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Master's thesis

Exploring Psychological Hormesis in Dutch adolescent rowers

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Are there deviations of the Master's thesis from the proposed plan?
☐No
☒Yes, please explain below the deviations
Minor deviations such as a different analysis and more refinement of the research questions.

Abstract

Stress is a broad physical reaction of an organism to the demands in life. When people are unable to cope adequately with stress, mental- and physical health problems occur. However, we are inclined to look at the negative effects of stress, while we could also use it to our benefit. This study investigated Psychological Hormesis (PH), the phenomenon of growing psychologically when exposed to a moderately dosed stressor, among 33 Dutch adolescent rowers. Using weekly measurements of objectively recorded indoor training sessions (INT) as an indicator of stress, and the subjective perceived exertion (RPE) of INT, I identified and classified latent PH trajectories. These trajectories were calculated based on logic and the use of the Psychological Hormesis Index (PHI), which is the quantification of the difference between psychological states such as experienced exertion. The results indicate that PH develops dynamically over time, with early responses to INT often predicting linear outcomes such as growth or decay. In addition, individual differences in adaptation are evident and cumulative exposure to properly doses INT can foster growth. This study thereby extends existing PH models by emphasizing time-varying processes, cumulative effects, and early predictors of adaptation. Overall, this contributes to a more dynamic and nuanced understanding of how everyday stress can influence PH across different individuals.

Keywords: stress, Psychological Hormesis, Dutch adolescent rowers, logic, trajectories

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1 Introduction

Stress, we all have felt it sometimes. It can be regarded as a broad physical reaction of an organism to the demands in life (Selye, 1976). Stress can manifest itself on the societal level as well as on the individual level. For example, during the COVID-19, countries had to motivate and limit their citizens to comply with the guidelines of the WHO, which was far from easy. When one zooms in, COVID-19 also impacted the social lives of the affected- and non-affected persons through social isolation which created stress (e.g., Su et al., 2022; Kim & Jung, 2021; Loades et al., 2020; Fernández et al., 2023).

Altogether, numerous studies to date have shown a consistent pattern of detrimental effects to their mental- and physical health when people are unable to cope with stress adequately (e.g., Thoits, 1982; Shapiro & Levendosky, 1999; Ball & Lee, 2000; Gibson & Leitenberg, 2001; Bal et al., 2003; Folkman & Moskowitz, 2004; Taylor & Stanton, 2007; Zimmer-Gembeck & Skinner, 2016; Sekhar et al., 2019; Turner et al., 2020; Schulz et al., 2022; Burnatowska et al., 2022; Schurr et al., 2024). However, we are inclined to look at the negative effects of stress, while there are also examples of positive effects.

1.1 Positive effects of stress

“Out of life’s school of war—what doesn’t kill me, makes me stronger.” (Nietschze, 1889) is a popularized statement which implies that humans can grow from stress. Whether and how people can grow from stress has been theorized about in psychology. A first example is the *Positive Disintegration Theory* (PDT; Dąbrowski, 1964), which argues that experiencing difficulties in live can be beneficial for the development of one’s personality. PDT assumes that mental development unfolds in different stages in response to perceived negative life events, with individuals possessing specific capacities called overexcitabilities (Wells & Falk, 2021). For instance, an individual who possess the emotional overexcitability experiences life more intensive than an individual who does not possess this overexcitability.

A second example is the *Post-Traumatic Growth* phenomena (PTG; Tedeschi & Calhoun, 1996). PTG occurs when a person experienced psychological growth after experiencing a traumatic event such as being more nicely to other people after losing a significant other. PTG manifests itself via five dimensions: 1) new possibilities or pathways in life, 2) a greater appreciation for life, 3) improved relationships, 4) a greater sense of personal strength, and 5) spiritual development. Xiaoli et al. (2019) show that, on average 53% of the people who have experienced traumatic events, have been grown afterwards.

Initial PDT research was mainly conducted on mental patients or sometimes (gifted) children (Dabrowski, 1967; Mendaglio & Tillier, 2006), has yet limited empirical support (Chang & Kuo, 2013), and the development stages are criticized to be inherently subjective (e.g., Marsh & Colangelo, 1983; Nelson, 1989; Harper et al., 2017; Schläppy, 2019). On the other hand, empirical findings on PTG predominantly stem from studies involving individuals who have encountered severe traumatic events, such as firefighters or military personnel (Habib et al., 2018). In contrast, the general population may not experience stressors of comparable intensity or frequency and can therefore not experience PTG. Or, empirical findings which stem from these specific populations are the results of selection effects: firefighters for example are different people than the general public because they choose a physical life-threatening job whereas others choose a job with less or no physical life-threatening properties at all. In addition, answers from questionaries (e.g., Post-Traumatic Growth Inventory; Tedeschi & Calhoun, 1996) may indicate growth, but they are post-hoc subjective perceptions, which may be unreliable (e.g., McFarland & Alvaro, 2000; Cho & Park, 2013; Gower et al., 2022).

Hence, despite the fact that there has been much discussion about whether stress can be beneficial for people, it remains unclear when, and how people can grow from stress (e.g., Meyerson et al., 2011; Ulloa et al., 2016; Mangelsdorf et al., 2019; Infurna & Jayawickreme, 2019; Jayawickreme et al., 2020; Henson et al., 2021). These findings imply that we need a more refined framework which is generalizable, objective, and less ambiguous in terms of whether growth has taken place after stress or not.

2 Theory

2.1 An integrative approach to explain growing from stress

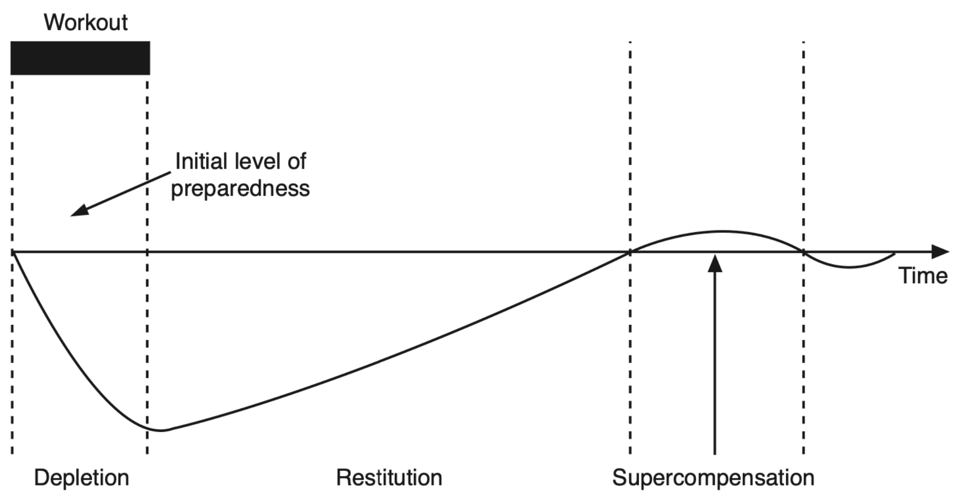
I propose that how people can grow from stress can best be understood by combining two frameworks: 1) general models from the science of strength training, and 2) hormesis. This is because the first framework explains on a broad level how enhancement can be realized and the second explains on a lower level how the dose of a stressor is related to enhancement.

2.1.1 General models from the science of strength training

The general models from the science of strength training are used for theorizing how athletic performance can be enhanced (Zatsiorsky et al., 2020). The basic notion behind these models is as follows: when a person exercises, he or she depletes energy (i.e., depletion), which is restored after a rest period (i.e., restitution) with an additional increase above the initial level (i.e., supercompensation) and is therefore called the *one-factor supercompensation model* (Figure 1).

Figure 1

The supercompensation model



Note. Taken from *Science and Practice of Strength Training* (p. 10), by Zatsiorsky, V. M., Kraemer, W. J., & Fry, A. C. 2020, Human Kinetics.

Enhanced athletic performance depends on four training laws: overload, accommodation, specificity, and individualization (Zatsiorsky et al., 2020). Overload is realized when the level of intensity and or the volume of a training stressor has increased compared to its previous level. Intensity can be characterized as the amount of resistance, and volume as the total amount of resistance in a certain time interval. Consider for example performing 10 repetitions in a strength training exercise with 74kg. The intensity is 74kg and the 10 repetitions is the volume. In the domain of psychology, overload can be realized when the level of psychological stress has increased compared to its previous level. Translated to the life of a student, if a student is anxious about the idea that he or she needs to presents his or her work, it will be more stressful (i.e., a higher intensity) for this student if it is a graded presentation compared to a practice presentation. Or, it will be more stressful if the student needs to present three times in a week compared to one time in a week (i.e., volume).

Accommodation is the law of stressor adaptation. When an individual is exposed to the same dosed (e.g., intensity and or volume) stressor over time, then the impact of this stressor eventually weakens. In other words, the individual has adapted to the training program. Consider again a student, his or her anxiousness decreases over time when he or she presents more often. This is because the student learns that the possible threat, such as getting laughed at or not doing a good job, is not realistic and learns to control his or her anxiousness, such as practiced in exposure therapy (e.g., Knowles & Tolin, 2022).

The law of specificity states that enhanced performance is the result of a stressor that is equal to or an approximation of the performance in question. For instance, when an individual wants to get stronger, he or she should lift weights instead of running. In the domain of psychology this would mean that the nervousness of a student when presenting in front of a group of professors, does not mean that this particular student is also nervous when presenting in front of fellow students. Indeed, so far obtained results from clinical studies suggests that adapting to social stress is context specific (Wood & Bhatnagar, 2015).

Last, the law of individualization states that the relationship between enhanced performance and a training stressor is moderated by genetic influences (e.g., Bathgate et al., 2018; Flück et al., 2019), hence epigenetic effects. Epigenetics explains how genes function when they are exposed to their local environment (Moore, 2016). For example, athletes who possess on average more muscle fibers which produce high power (i.e., Type IIa- and x muscle fibers) react stronger to strength training compared to athletes who possess on average more muscle fibers which are more suited for endurance work (i.e., Type I fibers) (e.g., Hopwood et al., 2023). Not only do we find differences in athletic performance as a result of the interaction between stress and genes, but also in healthy behavior (Plomin, 1990; Plomin et al., 1994) and neuroticism. In particular, when individuals are exposed to a certain stress condition as reflected in the nature (e.g., traumatic), timing (e.g., early childhood), and duration (i.e., acute or chronic) of stress (Dee et al., 2023), their tendency to show certain behavior varies depending on their genetic make-up and gender (Rohit et al., 2011). For instance, in alcohol misuse (Clarke et al., 2012), depression (Park et al., 2019), suicide (Dee et al., 2023), and aggression (Craig, 2007; Palumbo et al., 2018). This means that despite observing two genetically different (male or female) individuals who are exposed to the same stress condition, they probably show different behavior.

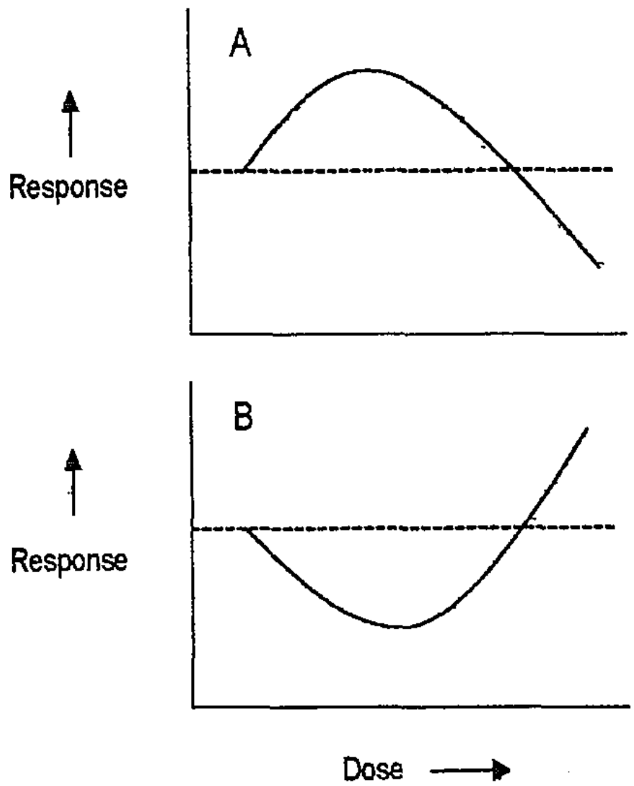
Athletic performance is thus a function of the amount of stress, the frequency of exposure, the specific properties of the stressor, and epigenetic effects. However, what is missing is a detailed explanation for how a stress dose is related to different outcomes such as enhanced athletic performance, and thus, also growing from stress in general. That is, the law of overload prescribes that athletic performance is going to be enhanced if the stress dose increases from one occasion to the following occasion. However, how much "more" is not captured and explained in this framework.

2.1.2 Hormesis

The hormesis framework originally derives from toxicology. According to this framework, organisms can enhance their structure on the cellular, tissue and organ, and at the whole organism level due to stimulatory effects caused by a low dose of toxins (e.g., Stebbing, 1982). This relationship is depicted in a so-called inverted "U-curved" (growth) or "J-curved" (e.g., mutagenesis) pattern, depending on the outcome measure (Calabrese, 2003), see Figure 2. For example, the U-curve is a result of an increasing stress dose from low to moderate, where the greatest gains are observed in the lowest point in the "valley" of the curve (i.e., hermetic vertex), but diminishing effects occur when the stress dose becomes too high. Or, a J-curve as a consequence of a low- to moderate stress dose which causes a reduction in adverse effects while high doses enhance adverse effects. Hormesis has been observed across species such as in bacteria (microorganisms), plants (e.g., algae), insects (invertebrates), fish (vertebrates), and humans (e.g., vaccinations) probably because it played an important role in the evolution of life on earth (Constantini & Borremans, 2019). In this thesis I will build upon this framework, given the potential it has for the social and behavioral sciences. Indeed, scholars such as Oshri (2023), Oshri et al. (2022; 2024), Kyriazis et al. (2024), and Hill et al. (2024) argue that hormesis can be observed in human behavior. In particular, Oshri (2023) refers to this particular hormesis form as “psychosocial hormesis” or “psychological hormesis”. In this study I will refer to the latter definition with the abbreviation of PH.

Figure 2

Hormesis as the dose-response model



Note. The inverted “U-curve” (A) and “J-curve” (B). Reprinted from “The Maturing of Hormesis as a Credible Dose-Response Model”, by E. J. Calabrese, *Nonlinearity in Biology, Toxicology, and Medicine*, *1*(3), 321. Copyright 2003 by Calabrese, E. J.

2.1.3 Psychological Hormesis

PH occurs throughout the lifespan of individuals, ranging from childhood to late adulthood, with curvilinear effects (Oshri, 2023) and can, according to Hill et al. (2024), manifest itself in: eustress and distress, psychological momentum, emotion regulation, motivation and confidence, and cognitive performance.

2.1.3.1 Eustress and distress

The reaction to a stressor depends on how relevant it is for the person in question, and second, whether the stressor could be handled at all. If the latter is the case, then the stressor is beneficial because it is interpreted as a challenge. If a person is not able to cope with the stressor than it is being perceived as a threat (e.g., Kyriazis et al., 2024).

2.1.3.2 Psychological momentum

People can increase their effort, such as in a sports game or training when the stress dose has increased. For example, when cyclists start lagging behind in a competitive race, this setback may trigger increased efforts (e.g., Perreault et al., 1998; Briki et al., 2013). However, when they have fallen too far behind or they are too much in front, they typically decrease their effort.

2.1.3.3 Emotion regulation

Emotions such as anxiety helps in increasing performance by focusing more on the task at hand. In a so-called state of flow (Csikszentmihalyi, 2014), people perform and feel better in any task depending how much the task difficulty aligns with the capacity of the individual. For instance, when a person enjoys playing piano, he or she performs better at it when the piece of music is difficult (e.g., de Manzano et al., 2010). However, when the piece of music becomes more difficult to play as a result of social pressure, and hence anxiousness, this can lead to impaired performance (e.g., Yoshie et al., 2009).

2.1.3.4 Motivation

People strive to achieve goals. When goals are in reach the will to act increases, but unrealistic goals or goals that are too challenging can diminish effort. For example, a student that is not able to muster enough motivation to study for an exam because the subject is perceived to be too difficult (e.g., van Lent, 2019). Hence, the student lacks the competency to be motivated. However, students will increase their effort to study when they experience more self-confidence in their study abilities because of an increase in skills (e.g., Ruiz-Gallardo et al., 2013), and thus the stressor (e.g., school tasks or exams) is more in line with their improved skills.

2.1.3.5 Cognitive performance

Cognitive processes such as 1) vision, 2) impulse regulation, and 3) memory are enhanced when a moderately dosed stressor is present. First, focused attention (i.e., concentrating on a specific stimuli) and selective attention (i.e., filtering out competing stimuli), can be enhanced while people experience psychological stress (e.g., time pressure or evaluating peer performance) as observed in improved performance in tests such as the "Rapid Serial Visual Processing" (Shapiro et al., 1997) and "Stroop" (e.g., Trenerry et al., 1989) (Momin et al., 2020). However, too much or prolonged psychological stress impairs the ability to process visual information (e.g., Singh & Sunny, 2017) or can cause vision loss (e.g., Sabel et al., 2018). Second, problematic behavior as a consequence of stress gets more regulated if the cause was not too severe. For example, Oshri et al. (2024) found that when adolescents grow up, experiencing threats, deprivation, and unpredictable or chaotic behavior at home, are associated with internalizing- and externalizing problem behavior. For example, being unhappy and destructive against the environment respectively. However, low- to moderate levels of these stressors were associated with less problematic behavior. Third, when learning a new task that is challenging can enhance memory. For instance, learning to ride a motorcycle one has to perform several tasks simultaneously, such as maintaining balance, shifting gears, and operate the clutch. Repeating these tasks will result in an improved riding ability because one has stored the necessary information in the brain (Vaughn et al., 2021). However, suddenly experiencing a high dosed stress during learning, such as experiencing a (non)-lethal traffic accident impairs memorizing these tasks (Iverson et al., 2008).

Taken together, PH can be observed in various ways among male and female individuals in different stages of their lives, when they are exposed to moderately doses stress. Experiencing too much stress will result in detrimental effects. However, what an appropriate stress dose includes remains yet unknown.

2.2 Current challenges and research aim

The hormesis framework teaches us that a certain stress dose (i.e., low- to moderate) has beneficial effects on human performance, but it remains unclear what this stress dose exactly entails. To overcome this, we need to formulate mechanisms which describe how a specific stressor can lead to hormetic effects as argued by Oshri (2023). Second, I argue that it is ethically undesirable to put people deliberately in danger for observing how stress can help people grow psychologically. A promising alternative is the use observational data stemming from a fairly controlled environment in which people are willingly exposed to everyday life stress such as in sports. Third, enough data needs to be collected for observing growing from stress because it takes time to develop (Hill et al., 2024). For example, if one follows a person over a long time then yearly data could be enough. If data is sampled within a shorter time frame such as within a year, weekly data results in more precision. Fourth, for understanding how people might react to stress in the future, it is worthwhile to investigate how people respond to different stressor types and time windows (i.e., dose response profiles; Hill et al., 2024). I therefore aim to answer the following research questions within the context of a longitudinal observational study of six months with multiple measurements per week, because then should we be able to capture PH:

1. *How can we quantify PH?*
2. *How can we identify latent PH classes and how do they evolve over time, so called latent PH trajectories?*
3. *How can we classify latent PH trajectories?*

Insights into these questions provide knowledge in detecting how much stress is beneficial for developing PH, whether we can observe PH due to everyday life stress, and how PH varies over time as a result of specific stressors. To my knowledge, this paper presents the first attempt to combine the natural sciences with the social sciences in the quest for understanding PH. The implications of addressing these challenges would be a next step into comprehending of how and when people can psychologically grow when dealing with everyday life stress.

3 Method

3.1 Participants

Seventy Dutch adolescent rowers who train to become an elite (inter)national level were asked to participate in the study. The final sample consisted of 33 differently weighing male and female participants. The participants have trained roughly six times a week, which is a combination of indoor and outdoor training sessions. In addition, once in a while they completed a race. To ensure the anonymity of the sample, more detailed information is not provided.

3.2 Procedure

The sampling took place in a Dutch rower student club and the inclusion criteria were the best ergometer times. The sampling stopped if the sample consisted of a maximum of 48 participants. The data was collected from 18th of November 2024 until 6th of July 2025. Several training coaches of the club initiated a text message which were delivered on the smartphones of the participants asking to fill in a questionnaire, up to 30 minutes before and after the training sessions or races. The data was stored on an online private server hosted by the Rijksuniversiteit Groningen.

3.3 Measures

The first variable is *intensity* (INT). INT reflects the speed at which a rower has rowed during the indoor training sessions on a RP3 rowing machine (RP3, 2025). It is defined as:

$$INT = \frac{distance\ in\ meters}{time\ in\ seconds}. \tag{1.1}$$

I used speed as an indicator of stress because increasing the intensity of an exercise (such as rowing faster) relates to, among other things, an increasing heart rate and the buildup of lactic acid, which in turn leads to elevated stress levels (e.g., De Vries et al., 2000; Farrell et al., 1983). It also tests a rower's mental ability by forcing him/herself to row faster than what is comfortable.

In addition, the rowers in this study were during the indoor training sessions exposed to four types of stress: 1) three sets of 20 minutes rowing, with five minutes intra-set rest performing at 21 strokes per minute; 2) four series of five minutes rowing with five minutes intra-set rest with 30 to 33 strokes per minute; 3) one set of completing 2000 meters as fast as possible; and 4) three sets of completing 1000 meters rowing as fast as possible with four minutes intra-set rest. These four types were part of the rowing training regime.

The second variable is *perceived exertion* (RPE; Borg, 1982; Brink et al., 2010). RPE asks "How hard was the training/match?" and was measured on a Category-Ratio Scale (CRS) ranging from 6 ("very, very light") to 20 ("very, very hard"). I used RPE as a measure for the subjective experience of INT.

3.4 Analyses plan

I only included observations from the indoor training sessions, which consisted of the four types of stress. This is because only during the indoor training sessions were the conditions (e.g. distance and time) accurately recorded. This resulted in $N_{INT} \wedge N_{RPE} = 561$ observations in total. Each rower provided approximately one measurement per variable per week.

Before I analysed the data, I needed to account for the possibility of missing data which was the first step. Missing data could occur because of technical problems or participant related reasons. For example, the former relates to failed registration of the rowed distance or time of completion, and the latter relates to the absence of a rower from a training or competition or an unanswered item (i.e., item non-response).

Regarding technical problems, when the rowed distance and the time of completion did not occur, I assumed Missing Completely At Random (MCAR). However, if the registration of distance and completion time always fail at certain goal distances, above 5000m for example, I treated these data as Missing At Random (MAR). Another technical problem could be the non-arrival of the text messages before and after a training for completing the questionnaire. I also treated this as MCAR.

Regarding participant related reasons, the md.pattern() function in the "mice" package in R (Version 3.16; van Buuren & Groothuis-Oudshoorn, 2011) was used for visualizing the missing data patterns. After exploring the missing data patterns, I aimed at imputing the missing values with an *Exponential Weighted Moving Average* (EWMA) time series imputation by using the na_ma() function in the “imputeTS” package (Version 3.3; Moritz et al., 2017). This function imputes a missing time series value by a weighted moving average by using *K* observations to the left and right of the missing time series values. I used in particular an *Exponential Weighted Moving Average* (EWMA). This means that observations which are adjacent to the missing value in time (i.e., *K* is set to “1”) have a weight of $\frac{1}{2}^{1}$, when K is set to “2” the weight becomes $\frac{1}{2}^{2}$, et cetera.

3.4.1 Research aim 1: quantifying PH

Before I could quantify PH, I needed to determine when PH can occur in principle. Because three outcomes in INT and RPE are possible (i.e., an increase, stagnation, and decrease), this will result in nine combinations (Table 1).

Table 1

Possible mechanisms for PH considering two input variables

Nr	Condition	Outcome
1	If INT increases and RPE increases	PH depends on the relative change
2	If INT increases, but RPE stays the same	Growth
3	If INT increases and RPE decreases	Extreme growth
4	If INT stays the same, but RPE increases	Decay
5	If INT stays the same and RPE stays the same	Stagnation
6	If INT stays the same, but RPE decreases	Growth
7	If INT decreases, but RPE increases	Extreme decay
8	If INT decreases, but RPE stays the same	Decay
9	If INT decreases and RPE decreases	PH depends on the relative change

Subsequently, I propose that we quantify PH by comparing two states. In this study, I looked at a state of *experienced exertion*: a person underwent stress and subsequently this person interprets it. In other words, it is a variable which reflects the relationship between INT and RPE. From now on I will refer to “state” as an abbreviation of a state of experienced exertion. The idea is to scale each state in order to compare them. For example, the stressor of rowing 500 meters on measurement occasion *i* has a different influence than rowing 1000 meters on measurement occasion *i + 1*. If a person rowed 500 meters and perceived the exertion to be a “10”, then this state gets a value which is subtracted from the value from a previous state.

3.4.2 Research aim 2: identifying latent PH classes evolving over time

Reaching research goal 2 consisted of two sub steps: 1) identifying latent classes, and 2) modeling these classes over time.

1. *Identifying latent classes*

The identification of these latent classes was done according to the recommended procedure of Wardenaar (2022) by using the R-package *FlexMix* (Version 2.3-20; Leisch, 2004) with its stepFlexmix() function. The first step was fitting a *Latent Class Growth Analysis* (LCGA; e.g., de Vries et al., 2020). A LCGA can identify latent trajectories of variables in groups. The model that was derived from this LCGA was used as a baseline model because it assumes homogeneity of within-class variance over time, this is done by fixing the intercepts and slopes of the latent classes, which will therefore be the most constricted model.

However, heterogeneity of within-class variances over time is more plausible. I therefore used *Growth Mixture Models* (GMMs; Muthén, 2004) as well. This is because these models relax the assumption of homogeneity of within-class variance over time. The second and last step was therefore fitting a GMM to the data by only freeing the class-specific slopes. This is because I assumed that all rowers had the same starting values (i.e., $PH = 0$) during the beginning of the rowing season.

For determining which model was more appropriate, I evaluated the *Integrated Completed Likelihood* (ICL; Biernacki et al., 2000). Lower ICL values indicate better class optimizations and better model form (e.g., LCGA or GMM). In addition, I also visually inspected the fit of the models by the use of *rootograms* (Kleiber & Zeileis, 2016). Rootograms show the square root of the frequency of observations. In particular, these rootograms will show the distribution of the observations who have a posterior non-zero probability of being assigned to a latent class. In other words, whether there is a good categorization or not (i.e., only a low- or high probability of being assigned to a latent class).

I chose the model and its identified number of classes according to the lowest ICL, in combination with a clear distinction of being assigned to a latent class or not, as shown by the rootograms.

2. *Evolution of latent PH classes over time*

For capturing the nature of the evolution of PH classes over time I fitted the LCGAs and the GMMs with linear- and nonlinear effects of time on PHI. In particular, a polynomial of the first, second, and third degree was used.

3.4.3 Research aim 3: classifying latent PH trajectories

Visualizations of the latent trajectories of the rowers within these identified latent classes helped me classifying them. In particular, I generated line charts because they are appropriate charts for showing changes over time (Kirk, 2019). Each latent trajectory was subsequently colored according to a set of rules derived using logic.

4 Results[1]

My research questions were: 1) how can we quantify PH? 2) how can we identify latent PH classes evolving over time? And 3) how can we classify these latent PH classes based on PHI trajectories?

4.1 Research question 1

I quantify PH via an index, which I call the *PHI*, and is defined as:

$$\Delta PH_{i,m} = \Delta SS_{i,m} * 100, \quad (2.1)$$

where $\Delta PH_{i,m}$ is the change in percentage of PH that occurred for person *i* on measurement occasion m. $\Delta SS_{i,m}$ is the relative difference of a scaled state of person *i* between measurement occasion m and m-1:

$$\Delta SS_{i,m} = SS(INT_{i,m}, RPE_{i,m}) - SS(INT_{i,m-1}, RPE_{i,m-1}) \quad (2.2)$$

$SS(INT_{i,m}, RPE_{i,m})$ is the scaled state which ranges from "-1" to "1" of person *i* on measurement occasion m:

$$\frac{S_{wn}(INT_{i,m}, RPE_{i,m})}{S_{wn}(INT_{max}, RPE_{min})}, \quad (2.3)$$

and $S_{wn}(INT_{max}, RPE_{min})$ is the most optimal possible state because it is the result of the highest possible intensity while experiencing the lowest amount of exertion. It is thus a reference condition. $S_{wn}(INT_{i,m}, RPE_{i,m})$ is the weighted normalized state and is defined as follows:

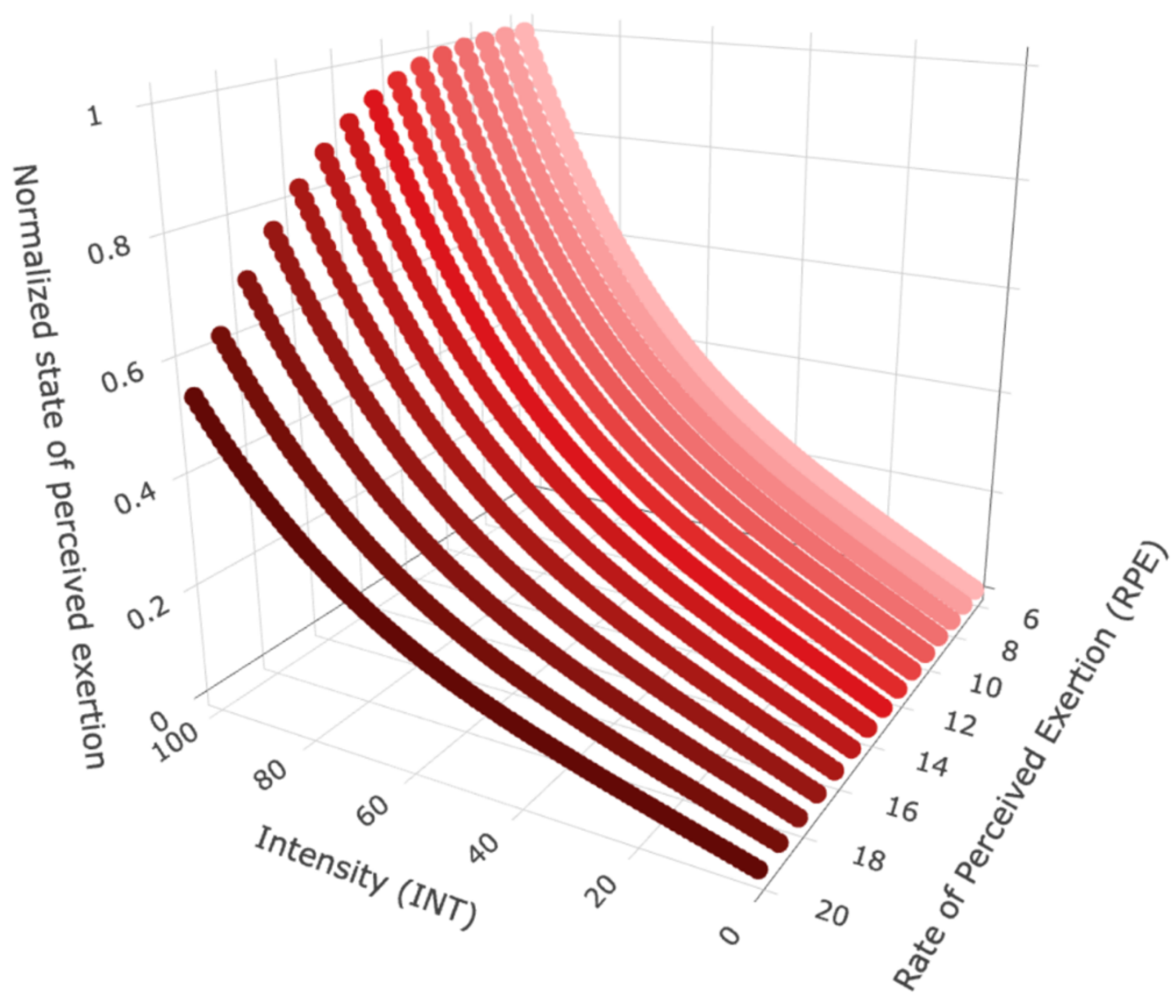
$$S_{wn}(INT_{i,m}, RPE_{i,m}) = \frac{\frac{INT_{i,m}}{INT_{max}} + (\frac{INT_{i,m}}{INT_{max}})^{\gamma}}{1 + e^{(\beta(\frac{RPE_{i,m} - RPE_{min}}{RPE_{max} - RPE_{min}})^{\omega_{RPE_{i,m}}}}} \quad (2.4)$$

[1] Before adjusting- and analyzing the data, I evaluated the missing data per subset for the entire dataset, which are three groups. I will from now on refer to these subsets as "category" or "group". For an overview of the amount of missing data per rower, see Appendix I. I imputed the missing RPE values for getting a sense of what the results might look like if RPE was completely observed. In addition, the univariate and bivariate descriptives of RPE and INT can be found in Appendix II.

γ is a weighted factor for INT, β influences the exponential growth at high RPE values, and e is Napier's constant. The denominator of $S_{wn}(INT_{i,m}, RPE_{i,m})$ will be higher if RPE increases which will lead to a lower value. For a graphical depiction of $S_{wn}(INT_{i,m}, RPE_{i,m})$, see Figure 2. $INT_{i,m}$ is relative because it is the product of the distance rowed divided by the INT_{max} which is a record of that particular distance for a given category. For an overview of all used records, see Table 6 in Appendix III. RPE is scaled according to a min-max normalization, which ensures that changes across the entire scale contribute equally.

Figure 2

The distribution S_{wn} with the parameter settings: $\gamma = 4;\ c = -1;\ \beta = 1;\ k = 2$



Last, $\omega_{RPE_{i,m}}$ is a logistic dynamic weighted function as defined as:

$$\omega_{RPE_{i,m}} = 1 + k\left(\frac{1}{1+e^{c\left(RPE_{i,m}-RPE_{min}\right)}}\right), \tag{2.5}$$

where k is a parameter that controls the weight, and c is a parameter which influences the steepness for the logistic transformation. The higher the RPE, the higher $\omega_{RPE_{i,m}}$ will be.

I chose these parameter settings because it resulted in a function that makes theoretically and empirically sense. For example, a change in intensity from 90% to 95% is more difficult than a change from 85% to 90%. This is standard fare in training physiology (e.g., Sietsema., et al., 2021) and therefore a γ of "4" is chosen. It makes intuitively sense to weigh changes at the lower end of the RPE scale more than at the higher end of the scale. This is because interpreting a RPE change of "7" to "6" indicates more growth than a change of "20" to "19"[2]. Last, the particular settings of c and k are chosen because it visually reflects how I perceive the distribution of all possible $S_{wn}\left(INT_{i,m}, RPE_{i,m}\right)$ values should look like. Small deviations from these parameter settings would have led to a distinct or non-sensible function.

For calculating the PHI, I used the following algorithm:

1. Start at the second measurement occasion in the rowing season for the first rower;
2. Check whether RPE is observed:
    a. If yes: search backward to find the last previous measurement occasion for the same rower with an observed RPE value;
        i. If such a measurement occasion exists:
            1. Calculate $\Delta PH_{i,m}$;

[2] However, it is empirically impossible to detect RPE changes at the lower end of this RPE scale at higher intensities. For example, it is very unlikely that a world record holder in rowing breaks his or her own record by saying that the exertion of the improvement was very low, such as a "7". On the other hand, it is far more likely that this world record holder would report a "19". I therefore chose to weigh higher RPE values more than lower RPE values and at the same time restricting the distribution to a maximum of "1", hence the logistic dynamic weighted function.

        2. Add this PHI value cumulatively to the previously calculated PHI value (if observed); otherwise, use the new PHI as starting value;

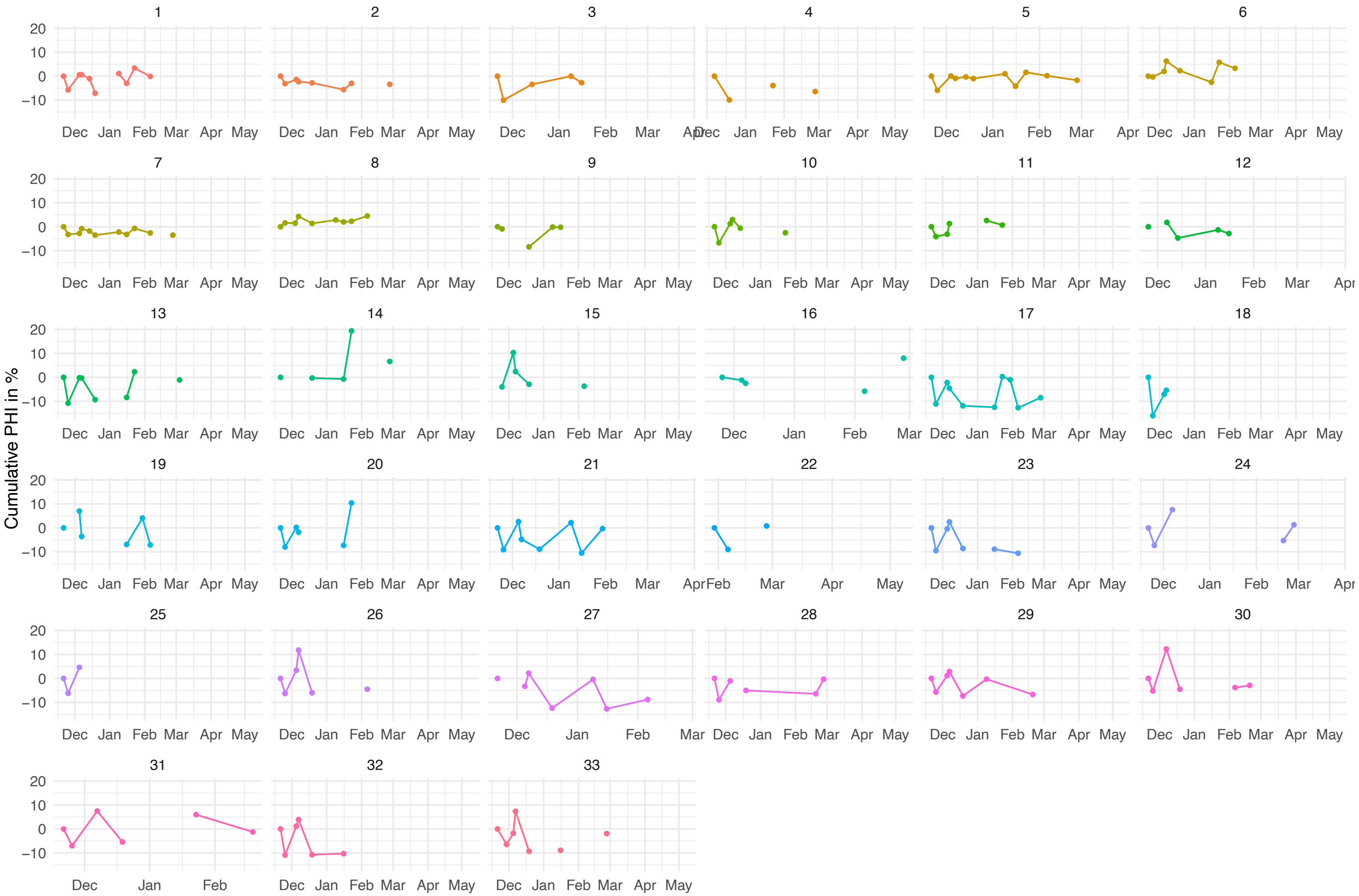
    b. If no: skip this measurement occasion;

3. Proceed to the next measurement occasion and repeat steps above;
4. Repeat step 1 to 3 for the remaining rowers.

For an overview of the PH trajectories based on the PHI, see Figure 3.

Figure 3

Psychological Hormesis over time across the whole sample



4.2 Research question 2

Table 2 shows the results of the executed LCGAs and GMMs. Despite the good categorization as shown in the rootograms, the ICL and the sample size per class suggests that one latent class with fixed intercepts but random slopes is the optimal and most plausible solution. This means that there is an average linear growth in PHI quantified by a fixed PHI intercept and a fixed slope with normally distributed variance around it. The latter explains the between-subject heterogeneity of PHI over time.

Table 2

Results of the LCGA and GMM with PHI as the dependent variable and the measurement occasion as the independent variable

No. of classes	*ICL*	*Sample Size per Class Based on Most Likely Class Membership*
LCGA (linear)		
1	1317.161	33
2	1327.846	30/3
3	1348.093	26/4/3
LCGA (quadratic)		
1	1322.469	33
2	1338.566	30/3
3	1365.535	25/5/3
LCGA (cubic)		
1	1327.485	33
2	1348.150	30/3
3	1381.533	24/6/3
GMM (linear)		
1	1315.514	33
2	1338.574	30/3
3	1364.532	26/4/3
GMM (quadratic)		
1	1338.576	33
2	1370.799	33/3
3	1413.949	25/5/3
GMM (cubic)		
1	1359.696	33
3	1412.576	30/3
3	1477.798	24/6/3

Note. Every performed LCGA and GMM with the estimated classes were executed with 300 random starts. The variance of the slopes is freely estimated whereas the residual variances are fixed.

In addition, I investigated whether different class solutions exist between the non-RPE imputed dataset and the RPE imputed dataset. The optimal solution while using the

RPE imputed dataset is a two class GMM which evolve linear over time. There is a group of rowers who show, on average, stronger PH than the other group (Appendix III).

4.3 Research question 3

I used graphs and a set of rules for classifying the latent trajectories. The first rule states that, when a certain stressor type is induced, I consider it to be the reference point $PHI_{t_0}|stressor$, where *t* stands for time point with lower subscript “0”. When future PH values change over time: $PHI|stressor_{t_1}$ to $PHI|stressor_{t_{...}}$, $PHI|stressor_{t_N}$, where subscript t_N indicates the last observed PHI value, they are interpreted relatively to PHI_{t_0}. The second rule states that the nature of the PHI trajectory (e.g., growth) is determined by the last observed PHI value given the stressor type. For growth (*positive* adaptation) it holds that:

$$PHI_{growth}|stressor = PHI_{t_N} > PHI_{t_0},$$

whereas for decay (*negative* adaptation):

$$PHI_{decay}|stressor = PHI_{t_N} < PHI_{t_0},$$

and for constant (*no* adaptation):

$$PHI_{constant}|stressor = PHI_{t_N} \approx PHI_{t_0}.$$

The third rule says that the nature of the response (i.e., positive or negative) and the speed of the response (i.e., fast or slow) is determined by the difference between the first observed PHI value directly after the reference point. It holds for a *fast* response:

$$PHI_{fast}|stressor = PHI_{t_1} > PHI_{t_0},$$

for a *slow* response:

$$PHI_{low}|stressor = PHI_{t_1} < PHI_{t_0},$$

And for an *insensitive* response:

$$PHI_{insensitive}|stressor = PHI_{t_1} \approx PHI_{t_0}.$$

These rules lead to three (growth or decay or constant) times three (fast or slow or insensitive response) combinations. I identified in total five latent trajectories across the whole sample, which I will subsequently discuss while focusing only on the 3x20 (Figure 4) and 4x5 minutes stressor (Figure 5) for the sake of parsimony.

The first latent trajectory is *Constant (with an insensitive response)*. Rowers who have this trajectory did not grow when they were exposed to a particular stressor type. This is probably because there were only two observed PHI values which masks the trajectory.

The second latent trajectory is *Decay with a fast response*. It can be said that, despite that rowers who responded directly positive after being exposed to a certain stressor type, these rowers did not grow. This pattern indicates that the second time the rowers experienced a stressor which was properly dosed, whereas the resulting experienced stressors were too high dosed.

The third trajectory is *Decay with a slow response*. The direct response to the induced stressor type is negative, but when time increases, the response to the resulting stressors tends to orient in the direction of the reference point or exceeds it: $PHI_{t_N} \approx PHI_{t_0} \wedge PHI_{t_N} > PHI_{t_0}$. This pattern indicates that the stressor dose was in the beginning too high for these rowers, but the resulting stressor doses were better dosed. Nevertheless, this trajectory resulted in decay at the end. I expect that growth could have taken place for these rowers given that they have had more time and were exposed with the appropriate stress doses (i.e., the stress doses which resulted in the positively oriented change of the trajectory).

Figure 4

Classified latent PH trajectories across the whole sample given the 3x20 minutes stressor

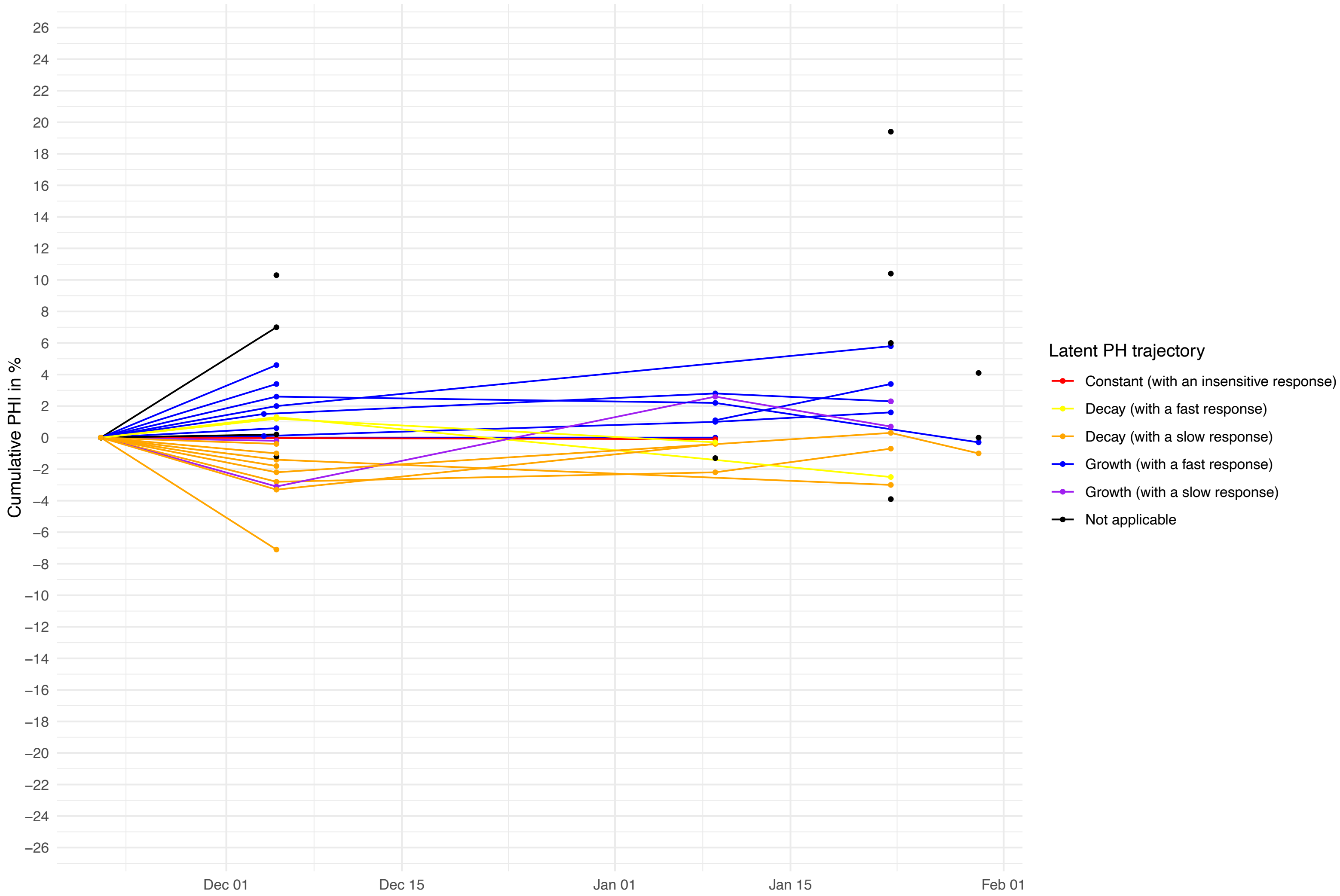
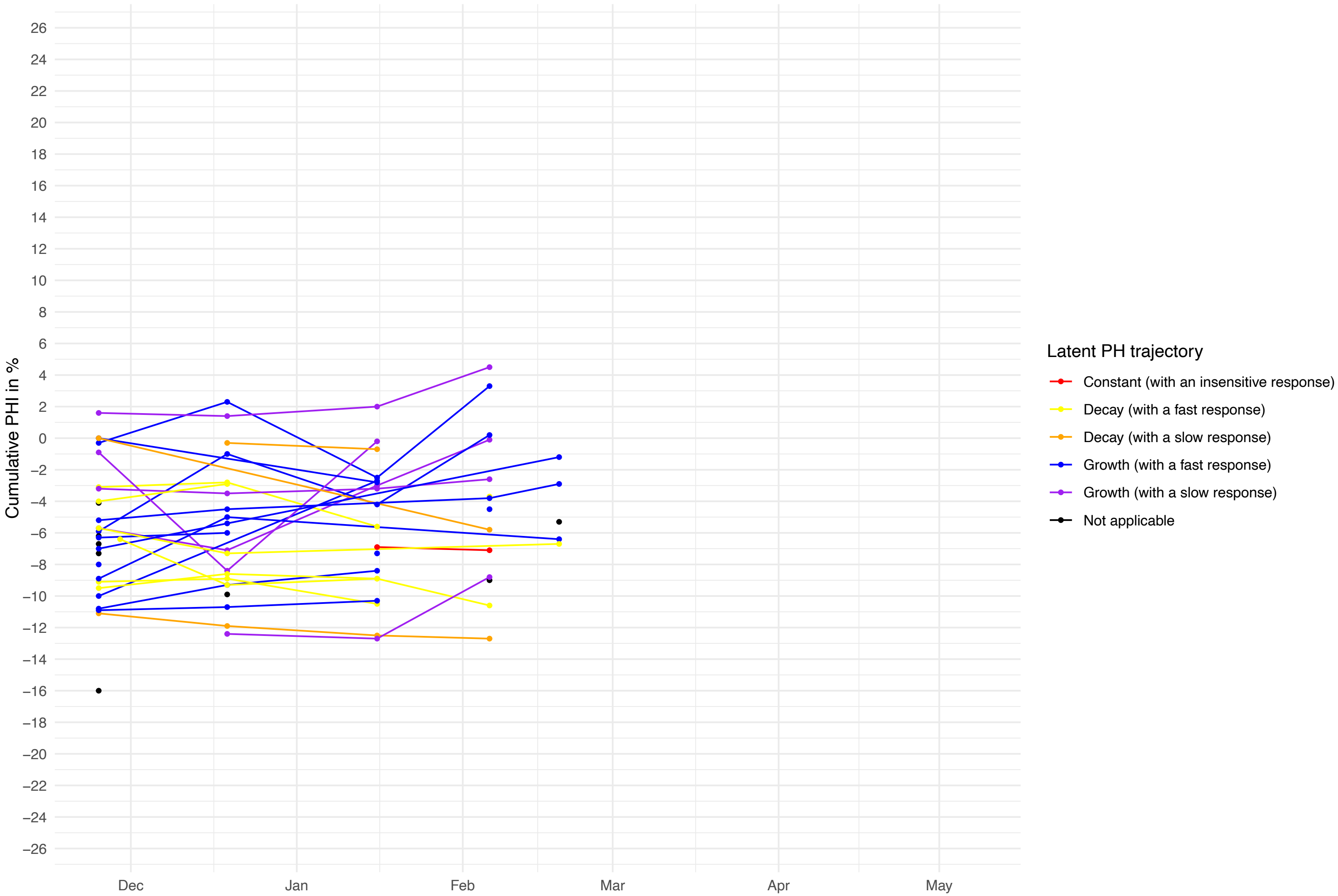


Figure 5

Classified latent PH trajectories across the whole sample given the 4x5 minutes stressor



The fourth trajectory is *Growth with a fast response*. The direct response to the induced stressor type is positive $PHI_{t_1} > PHI_{t_0}$ and when time increases growth continued and ended in growth $PHI_{t_N} > PHI_{t_0}$. This means informally, rowers with such a trajectory experienced a properly dosed stressor throughout the whole stressor type time period and could therefore grow.

The fifth trajectory is *Growth with a slow response*. The response directly after the first exposure to the certain stressor type is negative, but when time increases, the resulting PHI values are positive relative to the reference point: $PHI_{t_{1+1},} PHI_{t_{1+\dots,}} PHI_{t_N} > PHI_{t_0}$. Such a trajectory indicates that certain rowers needed more time to adapt in order to grow compared to other rowers, or that the stressor dose was first too high for them and the resulting stressor doses were better dosed which eventually led to their growth.

The sixth and last identified latent trajectory is the rest category *Not Applicable*. This is not a trajectory because only one PHI value is observed.

5 Discussion

In this study I investigated how we can quantify PH, identify latent PH classes evolving over time, so called PH trajectories, and how we can classify these trajectories. I therefore used data from a Dutch student rowing club which provided approximately weekly measurements of stress and the subjective experience of it. The results show that by incorporating information of an objectively measured physical stressor and the subjective psychological experience of this stressor, we can quantify PH by comparing two psychological states, in particular states of experienced exertion, despite being possibly different. For instance, when a rower experienced an exertion of a 3x20 minutes stressor it is possible to compare this state with a state of experienced exertion of a 2k max stressor. In addition, it is now possible to follow persons in their everyday living and capture how they respond to stress, without putting people in an experimental design with potentially harmful situations.

Without imputed missing RPE values, I was not able to find sufficient evidence for different latent classes. This is in line with Kim (2020) who shows that sufficient sample size is needed to identify multiple latent classes which unfolds differently over time. I showed that we can identify and distinguish PH patterns over time with the use of logic. It seems that the response to the stressor at the moment when is introduced, determines approximately the outcome: growth or decay. For example, almost all of the rowers who responded positively, by the occurrence of a first positive PHI value, ended with growth at the end. The same can be said about the rowers who at first responded negatively, they tend to decay at the end. There are some exceptions however, rowers who first respond negatively, respond positively to the resulting stressors. In sum, these results suggest that growing from a stressor can be predicted by the beginning stage of PH.

5.1 Theoretical implications

This study has several important theoretical implications. First, the results show some of the four laws in strength training (Zatsiorsky et al., 2020) reflected in the PH.

Considering the univariate descriptives (Appendix II) it can be derived that, when the training season continued, INT has increased but RPE remained constant. This is because almost every individual INT time series contained a trend-stationary process and RPE a stationary process. The former means that the INT time series becomes stationary if the deterministic trend is removed. In other words, despite the increasing stress dose over time, growth can still be realized. However, I did not find strong evidence for concluding that RPE remained constant during the training season. It is thus yet unclear whether the rowers adapted according to the law of overload, but the results suggests that this might be the case.

Another finding is that frequently being exposed to a certain stressor increases the adaptability of a person to that stressor. This is indicated by the upward change in direction of the PHI of several rowers. In other words, the subjective experience of a stressor follows the law of accommodation.

The law of specificity is to a lesser extent visible in the results. If we look at the change in direction of the PHI trajectories, then it can be observed that the rowers respond differently to each of the four types of stressors in this study. In particular, the more intense the stressor is, the more variation there is in PH. This is in line with Oshri (2023), PH as a function of a stress dose takes a pyramid-shaped distribution, where changes in PH can occur easily “on the top” when the stress dose decreases or increases around that level. However, for some stressor types I could not calculate enough PHI values to detect sudden changes, if they would appear. This might falsify the idea that the law of specificity is applicable to PH.

The law of individualization is however clearly visible due to the variation in PHI patterns between rowers given that they are exposed to the same kind of stressor. Taken the law of specificity and individualizations together, the results show that the degree of PH is indeed person specific as argued by Kyriazis et al. (2024). In sum these findings underscore the usefulness of applying the laws of strength training to the hormesis framework for understanding and predicting PH.

Second, by using a scaled objectively measured stressor and briefly after the exposure asking people their perception of exertion of this stressor, it is therefore possible to overcome the problem of unreliable measures of PH. For instance, only relying on post-hoc subjective beliefs about whether the stressor has initiated PH (McFarland & Alvaro, 2000; Cho & Park, 2013; Gower et al., 2022). In addition, it was unclear whether a non-specific population can also grow from stress. For example, some literature focused on how military personnel and firefighters can grow after experiencing traumatic experiences (Habib et al., 2018), or how internalized- and externalized problematic behavior such as feeling unhappy and being destructive towards the environment respectively, are related to childhood stress experiences (Oshri et al., 2024). I used a sample that reflects a non-specific population (i.e., students) which executed weekly indoor rowing training session. Using the PHI, I have showed that a non-specific population can also grow from everyday life stress such as training in sports. In particular, PH seems to develop linear over time, as suggested by the LCGA and GMM output.

Third, by plotting PH over time, one can get a feeling of how much stress a person can handle at the moment and whether he or she eventually has grown or decayed. For example, if a person does not respond positively, this is might indicate that the stress dose for this particular person needs to be lowered at the upcoming occasion, or this person needs more time to adapt to it. In other words, by the use of the PHI, one can determine whether the experienced stressor dose was optimal or not (i.e., dose-response profiles; Hill et al., 2024).

Fourth, outcomes in the PHI are objective because of the explicitly stated mechanisms which determine the PHI depending on the input. Therefore, one can objectively state whether a person has psychologically grown or not. This is in contrast to the development stages posed in PTG which are criticized to be inherently subjective (Marsh & Colangelo, 1983; Nelson, 1989; Harper et al., 2017; Schläppy, 2019).

Based on the results I conclude that this study highlights that, conceptualizing PH as a dynamic process that seems to evolve linear over time, is an improved alternative for considering PH as a static outcome (i.e., growth or mutagenesis; Calabrese, 2003). By using this alternative, we can detect outcomes such as growth, decay, or stagnation as indicated by PH trajectories. These outcomes depend on the dosage, timing, and sequencing of stress. The finding that the initial response, the first observed PHI value following exposure to a stressor, often predicts the eventual trajectory. This finding highlights the importance of early-phase reactions as potential indicators of longer-term adaptation. Furthermore, by considering PH as a cumulative process through the PHI algorithm, this study illustrates that growing from stress is the consequence of repeated and accumulated stressor exposures, rather than isolated events in which people experience stress as argued in PDT and PTG literature. Such refinements would render PH theory more dynamic and person-specific (Hill et al., 2024), aligning with recent literature to conceptualize resilience and adaptation as nonlinear processes unfolding over time (Oshri, 2023).

5.2 Limitations

This study has a few limitations. Completely observed RPE data is necessary to compute the PHI values of each rower. However, a lot of missing RPE data occurred after filtering on only indoor training sessions. Two problems occurred because of this. First, the plotted PHI trajectories do not show accurately how PH of all rowers has evolved over time. Second, the evolution of PH has prematurely stopped. This is because I assume that PH is a cumulative process. I addressed these problems by the following choices.

To see how all PH trajectories could look like if RPE was completely observed, I re-ran the analyses with imputed the missing PRE data via EWMA. However, EWMA neglects the influence of other variables, the nested structure of the person, and the effect of time on the RPE time series. This results in a biased estimate of the RPE time series and therefore a biased estimate of the PHI. Future research should address this issue of by incorporated missing data imputation techniques that can deal with 3D-data such as deep learning methods. These methods seem to perform substantial better in this context than conventional imputations methods (Kazijevs & Samad, 2023).

In order to deal with the premature stopping of the PHI evolution, I adjusted the algorithm behind the PHI for calculating more PHI values. I adjusted the algorithm by “jumping over” a missing PHI value to a subsequent observed PHI value and used that to compare it to the previous observed PHI value. For example, if rower *i* has an observed RPE value at measurement occasion two, not on three, but again at occasion four, the PHI value at this occasion is calculated by subtracting the difference between the observed state at occasion two and four. However, it might be the case that the PHI value at measurement occasion four is actually lower or higher than it should be if occasion three was observed and is therefore biased. In other words, this bias increases with every time step.

Last, I want to point out a few important notes about using the PHI for quantifying PH. First, the input of the PHI is arbitrary. For example, how much weight is used to weigh the stressor and which kind of psychological indicator is used in the denominator. The former can be addressed by the use of theory or logic, which I did in this study, but different options are possible. Still, the output will always be according to the chosen input which will result in reliable measuring PH. The latter is a question of what the main construct of interest is. For example, if one wants to know how people evolve in their perceived self-efficacy as a function of stress, one can use a variable that measures self-efficacy. Third, the input of the denominator in the PHI is a good measure for indicating the experienced difficulty of a stressor. However, it can be argued that incorporating more information such as adding more or different variables (e.g., physiological markers) can be beneficial. For example, Yoshie et al. (2009) used subjective measures of anxiety, heart rate, sweat rate, and electromyographic activity of muscles. Fourth, in this study I have used a stressor which is primarily physical which, in my view, was a good starting point for quantifying PH. For example, for studying whether repeatedly being exposed to social stress (e.g., letting students present several times during a course) can lead to PH (e.g., less presentation fear), we need to determine how we can quantify this sort of psychological stress. We also need to pay attention to the specific social stress because it has been argued that social stress is context dependent (Wood & Bhatnagar, 2015). In addition, we need to think of ways for properly scaling such a psychological stressor. Possible options are: 1) using the personal mean, 2) the mode, 3) the group mean (if one follows multiple students over time), the maximum value of a certain questionnaire (e.g., presentation fear questionnaire for students).

5.3 Conclusion and practical implications

I conclude that this study has showed that we can use observational data for studying whether a person has grown as a function of stress. This is useful because we can extend the use of the PHI with its algorithm and the rules to other domains than sports where people are frequently exposed to stress, such as at school or work. The information that will result from this can be used for better understanding when people can grow from stress in general. For instance, future research could follow a group of university bachelor students during their three-year studies and see whether these students develop PH. This is possible because during their studies they are repeatedly being exposed to several psychological stressors such as presenting, following practicals and performing exams. By letting these students fill in an RPE and psychological stress questionnaire that encompasses these stressors, we can follow their PH trajectories by using the PHI. In addition, this information could aid in helping people cope with stress in a healthy way, not only in the heat of the moment but also in the future. And maybe we can eventually confirm whether Nietzsche's statement from 150 years ago about getting stronger because of the things that hurt, but not kill us, is actually true (Nietzsche, 1889).

6 Literature

Bal, S., Van Oost, P., De Bourdeaudhuij, I., & Crombez, G. (2003). Avoidant coping as a mediator between self-reported sexual abuse and stress-related symptoms in adolescents. *Child Abuse & Neglect*, *27*(8), 883-897. https://doi.org/10.1016/S0145-2134(03)00137-6

Ball, K., & Lee, C. (2000). Relationships between psychological stress, coping and disordered eating: A review. *Psychology & Health*, *14*(6), 1007-1035. https://doi.org/10.1080/08870440008407364

Bathgate, K. E., Bagley, J. R., Jo, E., Talmadge, R. J., Tobias, I. S., Brown, L. E., Coburn, J. W., Arevalo, J. A., Segal, N. L., & Galpin, A. J. (2018). Muscle health and performance in monozygotic twins with 30 years of discordant exercise habits. *European Journal of Applied Physiology*, *118*, 2097-2110. https://doi.org/10.1007/s00421-018-3943-7

Biernacki, C., Celeux, G., & Govaert, G. (2000). Assessing a mixture model for clustering with the integrated completed likelihood. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *22*(7), 719-725. https://doi.org/10.1109/34.865189

Borg, G. A. V. (1982). Psychophysical bases of perceived exertion. *Medicine & Science in Sports & Exercise*, *14*(5), 377-381. https://doi.org/10.1249/00005768-198205000-00012

Briki, W., Den Hartigh, R. J. R., Markman, K. D., Micallef, J-P., & Gernigon, C. (2013). How psychological momentum changes in athletes during a sport competition. *Psychology of Sport and Exercise*, *14*(3), 389-396. https://doi.org/10.1016/j.psychsport.2012.11.009

Brink, M. S., Nederhof, E., Visscher, C., Schmikili, S. L., & Lemmink, K. A. P. M. (2010). Monitoring load, recovery, and performance in young elite soccer players. *Journal of Strength and Conditioning Research*, *24*(3), 597-603. https://doi.org/10.1519/JSC.0b013e3181c4d38b

Burnatowska, E., Surma, S., & Olszanecka-Glinianowicz, M. (2022). Relationships between Mental Health and Emotional Eating during the COVID-19 Pandemic: A Systematic Review. *Nutrients*, *14*(19), 3989. https://doi.org/10.3390/nu14193989

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, *45*(3), 1-67. https://doi.org/10.18637/jss.v045.i03

Cho, D., & Park, C. L. (2013). Growth following trauma: Overview and current status. *Terapia Psicológica*, *31*(1), 69-79. https://psycnet.apa.org/doi/10.4067/S0718-48082013000100007

Clarke, T. K., Nymberg, C., Schumann, G. (2012). Genetic and Environmental Determinants of Stress Responding. *Alcohol Research: current reviews*, *34*(4), 484-494.

Constantini, D., & Borremans, B. (2019). The linear no-threshold model is less realistic than threshold or hormesis-based models: An evolutionary perspective. *Chemico-Biological Interactions*, *301*, 26-33. https://doi.org/10.1016/j.cbi.2018.10.007

Craig, I. W. (2007). The importance of stress and genetic variation in human aggression. *BioEssays*, *2*(3), 227-236. https://doi.org/10.1002/bies.20538

Dee, G., Ryznar, R., & Dee, C. (2023). Epigenetic Changes Associated with Different Types of Stressors and Suicide. *Cells*, *12*(9), 1258. https://doi.org/10.3390/cells12091258

De Vries, W. R., Bernards, N. T., de Rooij, M. H., & Koppeschaar, H. P. (2000). Dynamic exercise discloses different time-related responses in stress hormones. *Psychosomatic Medicine*, *62*(6), 866-872.

Farrell, P. A., Garthwaite, T. L., & Gustafson, A. B. (1983). Plasma adrenocorticotropin and cortisol responses to submaximal and exhaustive exercise. *Journal of Applied Physiology*, *55*(5), 1441-1444.

Fernández, C. B-F., Lanza-León, P., & Cantarero-Prieto, D. (2023). A systematic review on suicide of social isolation/and loneliness: does COVID-19 make a difference? *Journal of Public Health*, *45*(3), 680-688. https://doi.org/10.1093/pubmed/fdad001

Flück, M., Kramer, M., Fitze, D. P., Kasper, S., Franchi., M. V., & Valdivieso, P. (2019). Cellular Aspects of Muscle Specialization Demonstrate Genotype – Phenotype Interaction Effects in Athletes. *Frontiers in Physiology*, *10*(526), 1-14. https://doi.org/10.3389/fphys.2019.00526

Folkman, S., & Moskowitz, J. T. (2004). Coping: Pitfalls and Promise. *Annual Review of Psychology*, *55*, 745-774. https://doi.org/10.1146/annurev.psych.55.090902.141456

Gibson, L. E., & Leitenberg, H. (2001). The impact of child sexual abuse and stigma on methods of coping with sexual assault among undergraduate women. *Child Abuse & Neglect*, *25*(10), 1343-1361. https://doi.org/10.1016/S0145-2134(01)00279-4

Gower, T., Pham, J., Jouriles, E. N., Rosenfield, D., & Bowen, H. J. (2022). Cognitive biases in perceptions of posttraumatic growth: A systematic review and meta-analysis. *Clinical Psychology Review*, *94*(102159). https://doi.org/10.1016/j.cpr.2022.102159

Habib, A., Stevelink, S. A. M., Greenberg, N., & Wiliamson, V. (2018). Post-traumatic growth in (ex-) military personnel: review and qualitative synthesis. *Occupational Medicine*, *68*(9), 617-625. https://doi.org/10.1093/occmed/kqy140

Harper, A., Cornish, L., Smith, S., & Merrotsy, P. (2017). Through the Dabrowksi Lens: A Frensh Examination of the Theory of Positive Disintegration. *Roeper Review*, *39*, 37-43. https://doi.org/10.1080/02783193.2016.1247395

Henson, C., Truchot, D., & Canevello, A. (2021). What promotes post traumatic growth? A systematic review. *European Journal of Trauma & Dissociation*, *5*(4), 100195. https://doi.org/10.1016/j.ejtd.2020.100195

Hopwood, H. J., Bellinger, P. M., Compton, H. R., Bourne, M. N., & Minahan, C. (2023). The Relevance of Muscle Fiber Type to Physical Characteristics and Performance in Team-Sport Athletes. *International Journal of Sports Physiology and Performance*, *18*(3), 223-230. https://doi.org/10.1123/ijspp.2022-0235

Hill, Y., Kiefer, A. W., Oudejans, R. R. D., Baetzner, A. S., & Den Hartigh, R. J. R. (2024). Adaptation to stressors: Hormesis as a framework for human performance. *New Ideas in Psychology*, *73*(101073). https://doi.org/10.1016/j.newideapsych.2024.101073

Infurna, F. J., & Jayawickreme, E. (2019). Fixing the Growth Illusion: New Directions for Research in Resilience and Posttraumatic Growth. *Current Directions in Psychological Science*, *28*(2), 152-158. https://doi.org/10.1177/0963721419827017

Iverson, G. L., Brooks, B. L., & Ashton, V. L. (2008). Cognitive Impairment Consequent to Motor Vehicle Collisions: Foundations for Clinical and Forensic Practice. In M. P. Duckworth, T. Iezzi, & W. T. O'Donohue (Eds.), *Motor Vehicle Collisions: Medical, Psychosocial and Legal Consequences* (pp. 243-309). Academic Press. https://doi.org/10.1016/B978-0-08-045048-3.00011-7

Jayawickreme, E., Infurna, F. J., Alajak, K., Blackie, L. E. R., Chopik, W. J., Chung, J. M., Dorfman, A., Fleeson, W., Forgeard, M. J. C., Frazier, P., Furr, R. M., Grossman, I., Heller, A. S., Laceulle, O. M., Lucas, R. E., Luhmann, M., Luong, G., Meijer, L., McLean, K. C., Park, C. L., Roepke, A. M., Sawaf, Z., Tennen, H., White, R. M. B., & Zonneveld, R. (2020). Post-traumatic growth as positive personality change: Challenges, opportunities, and recommendations. *Journal of Personality*, *89*(1), 145-165. https://doi.org/10.1111/jopy.12591

Kazijevs, M., & Samad, M. D. (2023). Deep imputation of missing values in time series health data: A review with benchmarking. *Journal of Biomedical Informatics*, *144*(104440), 1-18. https://doi.org/10.1016/j.jbi.2023.104440

Kendig, E. L., Le, H. H., & Belcher, S. M. (2010). Defining Hormesis: Evaluation of a Complex Concentration Response Phenomenon. *International Journal of Toxicology*, *29*(3),235-246. https://doi.org/10.1177/1091581810363012

Kim, S-Y. (2012). Sample Size Requirements in Single- and Multiphase Growth Mixture Models: A Monte Carle Simulation Study. *Structural Equation Modeling*, *19*, 457-476. https://doi.org/10.1080/10705511.2012.687672

Kim, H. H-s., & Jung, J. H. (2021). Social Isolation and Psychological Distress During the COVID-19 Pandemic: A Cross-National Analysis. *The Gerontologist*, *61*(1), 103-113. https://doi.org/10.1093/geront/gnaa168

Kirk, A. (2019). *Data Visualization* (2nd ed.). Sage.

Kleiber, C., & Zeileis, A. (2016). Visualizing Count Data Regressions Using Rootograms. *The American Statistician*, *70*(3), 296–303. https://doi.org/10.1080/00031305.2016.1173590

Knowles, K. A., & Tolin, D. F. (2022). Mechanisms of Action in Exposure Therapy. *Current Psychiatry Reports*, *24*, 861-869. https://doi.org/10.1007/s11920-022-01391-8

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root. *Journal of Econometrics*, *54*(1–3), 159–178. https://doi.org/10.1016/0304-4076(92)90104-Y

Kyriazis, M., Fontana, A., Jacob, U. M., Fritsch, T., & Calabrese, V. (2024). Are you feeling comfortable? – Measuring clinical hormesis. *Translational Medicine of Aging*, *8*, 33-38. https://doi.org/10.1016/j.tma.2024.08.001

Leisch, F. (2004). FlexMix: A General Framework for Finite Mixture Models and Latent Class Regression in R. *Journal of Statistical Software*, *11*(8), 1-18. https://doi.org/10.18637/jss.v011.i08

van Lent, M. (2019). Goal Setting, Information, and Goal Revision: A Field Experiment. *German Economic Review*, *20*(4), e949-e972. https://doi.org/10.1111/geer.12199

Loades, M. E., Chatburn, E., Higson-Sweeney, N., Reynolds, S., Shafran, R., Brigden, A., Linney, C., McManus, M. N., Borwick, C., & Crawley, E. (2020). Rapid Systematic Review: The Impact of Social isolation and Loneliness on the Mental health of children and Adolescents in the context of COVID-19. *Journal of the American Academy of Child & Adolescent Psychiatry*, *59*(11), 1218-1239.e3. https://doi.org/10.1016/j.jaac.2020.05.009

de Manzano, O., Theorell, T., & Harmat, L. (2010). The Psychophysiology of Flow During Piano Playing. *Emotion*, *10*(3), 301–311. https://doi.org/10.1037/a0018432

Mangelsdorf, J., Eid, M., & Luhmann, M. (2019). Does growth require suffering? A systematic review and meta-analysis on genuine posttraumatic and postecstatic growth. *Psychological Bulletin*, *145*(3), 302–338. https://doi.org/10.1037/bul0000173

Marsh, C. S., & Colangelo, N. (1983). The application of Dabrowski's concept of multilevelness to Allport's concept of unity. *Counseling and Values*, *27*(4), 213–228. https://doi.org/10.1002/j.2161-007X.1983.tb01137.x

McFarland, C., & Alvaro, C. (2000). The impact of motivation on temporal comparisons: Coping with traumatic events by perceiving personal growth. *Journal of Personality and Social Psychology*, *79*(3), 327–343. https://doi.org/10.1037/0022-3514.79.3.327

Mendaglio, S., & Tillier, W. (2006). Dabrowski's Theory of Positive Disintegration and Giftedness: Overexcitability Research Findings. *Journal for the Education of the Gifted*, *30*(1), 68-87. https://doi.org/10.1177/016235320603000104

Meyerson, D. A., Grant, K. E., Carter, J. S., & Kilmer, R. P. (2011). Posttraumatic growth among children and adolescents: A systematic review. *Clinical Psychology Review*, *31*(6), 949-964. https://doi.org/10.1016/j.cpr.2011.06.003

Csikszentmihalyi, M. (2014). *The Collected Works of Mihaly Csikszentmihaly*. Springer.

Moore, D. S. (2016). Behavioral epigenetics. *WIREs Mechanisms of Disease*, *9*(1), e1333. https://doi.org/10.1002/wsbm.1333

Momin, A., Bhattacharya, S., Sanyal, S., & Chakraborty, P. (2020). Visual Attention, Mental Stress and Gender: A Study Using Physiological Signals. *IEEE Access*, *8*, 165973-165988. https://doi.org/10.1109/ACCESS.2020.3022727

Moritz, S., & Vartz-Beielstein, T. (2017). imputeTS: Time Series Missing Value Imputation in R (Version 3.3) R]. CRAN. https://cran.r-project.org/web/packages/imputeTS/index.html

Nelson, K. C. (1989). Dabrowski's Theory of Positive Disintegration. *Advanced Development Journal*, *1*, 1-14.

Nietzsche, F. (1889). *Götzen-Dämmerung oder Wie man mit dem Hammer philosophirt*.

Oshri, A., Cui, Z., Carvalho, C., & Liu, S. (2022). Is perceived stress linked to enhanced cognitive functioning and reduced risk for psychopathology? Testing the hormesis hypothesis. *Psychiatry Research*, *314*, 114644.

Oshri, A. (2023). The Hormesis Model for Building Resilience Through Adversity: Attention to Mechanism in Developmental Context. *Review of General Psychology*, *27*(3), 245-259. https://doi.org/10.1177/10892680221142020

Oshri, A., Howard, C. J., Zhang, L., Reck, A., Cui, Z., Liu, S., Duprey, E., Evans, A. I., Azarmehr, R., & Geier, C. F. (2024). Strengthening through adversity: The hormesis model in developmental psychopathology. *Development and Psychopathology*, *36*, 2390-2406. https://doi.org/ https://doi.org/10.1017/S0954579424000427

Palumbo, S., Mariotti, V., Iofrida, C., & Pellegrini, S. (2018). Genes and Aggressive Behavior: Epigenetic Mechanisms Underlying Individual Susceptibility to Aversive Environments. *Frontiers in Behavioral Neuroscience*, *12*(117). https://doi.org/10.3389/fnbeh.2018.00117

Park, C., Rosenblat, J. D., Brietzke, E., Pan, Z., Lee, Y., Cao, B., Zuckerman, H., Kalantarova, A., & McIntyre, R. S. (2019). Stress, epigenetics and depression: A systematic review. *Neuroscience and Biobehavioral Reviews*, *102*, 139-152. https://doi.org/10.1016/j.neubiorev.2019.04.010

Pearson, K. (1896). Mathematical Contributions to the Theory of Evolution. III. Regression, Heredity and Panmixia. *Philosophical Transactions of the Royal Society of London*, *187*, 253-318.

Perreault, S., Vallerand, R. J., Montgomery, D., & Provencher, P. (1998). Coming from Behind: On the Effect of Psychological Momentum on Sport Performance. *Journal of Sport and Exercise Psychology*, *20*(4), 421-436. https://doi.org/10.1123/jsep.20.4.421

Plomin, R. (1990). The Role of Inheritance in Behavior. *Science*, *248*(4952), 183-188. https://doi.org/10.1126/science.2183351

Plomin, R., Owen, M. J., & McGuffin, P. (1994). The Genetic Basis of Complex Human Behaviors. *Science*, *264*(5166), 1733-1739. https://doi.org/10.1126/science.8209254

R Core Team. (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing. https://www.R-project.org/

Richardson, D. C., & Dale, R. (2005). Looking to understand: the coupling between speakers' and listeners' eye movements and its relationship to discourse comprehension. *Cognitive Science*, *29*, 1045–1060. https://doi.org/10.1207/s15516709cog0000_29

Rohit, V., Yatan Pal Singh, B., & Shekhar, G. C. (2011). Gender differences in stress response: Role of developmental and biological determinants. *Industrial Psychiatry Journal*, *20*(1), 4-10. https://doi.org/10.4103/0972-6748.98407

RP3. (Assessed on 11th of May 2025). https://rp3rowing.com/

Ruiz-Gallardo, J-R., Verde, A., & Valdés, A. (2013). Garden-Based Learning: An Experience With "At Risk" Secondary Education Students. *The Journal of Environmental Education*. *44*(4), 252-270. https://doi.org/10.1080/00958964.2013.786669

Sabel, B. A., Wang, J., Cárdenas-Morales, L., Faiq, M., & Heim, C. (2018). Mental stress as a consequence and cause of vision loss: the dawn of psychosomatic ophthalmology for preventive and personalized medicine. *EPMA Journal*, *9*, 133-160. https://doi.org/10.1007/s13167-018-0136-8

Said E. Said, & Dickey, D. A. (1984). Testing for Unit Roots in Autoregressive-Moving Average Models of Unknown Order. *Biometrika*, *71*(3), 599–607. https://doi.org/10.2307/2336570

Schläppy M. L. (2019). Understanding Mental Health Through the Theory of Positive Disintegration: A Visual Aid. *Frontiers in psychology*, *10*, 1291. https://doi.org/10.3389/fpsyg.2019.01291

Schulz, C. T., Glatt, E. M., & Stamates, A. L. (2022). Risk factors associated with alcohol and drug use among bisexual women: A literature review. *Experimental Clinical Psychopharmacology*, *30*(5), 740-749. https://doi.org/10.1037/pha0000480

Schurr, T., Frajo-Apor, B., Pardeller, S., Plattner, B., Tutzer, F., Schmitt, A., Conca, A., Fronthaler, M., Haring, C., Holzner, B., Huber, M., Marksteiner, J., Miller, C., Perwanger, V., Pycha, R., Schmidt, M., Sperner-Unterweger, B., & Hofer, A. (2024). Overcoming times of crisis: unveiling coping strategies and mental health in a transational general population sample during and after the COVID-19 pandemic. *BMC Psychology*, *12*(493). https://doi.org/10.1186/s40359-024-02001-3

Sekhar, T. C., Sarvodaya, T., Bandna, G., & Kumar, K. S. (2019). Stress, Coping, and Immunologic Relevance An Empirical Review. *Journal of Medical Sciences*, *39*(3), 107-113. https://doi.org/10.4103/jmedsci.jmedsci_138_18

Selye, H. (1976). Stress without Distress. In Serban, G. (Ed.), *Psychopathology of Human Adaptation* (1st ed., pp. 137-146). Springer. https://doi.org/10.1007/978-1-4684-2238-2_9

Shapiro, K. L., Arnell, K. M., & Raymond, J. E. (1997). The attention blink. *Trends in Cognitive Sciences*, *1*(8), 291-296. https://doi.org/10.1016/s1364-6613(97)01094-2

Shapiro, D. L., & Levendosky, A. A. (1999). Adolescent survivors of childhood sexual abuse: The mediating role of attachment style and coping in psychological and interpersonal functioning. *Child abuse & neglect*, *23*(11), 1175-1191.

Sietsema, K. E., Sue, D. Y., Stringer, W. W., & Ward, S. A. (2021). Physiology of Exercise. In K. E. Sietsema., D. Y. Sue., W. W. Stringer., & S. A. Ward (Eds.), Wasserman & Whipp's principles of exercise testing and interpretation (6th ed.). Wolters Kluwer.

Singh, D., & Sunny, M. M. (2017). Emotion Induced Blindness Is More Sensitive to Changes in Arousal As Compared to Valence of the Emotional Distractor. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.01381

Stebbing, A. R. D. (1982). Hormesis – The stimulation of growth by low levels of inhibitors. *Science of The Total Environment*, *22*(3), 213-234. https://doi.org/10.1016/0048-9697(82)90066-3

Su, Y., Rao, W., Li, M., Caron, G., D'Arcy, C., & Meng, X. (2023). Prevalence of loneliness and social isolation among older adults during the COVID-19 pandemic: A systematic review and meta-analysis. *International Psychogeriatrics*, *35*(5), 229–241. https://doi.org/10.1017/S1041610222000199

Taylor, S. E., & Stanton, A. L. (2007). Coping resources, coping processes, and mental health. *Annual Review of Clinical Psychology*, *3*, 377-401. https://doi.org/10.1146/annurev.clinpsy.3.022806.091520

Tedeschi, R. G., & Calhoun, L. G. (1996). The Posttraumatic Growth Inventory: measuring the positive legacy of trauma. *Journal of traumatic stress*, *9*(3), 455–471. https://doi.org/10.1007/BF02103658

Thoits, P.A. (1982), Life stress, social support, and psychological vulnerability: Epidemiological considerations. *Journal of Community Psychology*, *10*(4), 341-362. https://doi.org/10.1002/1520-6629(198210)10:4<341::AID-JCOP2290100406>3.0.CO;2-J

Trapletti, A., Hornik, K., & LeBaron, B. (2024). Time Series Analysis and Computational Finance (Version 0.10-57) R package]. CRAN. https://cran.r-project.org/web/packages/tseries/index.html

Trenerry, M. R., Crosson, B. A., DeBoe, J., & Leber, W. R. (1989). *Stroop neuropsychological screening test*. Psychological Assessment Resources.

Ulloa, E., Guzman, M. L., Salazar, M., & Cala, C. (2016). Posttraumatic Growth and Sexual Violence: A Literature Review. *Journal of Aggression, Maltreatment & Trauma*, *25*(3), 286-304. https://doi.org/10.1080/10926771.2015.1079286

Vaughn, D. A., Maggiora, M. B., Vaughn, K. J., Maggiora, C. J., Tavakoli, A-V., Liang, W., Zava, D., Cohen, M. S., & Lenartowicz, A. (2021). *Brain Research*, *1752*(147203). https://doi.org/10.1016/j.brainres.2020.147203

Wardenaar, K. J. (2022). Latent Class Growth Analysis and Growth Mixture Modeling using R: A tutorial for two R-packages and a comparison with Mplus.

Wood, S. K., & Bhatnagar, S. (2015). Resilience to the effects of social stress: Evidence from clinical and preclinical studies on the role of coping strategies. *Neurobiology of Stress*, *1*, 164-173. https://doi.org/10.1016/j.ynstr.2014.11.002

Yin, K., Feng, L., & Cheung, W. K. (2020). Context-Aware Time Series Imputation for Multi-Analyte Clinical Data. *Journal of Healthcare Informatics Research*, *4*, 411-426. https://doi.org/10.1007/s41666-020-00075-3

Yoshie, M., Kudo, K., Murakoshi, T., & Ohtsuki, T. (2009). Music performance anxiety in skilled pianists: effects of social-evaluative performance situation on subjective, autonomic, and electromyographic reactions. *Experimental Brain Research*, *199*, 117-126. https://doi.org/10.1007/s00221-009-1979-y

Zatsiorsky, V. M., Kraemer, W. J., & Fry, A. C. (2020). *Science and Practice of Strength Training* (3rd ed.). Human Kinetics.

Zimmer-Gembeck, M.J. and Skinner, E.A. (2016). The Development of Coping: Implications for Psychopathology and Resilience. In D. Cicchetti (Ed.), *Developmental Psychopathology* (3rd ed., pp. 1-61). John Wiley & Sons, Inc. https://doi.org/10.1002/9781119125556.devpsy410

Xiaoli, W., Kaminga, A., Wenjie, D., Jing, D., Zhipeng, W., Xiongfeng, P., & Aizhong, L. (2019). The prevalence of moderate-to-high posttraumatic growth: A Systematic review and meta-analysis. *Journal of Affective Disorders*, *243*, 408-415. https://doi.org/10.1016/j.jad.2018.09.023

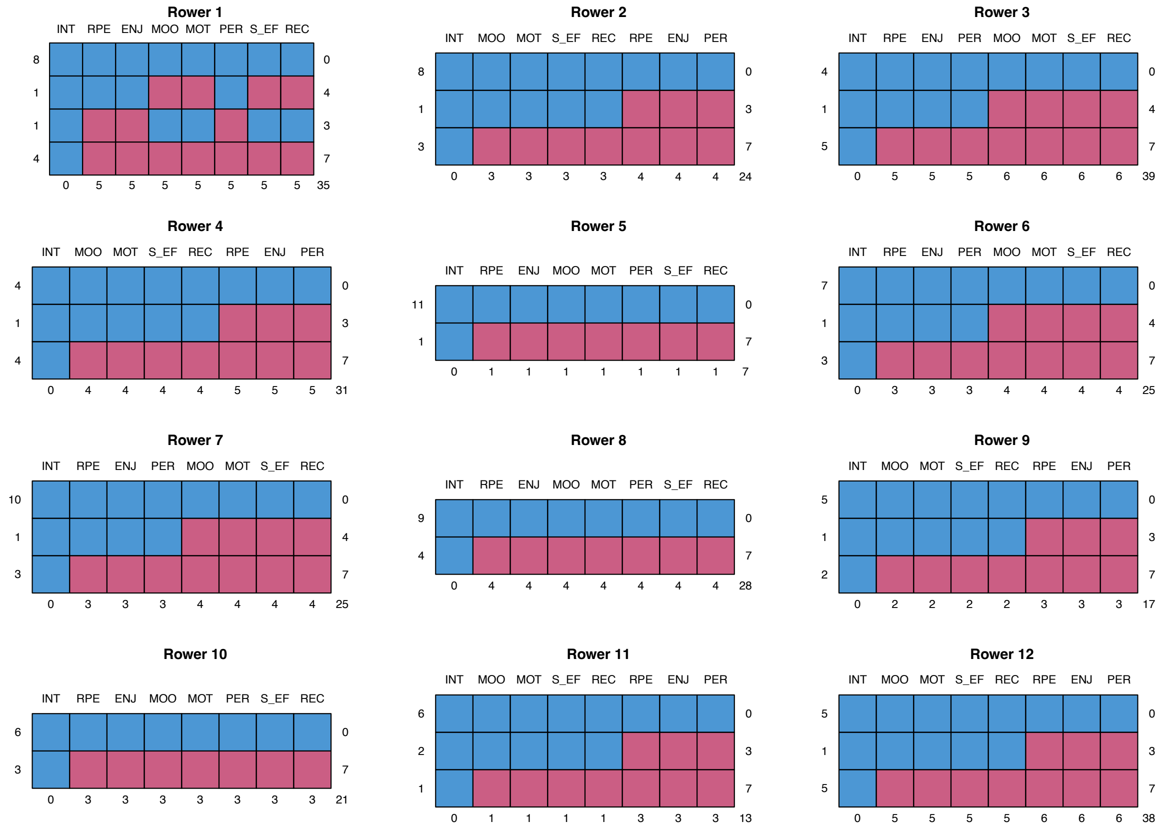
7 Appendix I: missing data

Amount of missing data after filtering on indoor training sessions

		Up to 30 min before				Up to 30 min after		
Rower	Total	REC	Self-Efficacy	Motivation	Mood	Performance	RPE	Enjoyment
	N (P)	*N* (P)	*N* (P)	*N* (P)	*N* (P)	*N* (P)	*N* (P)	*N* (P)
1	105 (.33)	15 (.33)	15 (.33)	15 (.33)	15 (.33)	15 (.33)	15 (.33)	15 (.33)
2	84 (.29)	12 (.25)	12 (.25)	12 (.25)	12 (.25)	12 (.33)	12 (.33)	12 (.33)
3	70 (.56)	10 (.60)	10 (.60)	10 (.60)	10 (.60)	10 (.50)	10 (.50)	10 (.50)
4	63 (.49)	9 (.44)	9 (.44)	9 (.44)	9 (.44)	9 (.56)	9 (.56)	9 (.56)
5	84 (.08)	12 (.08)	12 (.08)	12 (.08)	12 (.08)	12 (.08)	12 (.08)	12 (.08)
6	77 (.32)	11 (.36)	11 (.36)	11 (.36)	11 (.36)	11 (.27)	11 (.27)	11 (.27)
7	98 (.26)	14 (.29)	14 (.29)	14 (.29)	14 (.29)	14 (.21)	14 (.21)	14 (.21)
8	91 (.31)	13 (.31)	13 (.31)	13 (.31)	13 (.31)	13 (.31)	13 (.31)	13 (.31)
9	56 (.30)	8 (.25)	8 (.25)	8 (.25)	8 (.25)	8 (.38)	8 (.38)	8 (.38)
10	63 (.33)	9 (.33)	9 (.33)	9 (.33)	9 (.33)	9 (.33)	9 (.33)	9 (.33)
11	63 (.21)	9 (.11)	9 (.11)	9 (.11)	9 (.11)	9 (.33)	9 (.33)	9 (.33)
12	77 (.49)	11 (.45)	11 (.45)	11 (.45)	11 (.45)	11 (.55)	11 (.55)	11 (.55)
13	91 (.38)	13 (.38)	13 (.38)	13 (.38)	13 (.38)	13 (.38)	13 (.38)	13 (.38)
14	84 (.49)	12 (.42)	12 (.42)	12 (.42)	12 (.42)	12 (.58)	12 (.58)	12 (.58)
15	91 (.41)	13 (.31)	13 (.31)	13 (.31)	13 (.31)	13 (.54)	13 (.54)	13 (.54)
16	56 (.32)	8 (.38)	8 (.38)	8 (.38)	8 (.38)	8 (.25)	8 (.25)	8 (.25)
17	84 (.17)	12 (.17)	12 (.17)	12 (.17)	12 (.17)	12 (.17)	12 (.17)	12 (.17)
18	63 (.49)	9 (.44)	9 (.44)	9 (.44)	9 (.44)	9 (.56)	9 (.56)	9 (.56)
19	84 (.45)	12 (.42)	12 (.42)	12 (.42)	12 (.42)	12 (.50)	12 (.50)	12 (.50)
20	98 (.45)	14 (.36)	14 (.36)	14 (.36)	14 (.36)	14 (.57)	14 (.57)	14 (.57)
21	77 (.22)	11 (.18)	11 (.18)	11 (.18)	11 (.18)	11 (.27)	11 (.27)	11 (.27)
22	42 (.50)	6 (.50)	6 (.50)	6 (.50)	6 (.50)	6 (.50)	6 (.50)	6 (.50)
23	84 (.37)	12 (.33)	12 (.33)	12 (.33)	12 (.33)	12 (.42)	12 (.42)	12 (.42)
24	56 (.23)	8 (.12)	8 (.12)	8 (.12)	8 (.12)	8 (.38)	8 (.38)	8 (.38)
25	70 (.76)	10 (.80)	10 (.80)	10 (.80)	10 (.80)	10 (.70)	10 (.70)	10 (.70)
26	63 (.27)	9 (.22)	9 (.22)	9 (.22)	9 (.22)	9 (.33)	9 (.33)	9 (.33)
27	70 (.24)	10 (.20)	10 (.20)	10 (.20)	10 (.20)	10 (.30)	10 (.30)	10 (.30)
28	56 (.18)	8 (.12)	8 (.12)	8 (.12)	8 (.12)	8 (.25)	8 (.25)	8 (.25)
29	70 (.30)	10 (.30)	10 (.30)	10 (.30)	10 (.30)	10 (.30)	10 (.30)	10 (.30)
30	56 (.25)	8 (.25)	8 (.25)	8 (.25)	8 (.25)	8 (.25)	8 (.25)	8 (.25)
31	49 (.31)	7 (.43)	7 (.43)	7 (.43)	7 (.43)	7 (.14)	7 (.14)	7 (.14)
32	70 (.34)	10 (.30)	10 (.30)	10 (.30)	10 (.30)	10 (.40)	10 (.40)	10 (.40)
33	70 (.36)	10 (.40)	10 (.40)	10 (.40)	10 (.40)	10 (.30)	10 (.30)	10 (.30)

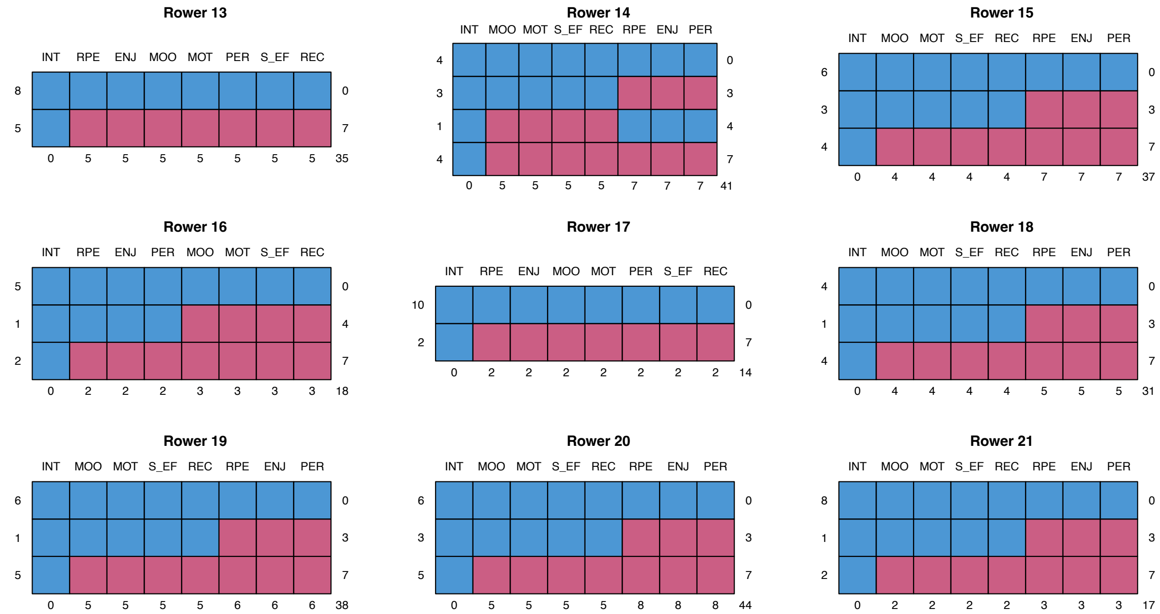
Note. *N* indicates the absolute number of observations including missing and observed values, whereas *P* indicates the proportion missing data per variable.

Missing data patterns of the first group after filter on indoor training sessions



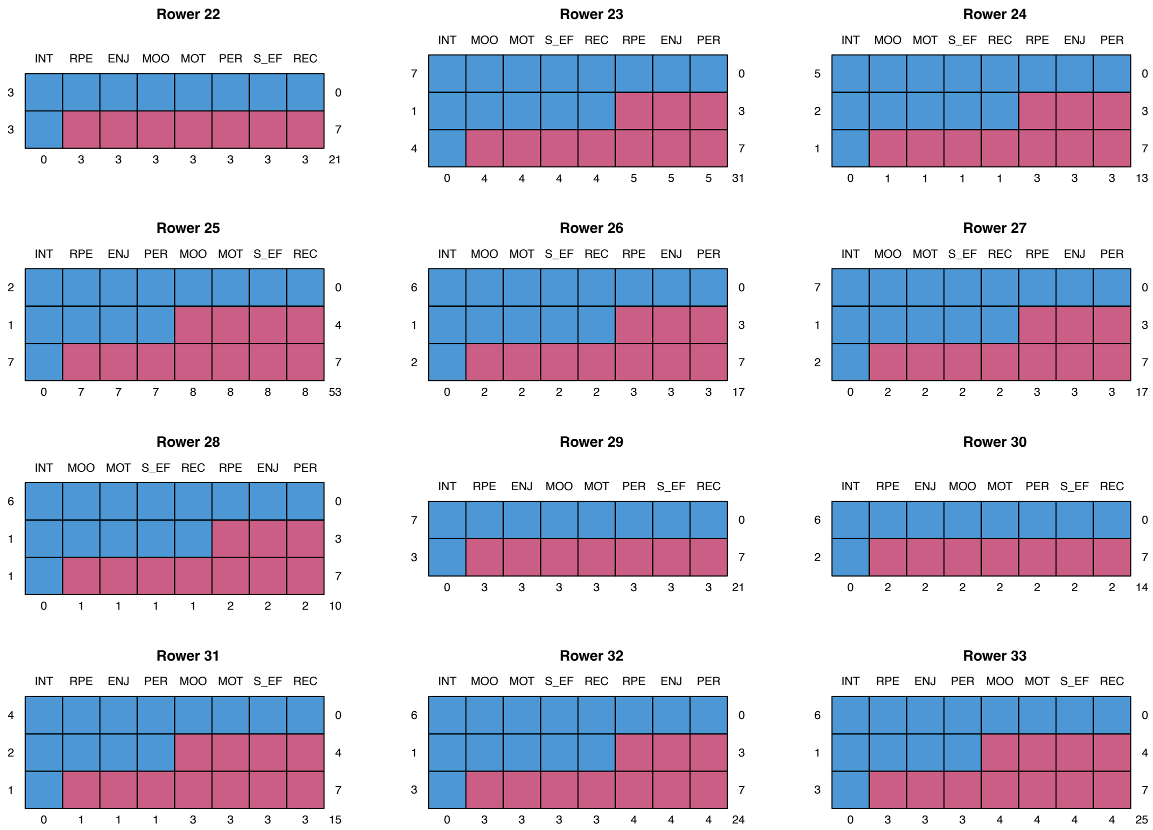
Note. "ENJ" indicates Enjoyment, "MOO" Mood, "MOT" Motivation, "PER" Performance, "S_EF" Self-Efficacy.

Missing data patterns of the second group



Note. "ENJ" indicates Enjoyment, "MOO" Mood, "MOT" Motivation, "PER" Performance, "S_EF" Self-Efficacy.

Missing data patterns of the third group



Note. "ENJ" indicates Enjoyment, "MOO" Mood, "MOT" Motivation, "PER" Performance, "S_EF" Self-Efficacy.

8 Appendix II: descriptives

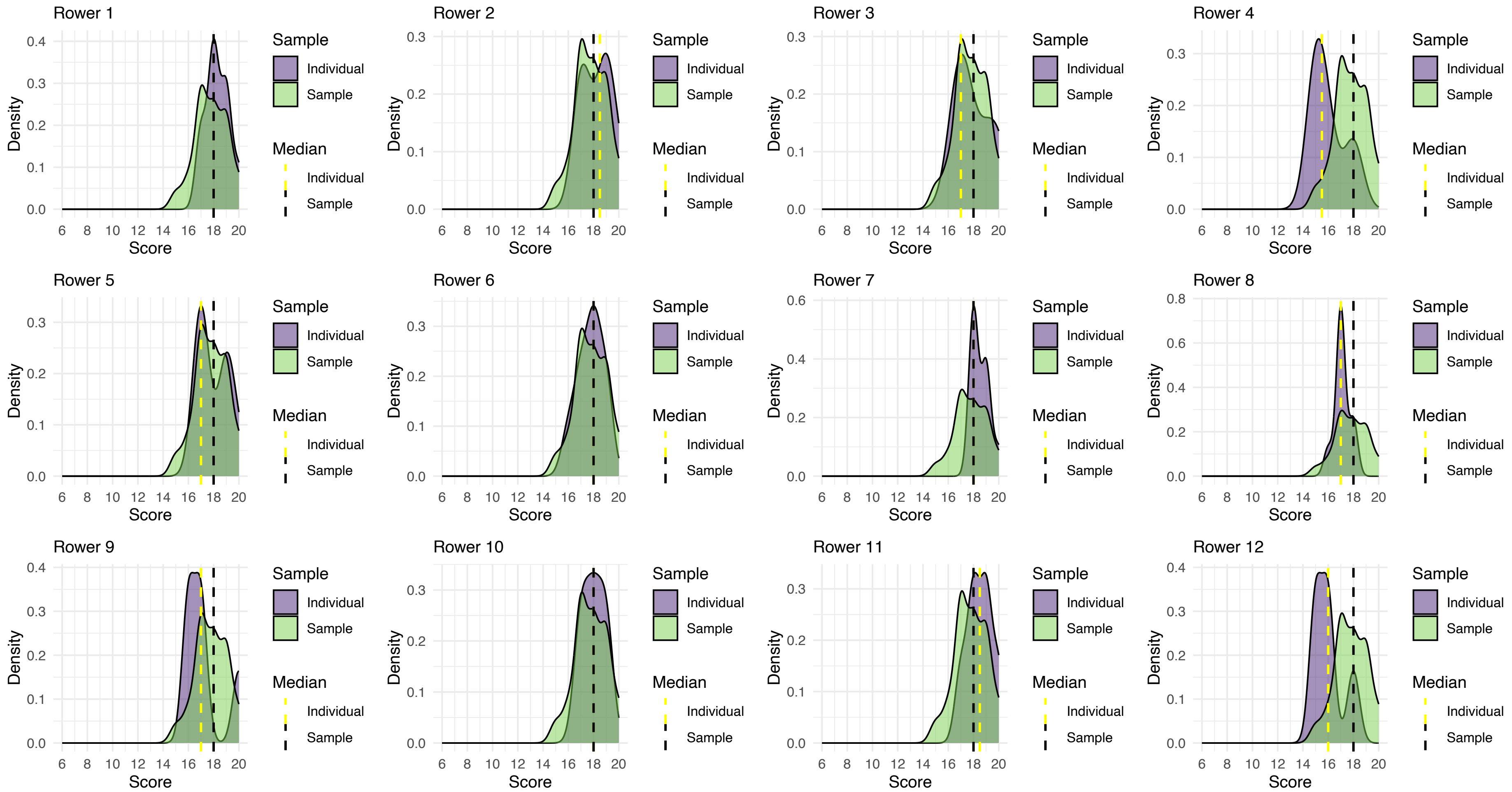
Univariate aggregated and individual RPE descriptives after filtering on indoor training sessions

Rower	*Min*	*Max*	*Mean (SD)*	*Mode*	*N*
Group	13	20	17.4 (1.4)	17	216
	15	20	17.8 (1.3)	17	88
1	17	20	18.3 (1.0)	18	10
2	17	20	18.2 (1.2)	17	8
3	17	20	18 (1.4)	17	5
4	15	18	16 (1.4)	15	4
5	17	20	18 (1.2)	17	11
6	16	19	17.8 (1.0)	18	8
7	18	20	18.5 (0.7)	18	11
8	16	18	17.1 (0.6)	17	9
9	16	20	17.2 (1.6)	17	5
10	17	19	18 (0.9)	17	6
11	17	20	18.5 (1.1)	18	6
12	15	18	16 (1.2)	15	5
	13	20	16.9 (1.5)	17	59
13	16	20	17.6 (1.2)	18	8
14	15	20	18.2 (1.9)	19	5
15	15	19	16.8(1.5)	16	5
16	15	17	16.2 (1.0)	17	6
17	15	20	16.1 (1.5)	15	10
18	16	19	17.5 (1.3)	16	4
19	16	19	17.3 (1.0)	17	6
20	13	17	15.5 (1.5)	17	6
21	17	18	17.5 (0.5)	18	8
	13	20	17.4 (1.5)	17	69
22	15	18	16.7 (1.5)	15	3
23	17	19	18 (0.8)	18	7
24	17	20	18.2 (1.1)	18	5
25	15	17	16.3 (1.2)	17	3
26	18	20	18.7 (0.8)	18	6
27	15	19	17.4 (1.6)	19	7
28	16	20	17.7 (1.4)	17	6
29	17	19	17.9 (0.7)	18	7
30	13	17	15 (1.3)	15	6
31	15	19	17.7 (1.8)	19	6
32	17	19	1.83 (1)	19	6
33	15	19	16.7 (1.4)	17	7

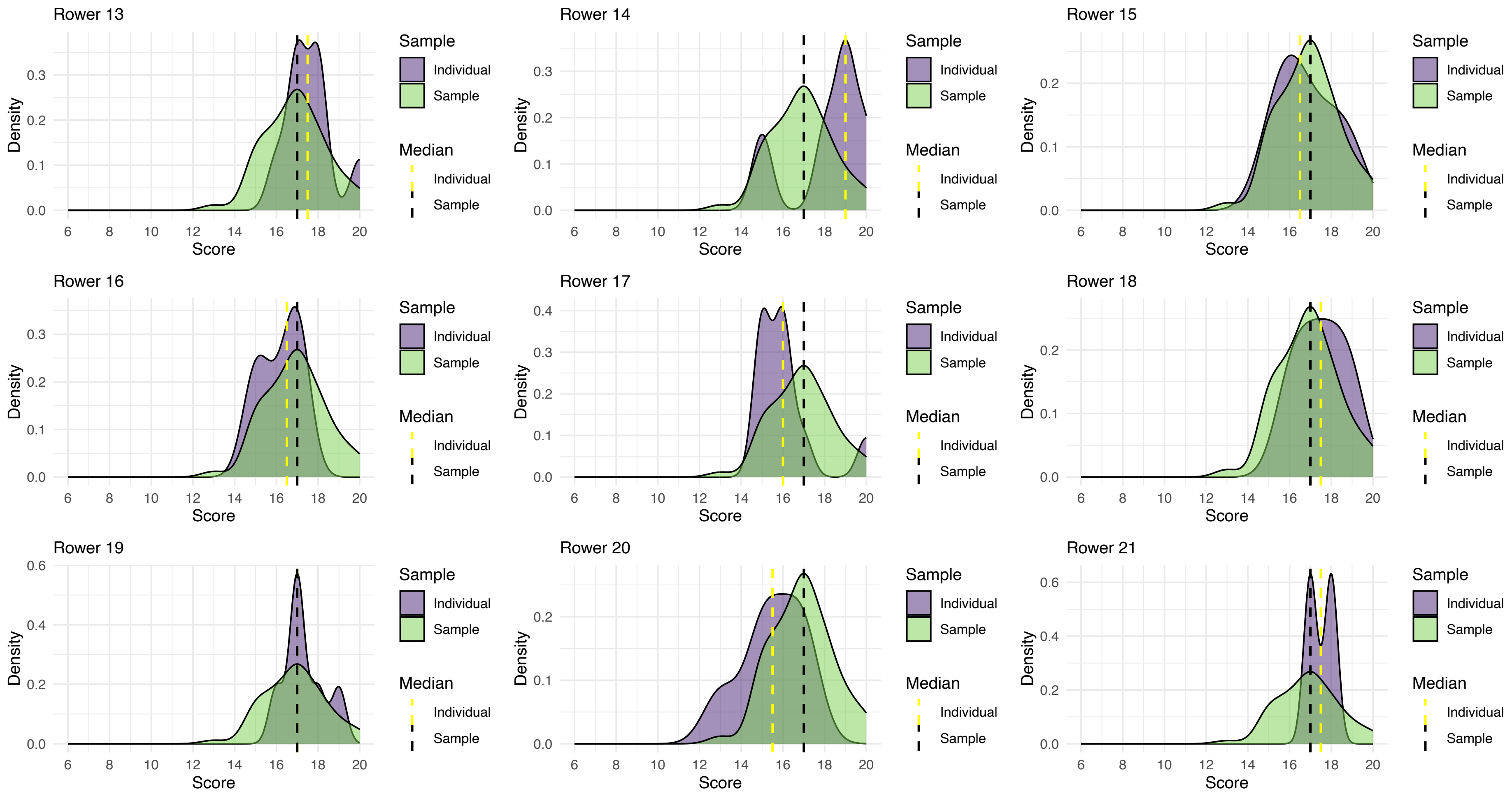
Univariate aggregated and individual INT descriptives after filtering on the indoor training sessions

Rower	*Min*	*Max*	*Mean (SD)*	*N*
Group	3.7	5.3	4.5 (0.4)	345
	3.7	4.7	4.2 (0.3)	133
1	3.8	4,4	4.2 (0.2)	15
2	3.9	4.5	4.3 (0.2)	12
3	4.0	4.6	4.3 (0.2)	10
4	3.8	4.5	4.2 (0.2)	9
5	3.9	4.6	4.3 (0.3)	12
6	3.8	4.4	4.1 (0.2)	11
7	3.9	4.4	4.2 (0.2)	14
8	3.7	4.4	4.1 (0.3)	13
9	3.9	4.4	4.2 (0.2)	8
10	3.9	4.5	4.2 (0.3)	9
11	3.7	4.3	4.0 (0.2)	9
12	4.1	4.7	4.5 (0.2)	11
	3.8	5	4.4 (0.3)	104
13	4.1	4.8	4.4 (0.3)	13
14	4.0	4.8	4.4 (0.2)	12
15	3.8	4.9	4.5 (0.3)	13
16	3.8	4.6	4.2 (0.3)	8
17	4.0	4.7	4.4 (0.2)	12
18	4.0	5.0	4.6 (0.3)	9
19	4.1	4.8	4.5 (0.3)	12
20	4.1	4.8	4.4 (0.2)	14
21	4.2	4.9	4.5 (0.3)	11
	4.1	5.3	4.8 (0.3)	108
22	4.1	5.0	4.7 (0.3)	6
23	4.3	5.1	4.8 (0.3)	12
24	4.2	5.1	4.7 (0.3)	8
25	4.3	5.1	4.8 (0.3)	10
26	4.5	5.3	5.0 (0.3)	9
27	4.2	5.2	4.7 (0.4)	10
28	4.3	5.1	4.8 (0.3)	8
29	4.1	5.0	4.6 (0.3)	10
30	4.3	5.0	4.7 (0.3)	8
31	4.4	5.1	4.7 (0.3)	7
32	4.4	5.2	4.9 (0.3)	10
33	4.2	5.1	4.7 (0.4)	10

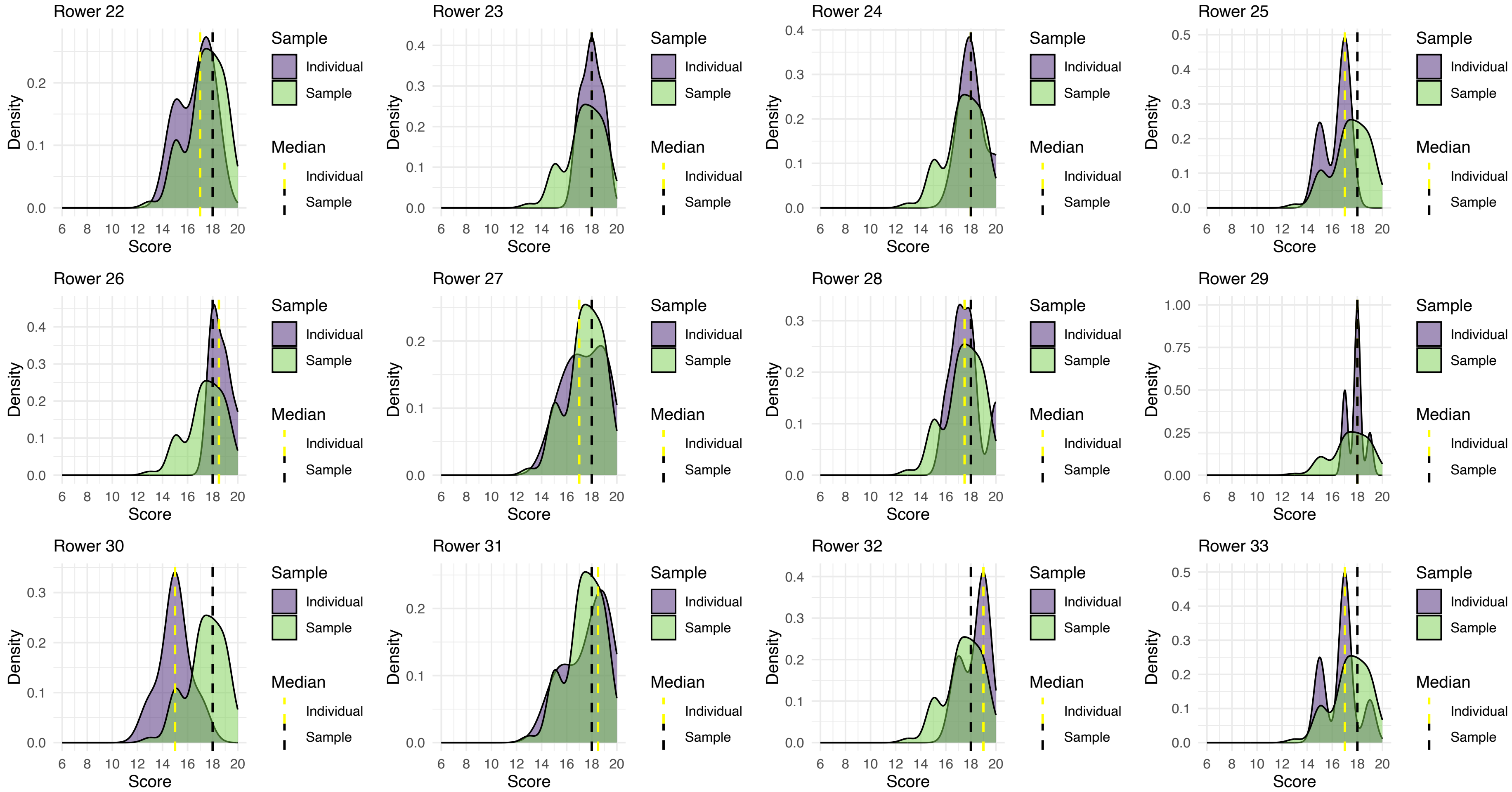
Univariate distribution of RPE of each rower and of group 1 as a whole aggregated over time



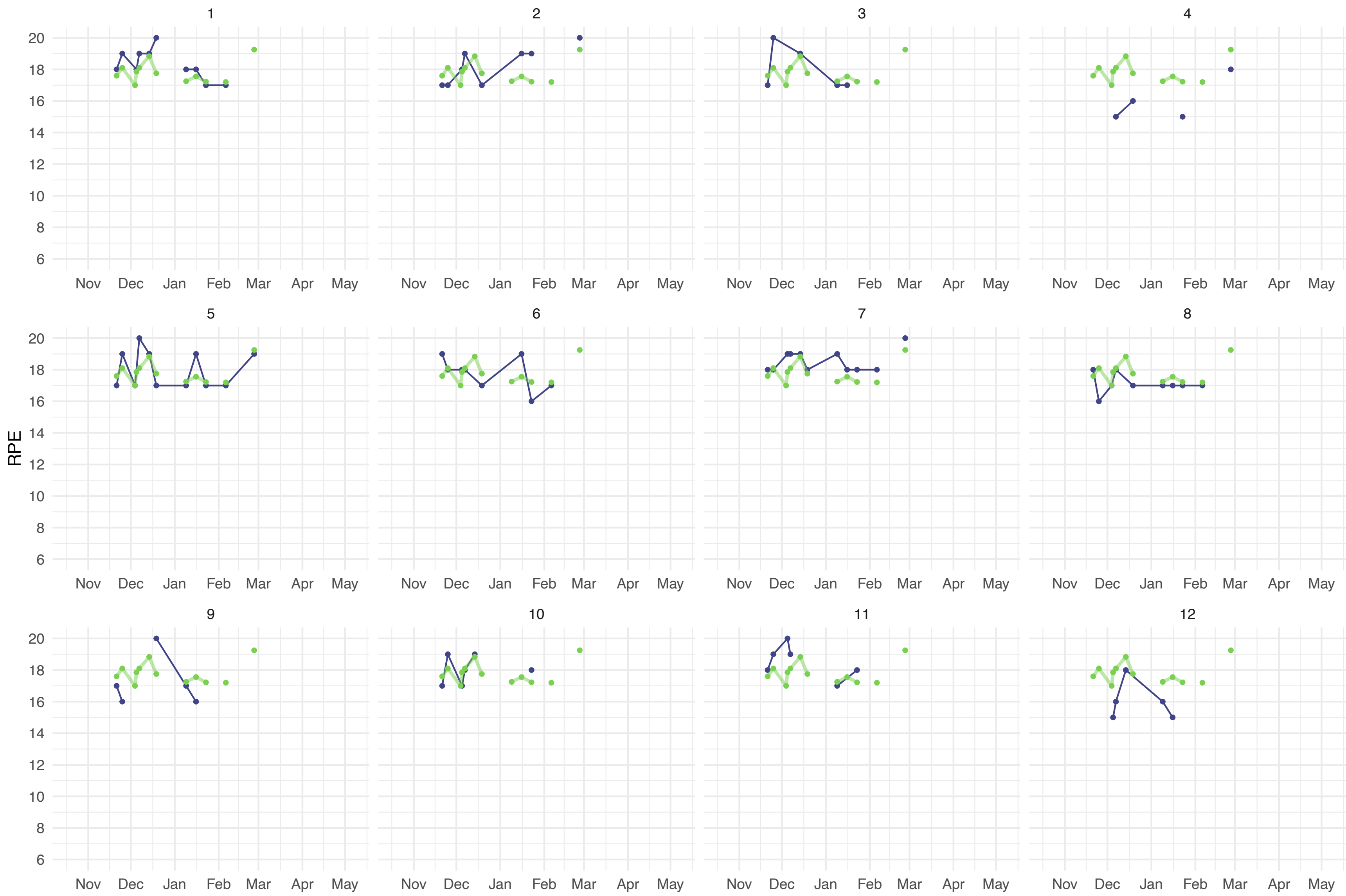
Univariate distribution of RPE of each rower and of group 2 as a whole aggregated over time



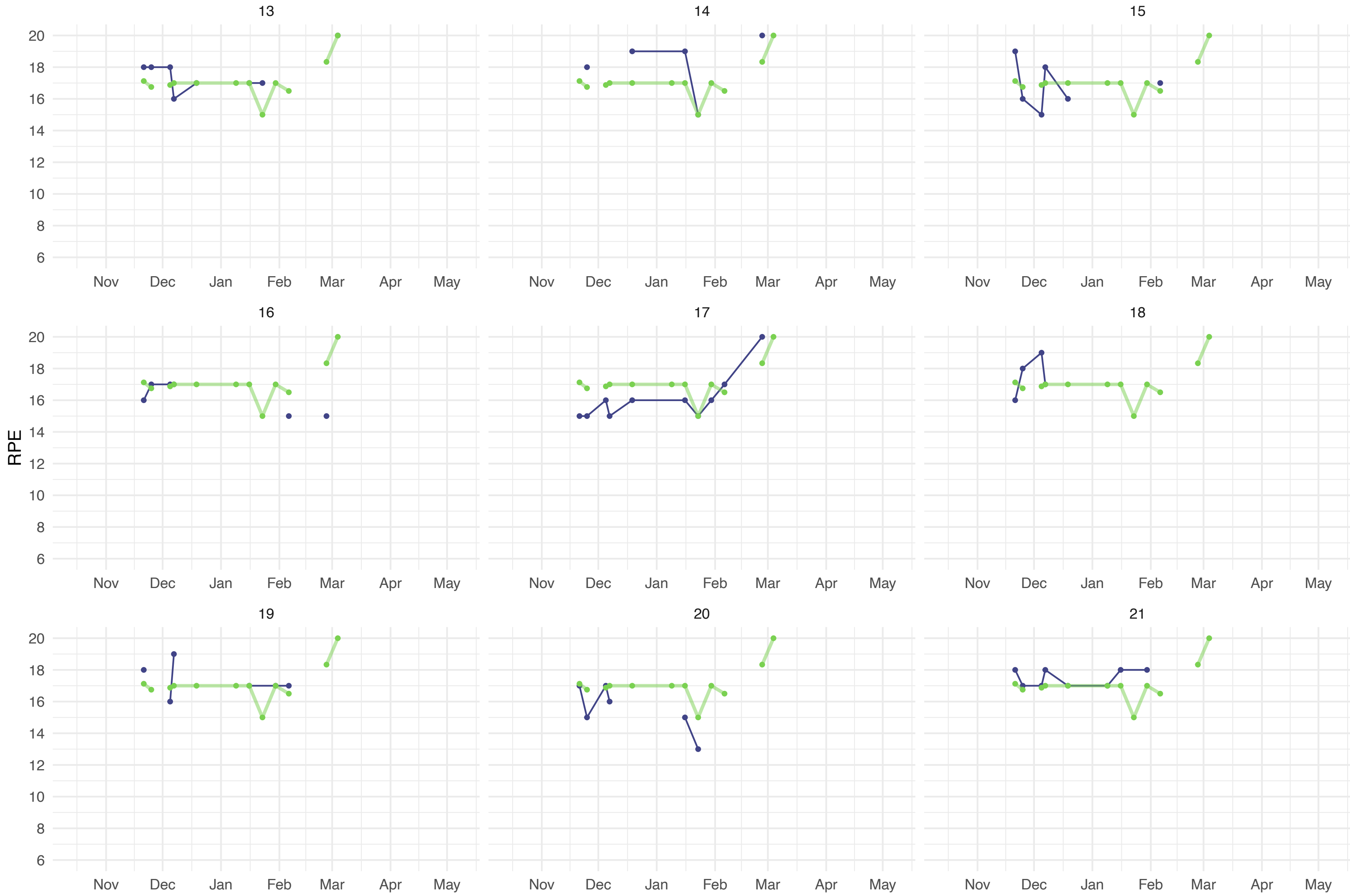
Univariate distribution of RPE of each rower and of group 3 as a whole aggregated over time



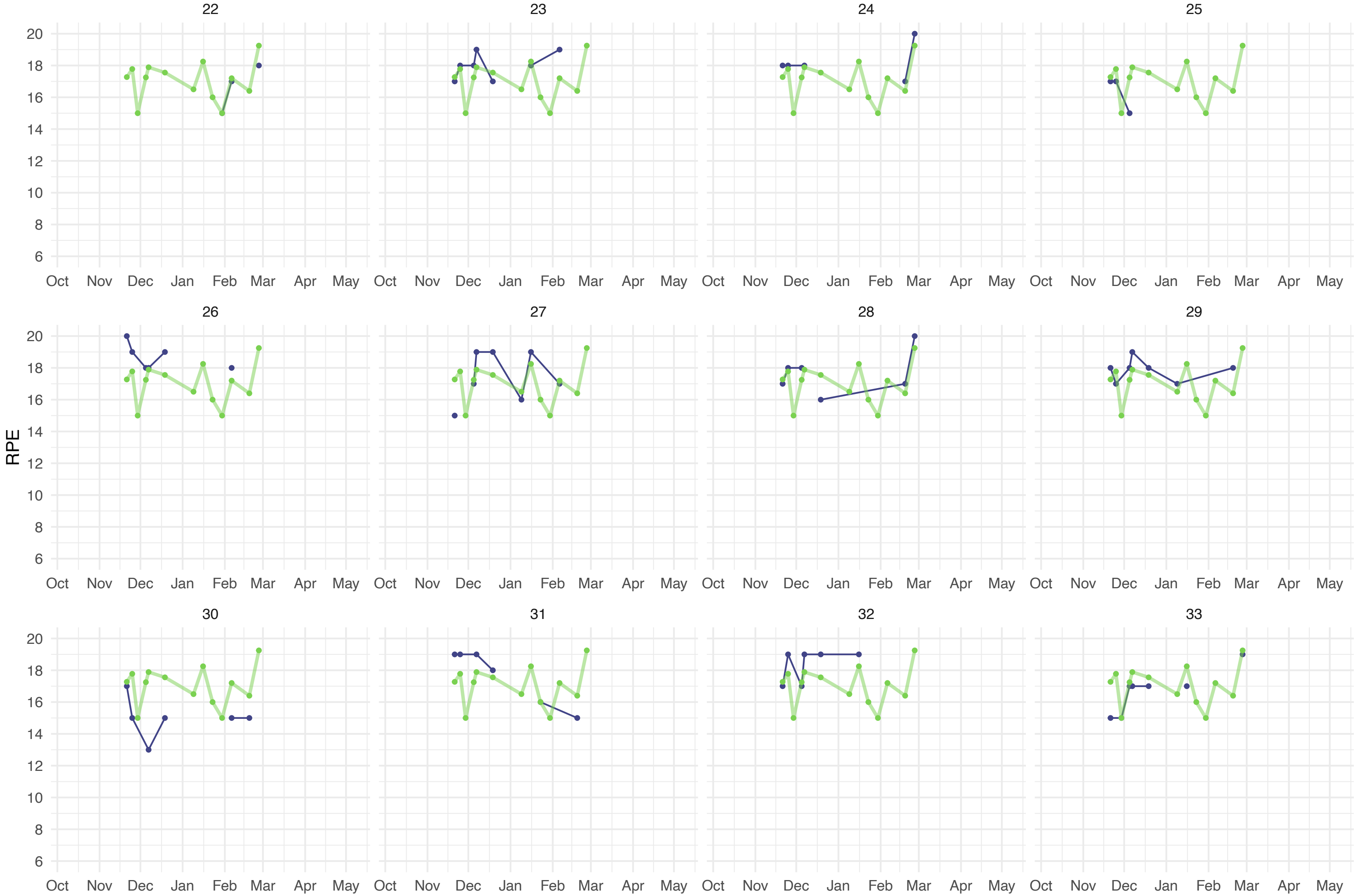
RPE time series of each rower (blue) in group 1 and aggregated (green)



RPE time series of each rower (blue) in group 2 and aggregated (green)



RPE time series of each rower (blue) in group 3 and aggregated (green)

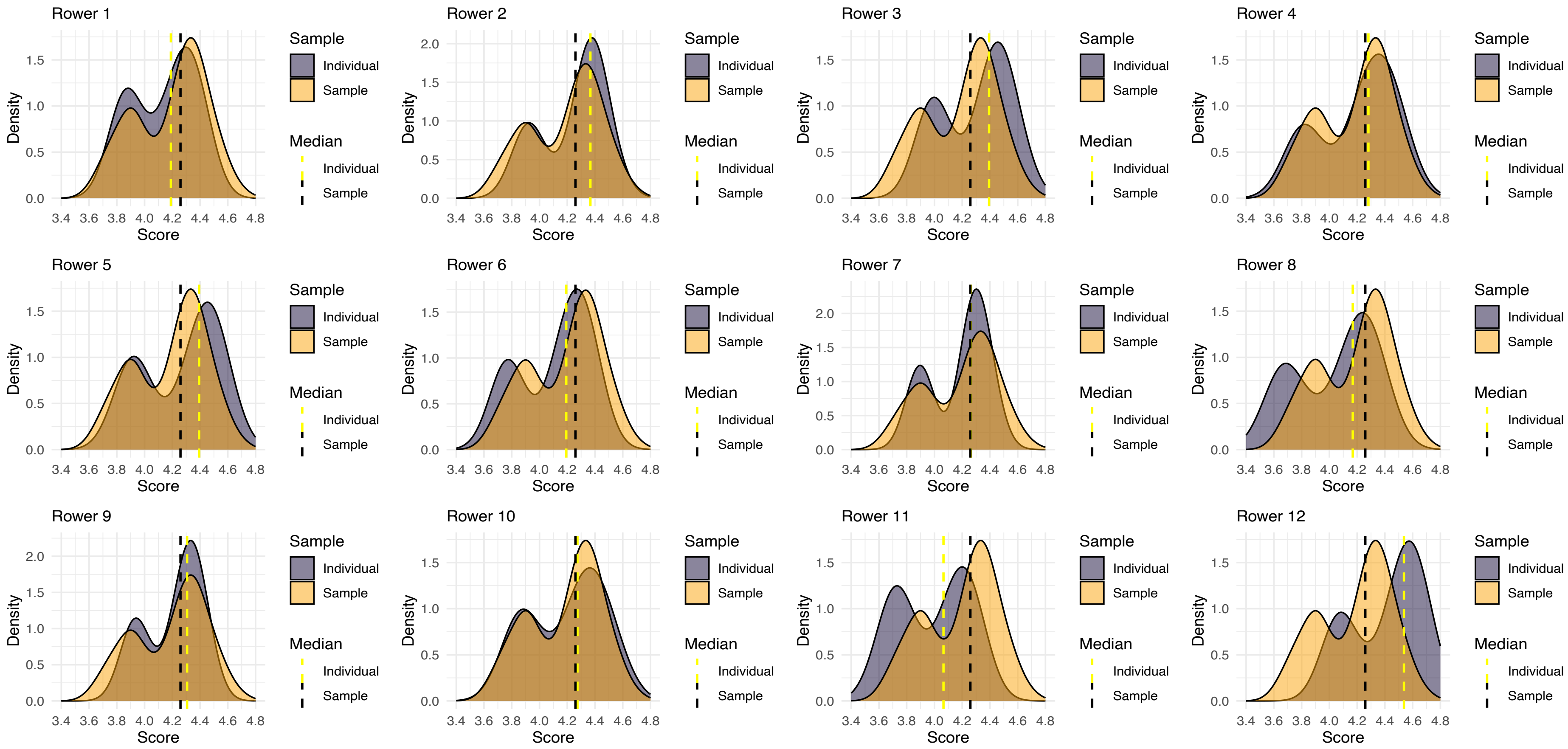


Summary of the executed ADF- and KPSS tests for testing stationarity of the RPE time series of each rower

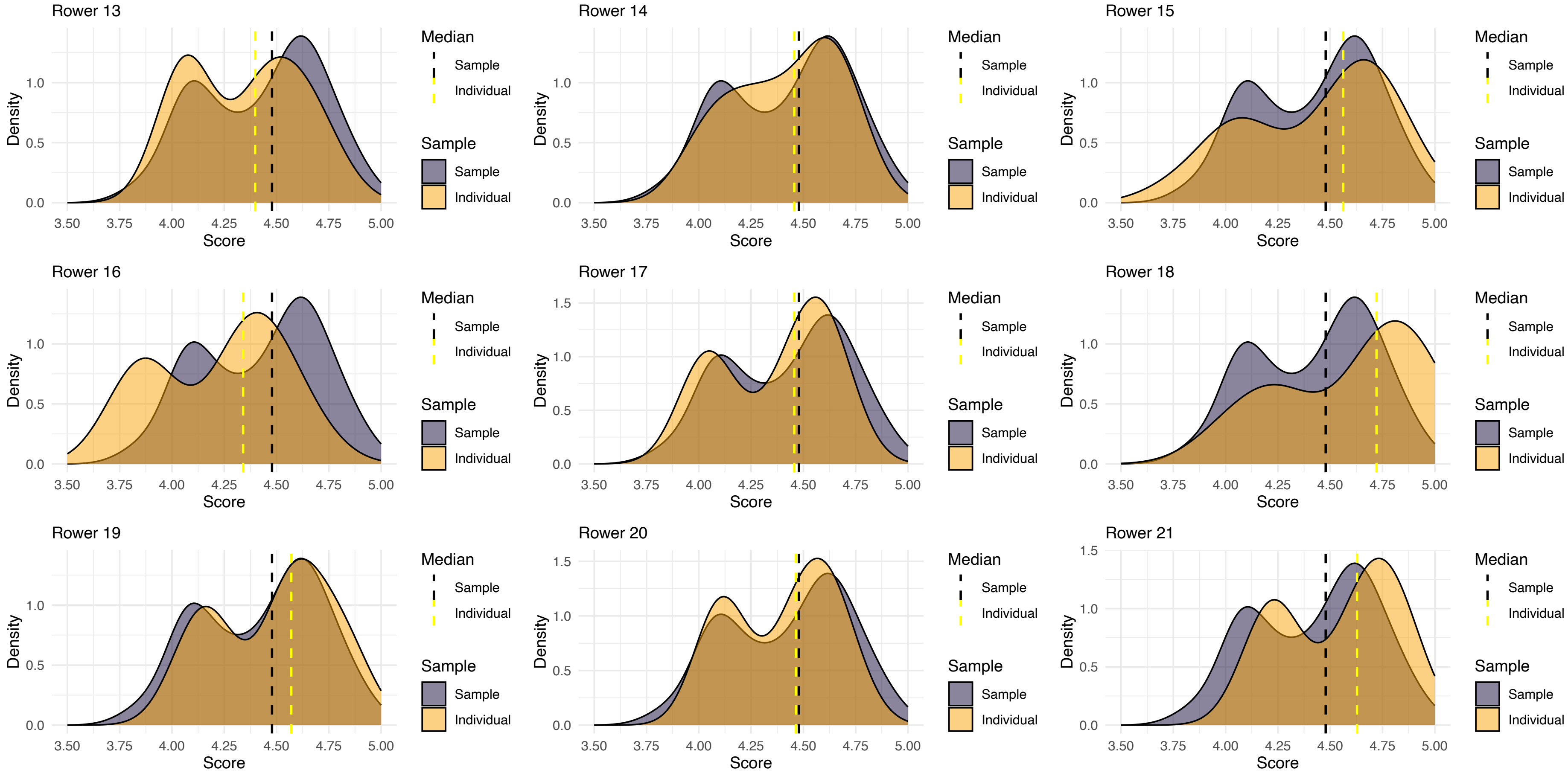
Rower	N	ADF test		KPSS test		Conclusion
		Lag	ADF_{τ}	Lag	$KPSS_{\hat{\eta}}$	
1	10	2	-1.47	2	0.13	Trend-stationary
2	8	1	-1.86	2	0.16*	Not stationary
3	5	-	-	1	0.14	Trend-stationary, but unreliable due to low variance
4	4	-	-	1	0.22*	Unreliable due to low variance
5	11	2	-3.25	2	0.13	Trend-stationary
6	8	1	-2.89	2	0.17*	Not stationary
7	11	2	-1.72	2	0.10	Trend-stationary
8	9	2	-4.61*	2	0.18*	Inconsistent
9	5	-	-	1	0.14	Trend-stationary, but unreliable due to low variance
10	6	-	-	1	0.14	Trend-stationary, but unreliable due to low variance
11	6	-	-	1	0.11	Trend-stationary, but unreliable due to low variance
12	5	-	-	1	0.13	Trend-stationary, but unreliable due to low variance
13	8	1	-0.01	2	0.15*	Not stationary
14	5	-	-	1	0.16*	Unreliable due to low variance
15	6	-	-	1	0.13	Trend-stationary, but unreliable due to low variance
16	6	-	-	1	0.13	Trend-stationary, but unreliable due to low variance
17	10	2	-0.11	1	0.13	Trend-stationary
18	4	-	-	1	0.17*	Unreliable due to low variance
19	6	-	-	1	0.16*	Unreliable due to low variance
20	6	-	-	1	0.13	Trend-stationary, but unreliable due to low variance
21	8	1	-3.54	2	0.22*	Not stationary
22	3	-	-	-	-	Time series is too short
23	7	1	-1.57	2	0.16*	Not stationary
24	5	1	-	1	0.16*	Unreliable due to low variance
25	3	-	-	-	-	Time series is too short
26	6	-	-	1	0.12	Trend-stationary, but unreliable due to low variance
27	7	1	-2.00	2	0.17*	Not stationary
28	6	-	-	1	0.11	Trend-stationary, but unreliable due to low variance
29	7	1	-2.03*	2	0.18*	Inconsistent
30	6	-	-	1	0.12	Trend-stationary, but unreliable due to low variance
31	6	-	-	1	0.13	Trend-stationary, but unreliable due to low variance
32	6	-	-	1	0.20*	Unreliable due to low variance
33	7	1	-2.20	2	0.17*	Not stationary

Note. For mapping the degree of RPE-stationarity, I performed the Augmented Dickey-Fuller (ADF) test (Said & Dickey, 1984), via the adf.test() function and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992) with the kpss.test() function, both in the "tseries" package (version 0.10-57; Trapletti et al., 2024). The ADF test tests whether a time series x contains a unit root (i.e., $H_0\colon \phi = 1$), where ϕ is the inertia or autocorrelation parameter. The lag parameter is determined by $length(x) - 1^{.33}$ and rounded to the nearest integer in the direction of "0". The KPSS test tests whether a time series x is level ($H_0\colon x_{\xi} = 0$) or trend-stationary ($H_0\colon x_{\sigma_u^2} = 0$). The lag parameter is calculated via $4(\frac{n}{100})^{.25}$ and is rounded in the same manner as with adf.test(). * Significant at p < .05.

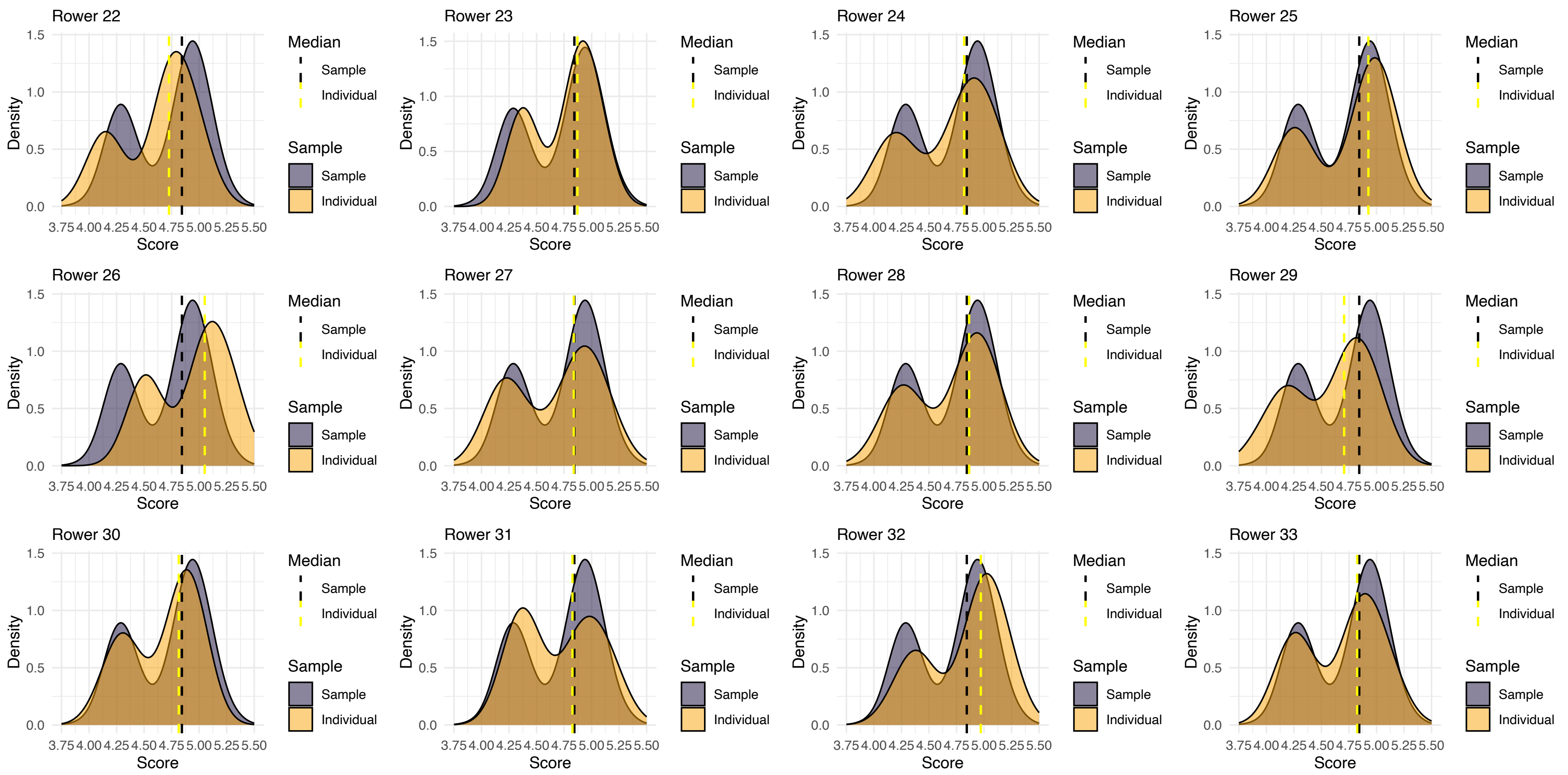
Univariate distribution of INT (of each rower in group 1 and aggregated) over time after filtering on the indoor training sessions



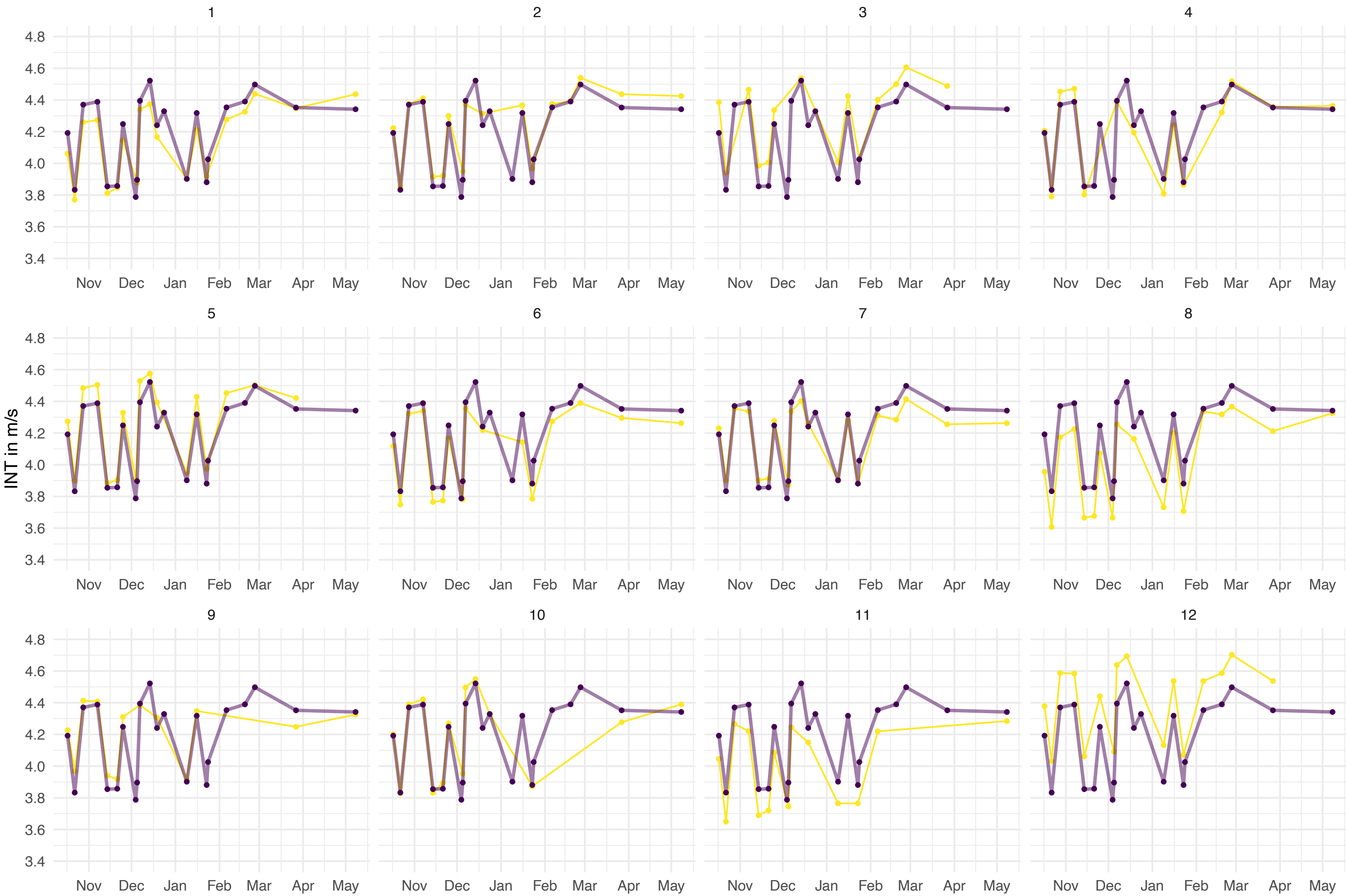
Univariate distribution of INT (of each rower in group 2 and aggregated) over time after filtering on the indoor training sessions



Univariate distribution of INT (of each rower in group 3 and aggregated) over time after filtering on the indoor training sessions

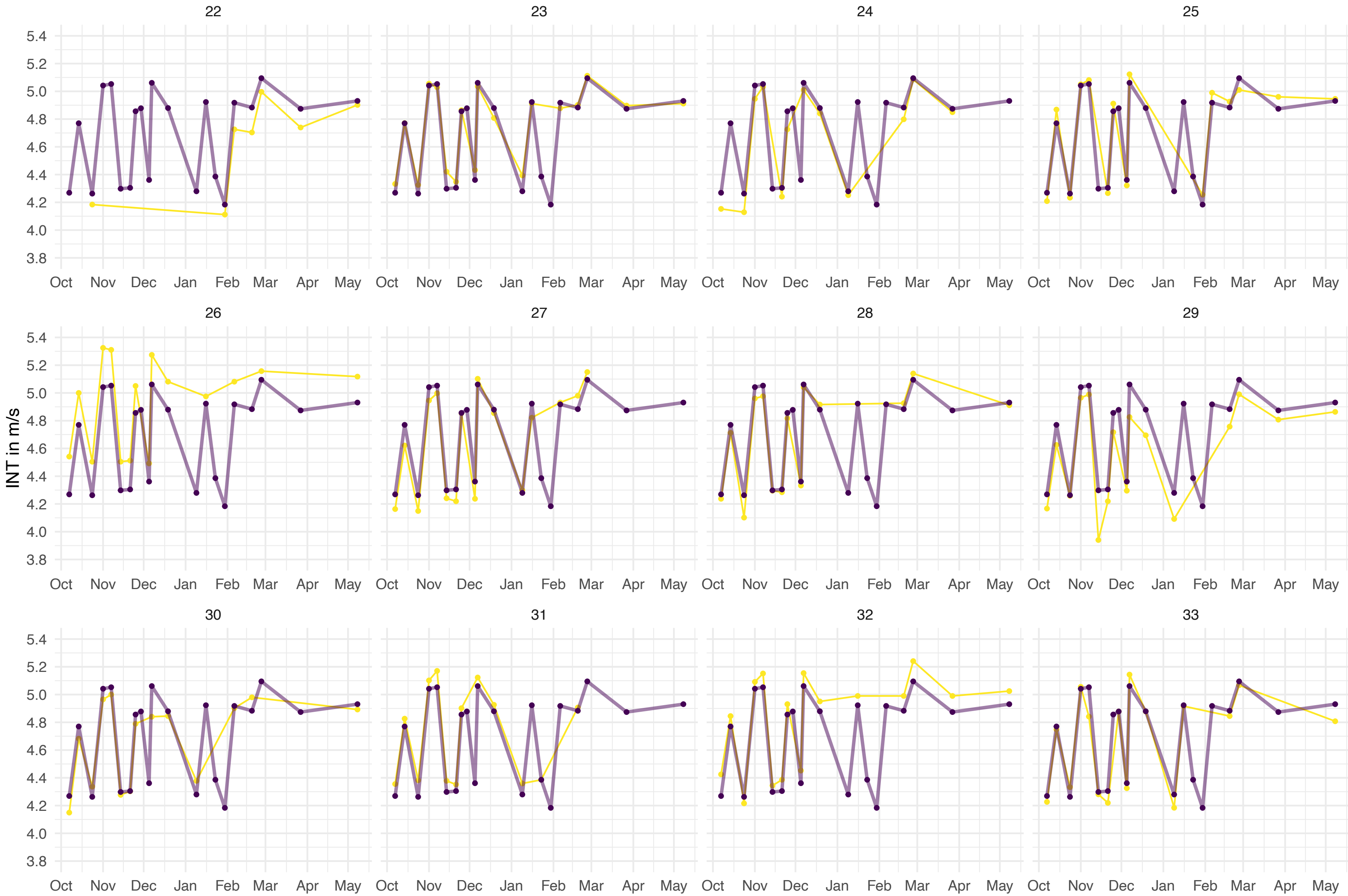


INT time series of each rower (yellow) in group 1 and aggregated (purple)



INT time series of each rower (yellow) in group 2 and aggregated (purple)

INT time series of each rower (yellow) in group 3 and aggregated (purple)



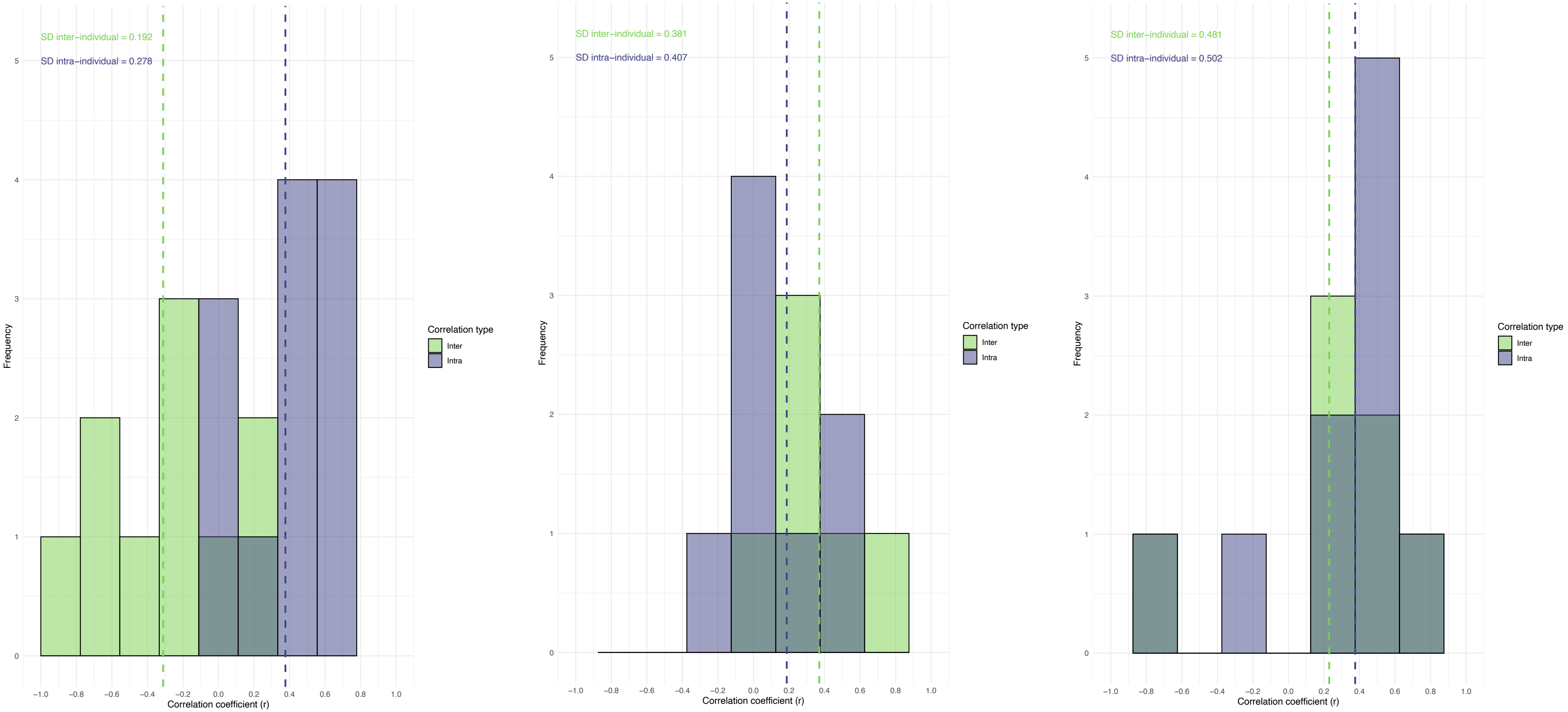
Summary of the executed ADF- and KPSS tests for testing stationarity of the INT time series of each rower

Rower	N	ADF test		KPSS test		Conclusion
		Lag	ADF_τ	Lag	$KPSS_{\hat{\eta}}$	
EJD						
1	20	2	-2.15	2	0.08	Trend-stationary
2	17	2	-2.62	2	0.10	Trend-stationary
3	14	2	-2.67	2	0.11	Trend-stationary
4	14	2	-0.81	2	0.12	Trend-stationary
5	17	2	-2.44	2	0.07	Trend-stationary
6	16	2	-2.55	2	0.09	Trend-stationary
7	19	2	-2.69	2	0.07	Trend-stationary
8	18	2	-2.22	2	0.10	Trend-stationary
9	13	2	-3.49	2	0.09	Trend-stationary
10	14	2	-2.05	2	0.08	Trend-stationary
11	14	2	-2.23	2	0.10	Trend-stationary
12	16	2	-2.42	2	0.08	Trend-stationary
EJL						
13	17	2	-1.51	2	0.11	Trend-stationary
14	17	2	-2.73	2	0.06	Trend-stationary
15	17	2	-2.36	2	0.08	Trend-stationary
16	11	2	-2.38	2	0.14	Trend-stationary
17	17	2	-2.42	2	0.08	Trend-stationary
18	14	2	-1.90	2	0.12	Trend-stationary
19	17	2	-2.65	2	0.10	Trend-stationary
20	19	2	-1.81	2	0.10	Trend-stationary
21	16	2	-1.92	2	0.10	Trend-stationary
EJZ						
22	7	1	-0.22	2	0.14	Trend-stationary
23	18	2	-2.61	2	0.08	Trend-stationary
24	12	2	-3.92*	2	0.13	Stationary
25	15	2	-2.10	2	0.08	Trend-stationary
26	15	2	-2.10	2	0.08	Trend-stationary
27	16	2	-2.37	2	0.09	Trend-stationary
28	14	2	-1.73	2	0.10	Trend-stationary
29	16	2	-1.91	2	0.10	Trend-stationary
30	14	2	-4.08*	2	0.08	Stationary
31	13	2	-6.27*	2	0.10	Stationary
32	16	2	-2.19	2	0.08	Trend-stationary
33	16	2	-2.68	2	0.08	Trend-stationary

Note. For mapping the degree of INT-stationarity, I performed the Augmented Dickey-Fuller (ADF) test (Said & Dickey, 1984), via the adf.test() function and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992) with the kpss.test() function, both in the "tseries" package (version 0.10-57; Trapletti et al., 2024). The ADF test tests whether a time series x contains a unit root (i.e., $H_0: \phi = 1$), where ϕ is the inertia or autocorrelation parameter. The lag parameter is determined by $length(x) - 1^{.33}$ and rounded to the nearest integer in the direction of "0". The KPSS test tests whether a time series x is level ($H_0: x_\xi = 0$) or trend-stationary ($H_0: x_{\sigma_u^2} = 0$). The lag parameter is calculated via $4(\frac{n}{100})^{.25}$ and is rounded in the same manner as with adf.test().

* Significant at $p < .05$.

Bivariate relationship (Pearson correlation) between INT & RPE for group 1, 2, and 3 respectively



9 Appendix III: main analyses

Records (in m/s) for determining the INT_{max} for each rower within a group based on each of the four indoor rowing events

Group	3x20 min	4x5 min	2k max	3x1k
1	4.665465[1]	5.30824[2]	5.235602[3]	5.09684[4]
2	4.822497[5]	6.087861[6]	5.464481[7]	5.733945[8]
3	5.466117[9]	6.958359[10]	6.109669[11]	5.851375[12]

Note. the average of two records adjacent in distance is taken for record 2, 5, 6, 9, and 10 via https://www.concept2.nl/nl/indoor-rowers/racing/records/world.

Results of the LCGA and GMM with PHI as the dependent variable and the measurement occasions as the independent variable with imputed RPE values

No. of classes	*ICL*	*Sample Size per Class Based on Most Likely Class Membership*
LCGA (linear)		
1	2176.340	33
2	2144.938	17/16
3	2148.217	18/12/3
LCGA (quadratic)		
1	2176.981	33
2	2149.726	17/16
3	2158.898	18/12/3
LCGA (cubic)		
1	2182.460	33
2	2160.979	18/15
3	2175.705	18/12/3
GMM (linear)		
1	2128.923	33
2	2143.568	21/12
3	2160.9787	18/12/3
GMM (quadratic)		
1	2194.525	33
2	2184.828	17/16
3	2211.552	18/12/3
GMM (cubic)		
1	2217.550	33
2	2231.154	18/15
3	2280.980	18/12/3

Note. Every performed LCGA and GMM with the estimated classes were executed with 300 random starts. The variance of the slopes is freely estimated whereas the residual variances are fixed.

The 2-class LCGA solution with RPE imputed and time as a linear function