval* (I_1) was significantly positive, indicating an increase in HR, as hypothesized. Further, the mean slopes of the *teaching interval* (I_2), *post-teaching interval* (I_3), and *interview interval* (I_4) were significantly negative, indicating a decrease in HR. For the last interval, the *end interval* (I_5), the mean slope was negative, but did not differ significantly from zero.

Research question 2: predicting mean standardized HR and mean slopes

Table 3 shows the correlations among mean standardized HR/mean slopes, teaching experience ($M = 5.64$, $SD = 9.46$), disruption appraisal ($M = 5.19$, $SD = 2.87$), and confidence appraisal ($M = 7.81$, $SD = 1.97$). Correlations with HR measures were mostly very small and statistically non-significant. Correlations among teaching experience and appraisals (not shown in Table 3) were significant: more experienced teachers had lower disruption appraisals ($r = -0.36$, $p < 0.05$), and higher confidence appraisals ($r = 0.44$, $p < 0.05$). Moreover, the two appraisal variables were negatively correlated ($r = -0.37$, $p < 0.05$).

TABLE 1 Mean HR, standard deviations HR, and range of teachers' HR over the course of the entire study and the five intervals (unstandardized in BPM/z-standardized).

Interval	*M* HR	*SD* HR	Min	Max
Overall course of 2 h	90.09/0.04[a]	15.76/0.99[a]	51[b]/−4.03	164/4.56
Pre-teaching interval (I_1)	96.28/0.48	14.11/0.88	56/−3.56	139/3.24
Teaching interval (I_2)	100.80/0.85	16.23/0.77	63/−2.18	164/4.37
Post-teaching interval (I_3)	93.61/0.27	14.01/0.76	60/−2.17	150/3.06
Interview interval (I_4)	82.32/−0.72	11.85/0.74	51/−2.51	132/4.39
End interval (I_5)	77.95/−1.07	11.14/0.57	50[b]/−2.68	120/2.96

Mean heart rate (*M* HR), standard deviations (*SD* HR) of HR, and HR range (minimum and maximum values) are presented for the entire study and across five intervals in both unstandardized beats per minute (BPM) and z-standardized scores. [a]Please note that the standardized *M* and *SD* of the overall course were not exactly 0 and 1 due to rounding differences. [b]Deviations in the minimum values between the overall course and the *end interval* (I_5) can be explained by the fact that the study duration was capped at 2 h for the overall analysis, while the end intervals were determined individually for each participant. This discrepancy arose because a few participants required more than 2 h to complete the study, leading to differences in the recorded data.

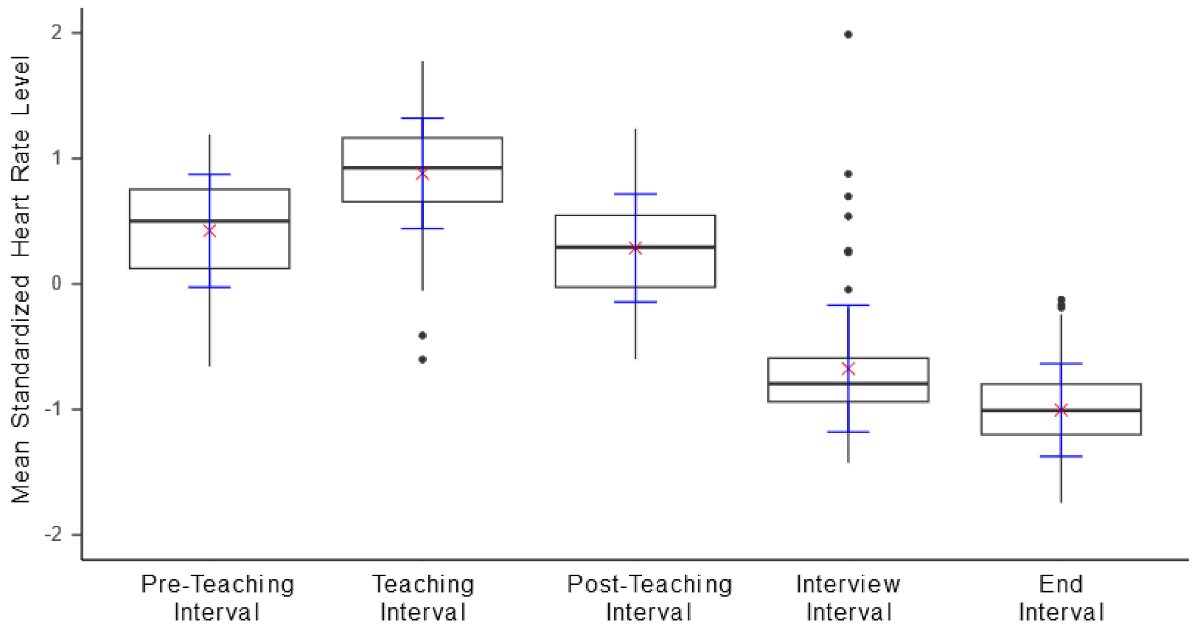

FIGURE 4
Distribution of the mean standardized heart rate levels for the five intervals. N = 81 participants per interval. In this figure shows the median (bold line), interquartile range (the box spanning the 25th–75th percentiles), the mean (red "x"), the standard deviation (blue vertical error bars), whiskers (lines extending to data points within 1.5 times the interquartile range), and outliers (individual dots beyond the whiskers).

Table 4 shows the results of the regression analyses. Teaching experience significantly predicted mean standardized HR level only in the *interview interval* (Table 4, Interview interval, Model 1), indicating a higher mean standardized HR level for teachers with more teaching experience. This relationship is, in fact, in the opposite direction as predicted by Hypothesis 2a. For all intervals, neither adding disruption appraisal (Hypothesis 2b) nor confidence appraisal (Hypothesis 2c) increased the amount of explained variance to a statistically significant extent.

When considering the effects of the three predictors in concert (Hypothesis 2d), the mean standardized HR level was significantly predicted only by disruption appraisal, and only in the *post-teaching interval* (Table 4, *Post-teaching* interval, Model 4), indicating a higher mean standardized HR level for teachers who felt more disrupted by the classroom events, when controlling for the other variables.

Concerning the explorative investigation of the effects of teaching experience and subjective appraisals on *changes* (i.e., mean slopes) in teachers' HR, teaching experience significantly predicted HR changes in the *pre-teaching interval* (Table 4, *Pre-teaching* interval, Model 1), indicating a less steep HR increase in teachers with more teaching experience. For all other intervals, no variable had significant predictive value.

TABLE 2 Means, standard deviation, and p-values for the mean intercepts and the mean slopes of the five intervals.

Interval	M (SD)		p	
	Intercept	Slope	Intercept	Slope
Pre-teaching interval (I_1)	0.052 (0.820)	0.085* (0.133)	0.57	<0.05
Teaching interval (I_2)	1.025* (0.690)	−0.039* (0.108)	< 0.05	<0.05
Post-teaching interval (I_3)	0.549* (0.547)	−0.060* (0.101)	< 0.05	<0.05
Interview interval (I_4)	−0.617* (0.614)	−0.022* (0.070)	< 0.05	<0.05
End interval (I_5)	−1.004* (0.500)	−0.012 (0.074)	< 0.05	0.14

M, Mean, SD; Standard Deviation; p, p-value. $^*p < 0.05$.

Discussion

Our study investigated how data from a wrist-worn fitness tracker could reveal the effects of stressors, such as classroom disruptions, on teachers' stress responses before, during, and after teaching units. Teachers' HR was assessed using a Fitbit® in a five-phase lab study, including a micro-teaching unit with disruptive events. We also examined whether HR variance was explained by teaching experience and self-reported stress appraisals (disruption appraisal and confidence appraisal).

Mapping teachers' HR in the context of a teaching unit

Using HR data from a commercially available and relatively low-cost fitness tracker, we mapped teachers' HR before, during, and after a stressful micro-teaching unit. HR increased in preparation for teaching, peaked while teaching, and decreased afterward, highlighting distinct physiological responses across different stages of the teaching process. Our study thus indicates

TABLE 3 Correlations between mean standardized HR level/mean slopes and the variables teaching experience, disruption appraisal, and confidence appraisal, for the five intervals.

Variable	Pre-teaching interval (I_1)	Teaching interval (I_2)	Post-teaching interval (I_3)	Interview interval (I_4)	End interval (I_5)
Teaching experience	−0.17/−0.27*	0.11/−0.02	−0.04/−0.03	0.24*/−0.20	0.04/0.11
Disruption appraisal	−0.01/0.16	−0.20/0.08	0.20/−0.14	−0.13/0.01	0.04/0.12
Confidence appraisal	−0.10/−0.18	0.06/0.09	0.04/−0.03	0.09/−0.19	−0.07/0.13

*$p < 0.05$.

that wrist-worn fitness trackers are a useful tool for identifying stressful periods in the context of teaching. Our findings are consistent with prior research that illustrates the variability of teachers' HR in relation to their activities and the stressors they encounter. For instance, earlier studies demonstrated that HR levels increase when teachers are placed in exposed positions, such as when engaging in teacher-centered activities or managing challenging student behaviors (Donker et al., 2018; Junker et al., 2021; Scheuch and Knothe, 1997; Sperka and Kittler, 1995), as well as with findings showing how HR changes align with activating events and stress-inducing tasks (Chalmers et al., 2021; Darnell and Krieg, 2019).

Predicting HR levels and changes

Addressing our second research question, we examined whether teaching experience and subjective stress appraisals predicted teachers' HR responses. Building on the model of teacher stress (Kyriacou and Sutcliffe, 1978; see Figure 1), we hypothesized that more experienced teachers with better classroom management skills at their disposal experience less physiological stress when dealing with classroom disruptions. However, the analyses did not provide evidence for a buffering effect of teaching experience on teachers' HR, i.e., more experienced teachers did not show lower HR levels during the stressful teaching phase than less experienced teachers. There are several possible explanations for this finding. First, teaching experience is inherently confounded with age (age and teaching experience correlated at $r = 0.94$ in our sample), and age has been shown to affect indicators of cardiovascular reactivity in various ways (Uchino et al., 2010). However, to avoid this kind of confounding influence, we had not used raw BPM data but standardized mean HR data for our analyses, thus controlling at least for inter-individual differences in mean HR. Second, as research on teacher professionalization has repeatedly shown, professional experience is not a guarantee for higher professional knowledge and skills (Kirschner et al., 2016). Rather, honing skills from professional experience necessitates a deliberate practice of choosing to improve, learning through experience, and integrating new knowledge into future performances (Dunn and Shriner, 1999). Thus, rather than professional experience alone, more direct assessments of classroom management skills, such as objective behavior-based tests, would be a better indicator of expertise that future studies could explore. Finally, and most importantly, the highly controlled teaching situation that we created in the lab might not have provided sufficient resemblance to the expert teachers' working conditions to let them effectively use their coping resources. In other words, since the situation was unfamiliar to both more experienced and less experienced teachers, their stress levels might have been more similar than in a more authentic classroom setting.

With regard to the predictive power of teachers' subjective appraisals of the classroom disruption during teaching, our hypotheses were not supported, as neither confidence appraisals nor disruptiveness appraisals predicted teachers' HR beyond teaching experience. This pattern suggests that self-reported appraisals and physiological stress responses may tap into different components of the stress process, or at least, into different aspects of the multifaceted stress response (Kyriacou and Sutcliffe, 1978). In addition, while HR was assessed in real-time during teaching, self-reported appraisals were given in retrospect during the interview following the teaching unit, and may be subject to biased (e.g., self-serving) reporting, or simply an inability to recall one's immediate reactions to a stressor. Importantly, despite the lack of predictive effects for subjective appraisals, teachers' HR showed the expected temporal pattern across study intervals, supporting the sensitivity of HR to situational demands in this setting. Beyond the cognitive appraisal processes, it is well-established that teachers' subjective stress perception is shaped by a multifactorial set of conditions, such as workload, student misbehavior, time pressure, and lack of resources (Kyriacou, 2001), which may not always align with short-term physiological activation. This complex interplay may explain why the predictors in our model accounted for only a limited proportion of variance in HR, even though HR showed clear situational sensitivity across intervals.

Importantly, however, when controlling for all other factors, teachers who reported having perceived the events as more disruptive showed a higher HR ($\beta = 0.25$) in the phase immediately following the micro-teaching unit. This finding is consistent with the idea that differences in HR levels, as an indicator of the physiological stress response, can be linked to the cognitive appraisal of stressors.

Limitations and future directions

While the laboratory setting of the study allowed for a controlled implementation of stressors and high internal validity, it was not an authentic classroom environment, raising questions about its external validity. Most importantly, the teachers and their students did not have a shared history, and only a very thin basis for establishing a positive teacher-student relationship, which is a core characteristic of effective classroom management (Beaty-O'Ferrall et al., 2010; Rüedi, 2014). In addition, the micro-teaching unit was only about 15 min long, and thus much shorter than a regular school lesson, providing fewer opportunities for

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TABLE 4 Standardized regression coefficients of mean standardized heart rate level and mean slopes predicted by teaching experience, disruption appraisal, and confidence appraisal for the five intervals.

Interval	Model 1				Model 2				Model 3				Model 4			
	Mean std. HR level		Mean slopes		Mean std. HR level		Mean slopes		Mean std. HR level		Mean slopes		Mean std. HR level		Mean slopes	
	β (SE)	p	β (SE)	p	β (SE)	p	β (SE)	p	β (SE)	p	β (SE)	p	β (SE)	p	β (SE)	p
Pre-teaching interval (I_1)[a]																
Teaching experience	-0.17 (0.005)	0.12	−0.27* (0.002)	< 0.05												
R^2	0.030		0.071													
Teaching interval (I_2)																
Teaching experience	0.11 (0.002)	0.34	−0.02 (0.001)	0.83	0.04 (0.005)	0.73	0.01 (0.001)	0.96	0.10 (0.006)	0.42	−0.08 (0.001)	0.54	0.05 (0.006)	0.67	−0.05 (0.001)	0.72
Disruption appraisal					−0.18 (0.041)	0.13	0.08 (0.010)	0.50					−0.19 (0.042)	0.13	0.12 (0.010)	0.34
Confidence appraisal									0.01 (0.046)	0.92	0.12 (0.011)	0.34	−0.04 (0.047)	0.76	0.15 (0.012)	0.24
R^2	0.012		0.000		0.040		0.015		0.012		0.010		0.042		0.031	
ΔR^2					0.028		0.015		0.000		0.010		0.030		0.031	
Post-teaching interval (I_3)																
Teaching experience	−0.04 (0.005)	0.70	−0.03 (0.001)	0.80	0.04 (0.005)	0.76	−0.09 (0.001)	0.44	−0.08 (0.006)	0.55	−0.02 (0.001)	0.89	−0.01 (0.006)	0.91	−0.07 (0.001)	0.61
Disruption appraisal					0.22 (0.040)	0.07	−0.18 (0.009)	0.14					0.25* (0.041)	< 0.05	−0.20 (0.010)	0.12
Confidence appraisal									0.08 (0.045)	0.55	−0.03 (0.011)	0.83	0.14 (0.046)	0.27	−0.08 (0.011)	0.54
R^2	0.002		0.001		0.043		0.020		0.006		0.002		0.058		0.023	
ΔR^2					0.041		0.019		0.004		0.001		0.056		0.022	

(Continued)

TABLE 4 (Continued)

Interval	Model 1				Model 2				Model 3				Model 4			
	Mean std. HR level		Mean slopes		Mean std. HR level		Mean slopes		Mean std. HR level		Mean slopes		Mean std. HR level		Mean slopes	
	β (SE)	*p*	β (SE)	*p*	β (SE)	*p*	β (SE)	*p*	β (SE)	*p*	β (SE)	*p*	β (SE)	*p*	β (SE)	*p*
Interview interval (I_4)																
Teaching experience	0.24* (0.006)	< 0.05	−0.20 (0.001)	0.07	0.22 (0.006)	0.06	−0.23 (0.001)	0.06	0.25* (0.006)	< 0.05	−0.14 (0.001)	0.25	0.23 (0.007)	0.07	−0.17 (0.001)	0.18
Disruption appraisal					−0.05 (0.045)	0.66	−0.08 (0.006)	0.52					−0.06 (0.047)	0.61	−0.12 (0.007)	0.34
Confidence appraisal									−0.02 (0.050)	0.85	−0.13 (0.007)	0.29	−0.04 (0.052)	0.76	−0.16 (0.007)	0.20
R^2	0.058		0.040		0.060		0.050		0.058		0.054		0.061		0.069	
ΔR^2					0.002		0.010		0.000		0.014		0.003		0.029	
End interval (I_5)																
Teaching experience	0.04 (0.004)	0.70	0.11 (0.001)	0.32	0.07 (0.005)	0.58	0.18 (0.001)	0.13	0.09 (0.005)	0.46	0.07 (0.001)	0.58	0.10 (0.005)	0.43	0.12 (0.001)	0.33
Disruption appraisal					0.06 (0.035)	0.60	0.19 (0.007)	0.12					0.04 (0.037)	0.76	0.23 (0.007)	0.07
Confidence appraisal									−0.11 (0.039)	0.38	0.10 (0.008)	0.43	−0.10 (0.041)	0.44	0.16 (0.008)	0.22
R^2	0.002		0.013		0.005		0.053		0.012		0.025		0.013		0.078	
ΔR^2					0.003		0.040		0.010		0.012		0.011		0.065	

In Model 1, mean standardized HR level and mean slopes were predicted only by teaching experience. In Model 2, solely disruption appraisal was added to teaching experience as a second predictor. In Model 3, solely confidence appraisal was added to teaching experience as a second predictor. In Model 4, all three predictors were considered in concert. [a]We calculated only Model 1 for the *pre-teaching interval (I_1)* because the classroom events and their corresponding appraisals had not yet occurred in this interval. *$p < 0.05$.

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experienced teachers to build up an engaging lesson. Finally, the onset of disruptive student behavior was scripted, following an experimental time schedule, which was not affected by the behavior of the teacher. Thus, the setting may have masked the effects of teaching experience by providing too few opportunities for experienced teachers to demonstrate their true classroom management skills, in particular regarding the prevention of disruptions. In subsequent studies, it would therefore be insightful to assess teachers' HR in more authentic classroom settings over a longer period of time (e.g., days, weeks, or even months). Extended observation of teachers' HR in authentic classroom settings could reveal how factors such as student behavior, teaching methods, or organizational and administrative demands contribute to fluctuations in physiological arousal, uncovering insights into the sustained physiological demands of teaching that short-term studies may overlook. In line with this, future studies should also link teachers' actual classroom behavior to potential stressors (e.g., classroom disruptions, noise levels, or instructional demands) to better understand how coping strategies manifest physiologically in real-time contexts.

Another limitation concerns the assessment of teachers' HR. While our results demonstrate the usefulness of drawing upon easily available HR data from ubiquitous, low-cost, unintrusive fitness trackers to estimate teacher stress, there are some shortcomings of this type of assessment method. First, while fitness trackers typically yield HR data, heart rate variability (HRV) has been demonstrated to be an even more accurate indicator of stress (Wettstein et al., 2020). Prior research emphasized that HRV captures autonomic regulation and stress reactivity more comprehensively than HR alone (Drury et al., 2019; Laborde et al., 2022). While standard fitness trackers did not provide HRV at the time of our data collection, more recent products now include this function. In addition, field-based HRV studies demonstrated that stress responses can be captured with high ecological validity outside of laboratory contexts (Drury et al., 2021). These advances suggest that future research should combine HR and HRV measures to provide a more complete picture of teachers' physiological stress responses.

Second, we did not record participants' resting HR, which is generally considered an important baseline for determining inter- and intrapersonal differences in cardiovascular health and reactivity (Heneghan et al., 2019; Nanchen, 2018). A clean baseline HR requires a resting phase without physical movement or emotional stress, ideally 15 min before the beginning of the activity, which is very difficult to achieve in practice (Sammito et al., 2024), e.g., when assessing teacher HR before and during teaching. Instead, our study explored the possibility of substituting baseline HR measurement via z-standardization within participants. As a result, the absolute standardized values of each participant must always be interpreted in the context of the standardization sample. However, for statistical analyses based on the whole sample, the standardization fulfilled the aim of controlling for differences in individual HR due to, for example, age-related differences.

In addition, cardiovascular responses can be affected by non-stress factors such as circadian rhythm, physical activity, general fitness, lifestyle variables, e.g., caffeine intake, and contextual influences, e.g., room temperature or noise (Laborde et al., 2022; Sammito et al., 2024). Although our controlled laboratory setting reduced some variability, such influences cannot be ruled out entirely. Future studies may therefore benefit from combining physiological measures with systematic recording of contextual and behavioral data to better isolate stress-related effects.

Finally, depending on the brand and model of fitness trackers used, the precision of the HR measurement might vary. Research on the reliability of the deployed Fitbit® device has proven that this brand is generally accurate in controlled settings and for moderate activity levels (Fuller et al., 2020; Hajj-Boutros et al., 2023; Jo et al., 2016; Wallen et al., 2016), as was the case in our study. For example, the Fitbit® fitness tracker had previously shown good HR measurement accuracy during resting phases (Jo et al., 2016; Muggeridge et al., 2021) and for activities such as walking, jogging, and running (Hajj-Boutros et al., 2023). Nevertheless, Gagnon et al. (2022) emphasized that Fitbit® trackers cannot replace ECG when high-precision measurement is paramount. Despite these considerations, the Fitbit® model appeared suitable for our study purposes, as physical strain was moderate.

Furthermore, while we assessed teachers' appraisals of the stressful classroom disruptions using a Stimulated Recall Interview (SRI) in which they could review the exact situation, these appraisal ratings were still *post hoc* self-reports, which limits the interpretation of our results. While SRIs provide a detailed and reflective understanding of the stressor in question, the delayed nature of the response made it difficult to capture the immediate, in-the-moment appraisal that occurred when the stressful event actually took place.

Implications

Building on the study's findings, the following section outlines implications for future research using wearable technology and for improving teachers' professional wellbeing in educational contexts.

Hands-on advice for using wrist-worn fitness trackers for research

For researchers aiming to collect data using fitness trackers, there are practical aspects to consider regarding the design, data collection procedure, and data analysis phases of research projects (for an additional overview, see Nelson et al., 2020):

(1) Choosing a suitable fitness tracker model:

Before data collection, researchers should decide which model of fitness tracker is suitable for the research context and measurement requirements. Wrist-worn devices are practical and cost-effective but cannot replace medical-grade ECG when high precision is required (Gagnon et al., 2022). Accuracy varies across brands and movement intensities; for example, Fitbit® devices may underestimate HR at higher activity levels such as cycling (Jachymek et al., 2022; Jo et al., 2016; Montoye et al., 2017; Thomson et al., 2019). Systematic reviews (e.g., Fuller et al., 2020) provide guidance regarding validity and reliability across models and study contexts. Practical considerations include cost, which ranges from low-budget consumer models to more advanced devices, and the availability of additional physiological parameters such as HRV. Given that physiological data constitute sensitive personal information, device ecosystems and data export pathways must comply with ethical and legal requirements, including secure storage, anonymization, and restricted access.

(2) Operating the fitness tracker:

To ensure accurate HR recording, attention must be paid to wristband fit, correct positioning, and whether the device is placed on the dominant or non-dominant wrist. This is particularly relevant in studies with children or participants engaging in movement. Prior to each session, researchers should check device battery status, firmware updates, sensor functionality, and proper synchronization. If the study aims to analyze physiological responses during specific segments, such as teaching vs. breaks, it is crucial to synchronize device timestamps with external timekeeping systems (e.g., experiment logs, cameras). This alignment facilitates precise matching of physiological signals with events of interest and increases the validity of contextualized analysis.

(3) Extracting and analyzing fitness tracker data:

Researchers should verify that raw HR data can be exported for analysis (e.g., as.csv files). Export timelines must be considered, as some commercial platforms automatically delete or archive older data. Additionally, it is essential to confirm the sampling rate during data collection, since movement, wristband looseness, or skin contact issues may temporarily reduce the frequency of HR recordings (e.g., from expected 1–5-s intervals to occasional 15-s readings). Careful data screening and cleaning are therefore required to ensure data quality and to identify potential artifacts, particularly in dynamic settings such as teaching.

Taken together, careful device choice, systematic preparation, and proactive data management are crucial for harnessing the benefits of wearable technology in educational research while maintaining data quality, participant safety, and ethical compliance.

Practical implications for teacher wellbeing and classroom practice

Our findings suggest that wearable HR assessment can be used to detect teachers' stress responses in real time, with important implications for both educators' wellbeing and student learning. Chronic occupational stress among teachers is widespread and has been shown to increase the risk of burnout, anxiety, and depression, highlighting the need for early identification and prevention (Agyapong et al., 2023; Emeljanovas et al., 2023). Physiological indicators can complement self-report data by offering more objective insights into stress load and health risk. A systematic review of stress biomarkers demonstrates that cardiovascular parameters provide reliable signals of teachers' occupational stress and can function as early warning indicators for adverse health trajectories (McGee et al., 2023). By combining subjective and physiological information, wearable devices could offer practical feedback to teachers about their stress levels and might help prevent escalation into chronic health problems.

Importantly, teacher stress is not only a matter of individual health but also directly affects classroom dynamics and student outcomes. Empirical work shows that teacher profiles marked by higher stress and burnout are associated with less effective instructional practices and poorer student performance (Herman et al., 2020). Qualitative classroom research further highlights that disruptive student behavior and difficult working conditions are among the most common stressors, reducing teachers' instructional quality and limiting their emotional availability for students (Shernoff et al., 2011). Such processes not only impair immediate learning but can also accumulate over time, constraining students' wellbeing and academic achievement.

In this light, integrating wearable HR monitoring into teacher education and occupational health programs aligns with recent calls to apply ambulatory, multi-method assessment tools in classroom research to better capture the ecological validity of teacher stress (Wettstein et al., 2021). Therefore, wearable-based monitoring has the potential to protect teachers' mental health while simultaneously supporting the learning conditions that enable students' long-term academic performance.

Conclusion

This study aimed to achieve a more profound understanding of teacher stress and investigated whether HR data collected from teacher-worn fitness trackers are suitable for exploring links between HR, subjective stressor appraisal, and teaching experience. Results suggest that the widespread availability of HR data from wearable fitness trackers presents opportunities both to teachers for self-monitoring stress levels, and to researchers for assessing physiological indicators of stress. Our findings cater to Wettstein et al. (2021) call for the use of ambulatory assessment methods, particularly in the context of classroom management research, for gaining a deeper understanding of teacher stress and its impact on both psychological and physiological variables.

In summary, our study contributes to the understanding of stress in educational settings and underscores the potential of wearable fitness trackers in advancing research on teacher stress. By moving "from heartbeat to data," we can harness the power of wearable technology to provide teachers with the tools needed to better understand and manage their stress, ultimately enhancing their overall wellbeing. Beyond individual benefits, supporting teachers in sustainable stress regulation is essential for building healthier schools and learning environments, as teacher stress has been shown to undermine instructional quality and student outcomes (Herman et al., 2020; Shernoff et al., 2011). Reducing stress in teaching contexts may therefore not only protect teachers' mental health but also foster the long-term academic success of students.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Prof. Dr. Julian Schmitz; Leipzig University. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

MK: Writing – original draft, Investigation, Methodology, Formal analysis, Data curation, Conceptualization. CL: Writing – review & editing, Supervision, Conceptualization, Methodology. PK: Formal analysis, Data curation, Writing – review & editing. GK: Methodology, Conceptualization, Writing – review &; editing. AD: Supervision, Conceptualization, Writing – review & editing, Methodology.

Funding

The author(s) declared that financial support was received for this work and/or its publication. This work received intramural funding under the QualiFond programme of the Department of Education at the Leipzig University.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2025.1668861/full#supplementary-material

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