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# Resilience in sports: a multidisciplinary, dynamic, and personalized perspective

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**ABSTRACT**

Athletes are exposed to various psychological and physiological stressors, such as losing matches and high training loads. Understanding and improving the resilience of athletes is therefore crucial to prevent performance decrements and psychological or physical problems. In this review, resilience is conceptualized as a dynamic process of bouncing back to normal functioning following stressors. This process has been of wide interest in psychology, but also in the physiology and sports science literature (e.g. load and recovery). To improve our understanding of the process of resilience, we argue for a collaborative synthesis of knowledge from the domains of psychology, physiology, sports science, and data science. Accordingly, we propose a multidisciplinary, dynamic, and personalized research agenda on resilience. We explain how new technologies and data science applications are important future trends (1) to detect warning signals for resilience losses in (combinations of) psychological and physiological changes, and (2) to provide athletes and their coaches with personalized feedback about athletes' resilience.

Resilience is a key construct across disciplines, including psychology, medicine, physiology, and sports science (e.g. Bryan et al., 2019; Gijzel et al., 2020; Pincus & Metten, 2010; Scheffer et al., 2018). In this paper, we proceed from the cross-disciplinary conceptualization of human resilience as 'the capacity to bounce back to normal functioning after a perturbation' (Scheffer et al., 2018, p. 11883). In the domain of sport and exercise psychology, perturbations have typically been defined as stressors (Hill et al., 2018a,

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2018b). Such stressors are omnipresent in the environment of an athlete, and may be of a psychosocial nature (e.g. losing a match, maladaptive interactions with the coach, see Sarkar & Fletcher, 2014), physiological nature (e.g. high training loads, Halson, 2014; Kellmann et al., 2018), or non-typical, such as adversity experiences related to the current COVID-19 pandemic (e.g. Gupta & McCarthy, 2021). The way in which people respond to stressors has gained widespread multidisciplinary interest, particularly in the domains of psychology, physiology, and sports science. In these domains, researchers examined these processes under the terms psychological or physical resilience and load (or stress) and recovery (e.g. Brink et al., 2010; Bryan et al., 2019; Fletcher & Sarkar, 2013; Galli & Gonzalez, 2015; Gijzel et al., 2019; Hill et al., 2018a; Kenttä & Hassmén, 1998; Kuipers & Keizer, 1988; Reilly & Ekblom, 2005; Varadhan et al., 2018; Whitson et al., 2016).

Despite the apparent similarities and common aims (i.e. understanding and improving how athletes bounce back from stressors), the literature in psychology, physiology, and sports science can be considered as segmented rather than integrated. In this review, we aim to merge insights from these fields to develop a coherent perspective on resilience as *a dynamic process* (cf. Hill et al., 2018a, 2018b; Kalisch et al., 2019; Kuranova et al., 2020; Rector et al., 2021; Scheffer et al., 2018). Accordingly, an important methodological step is to study resilience processes across time (e.g. Bryan et al., 2019; Galli & Gonzalez, 2015; Galli & Pagano, 2018; Gupta & McCarthy, 2021; Hill et al., 2018a). That is, examining if and how the state of an athlete returns to the normal level following a stressor requires studying temporal processes of psychological, physiological, and/or performance measures (cf., Gijzel et al., 2017; Heidari et al., 2019; Hill et al., 2018b; Hill, Den Hartigh et al., 2020; Kalisch et al., 2019; Pincus & Metten, 2010; Scheffer et al., 2018; Seeman & Robbins, 1994; Van de Leemput et al., 2014). Relying on this approach, we specifically focus on 'warning signals' that indicate possible losses of psychological or physical resilience (e.g. Hill et al., 2018a; Rector et al., 2021; Scheffer et al., 2018; Van de Leemput et al., 2014). Detecting such warning signals requires new technologies, multimodal data collection, and the analysis of temporal processes. Data science applications are therefore needed, which may also deliver the tools for online dashboards to provide timely resilience feedback to coaches and athletes.

In the next sections, we present a multidisciplinary, dynamic, and personalized perspective based on knowledge from psychological and physical resilience. Next, we illustrate how recent developments in the field of data science can contribute to the analysis of dynamic, personalized resilience processes, thereby identifying warning signals (i.e. indicators of resilience losses) based on patterns in the data. Finally, we illustrate how our proposed perspective can be feasibly implemented in the field of sports, based on close collaborations between psychologists, sport scientists, data scientists, and practitioners in the sports field.

## Psychological resilience

Important to note is that various definitions of resilience exist in the domain of psychology (e.g. Bryan et al., 2019; Galli & Gonzalez, 2015; Sarkar & Fletcher, 2013; Smith et al., 2008; Southwick et al., 2014). As mentioned before, in this review we conceptualize

resilience as a dynamic process of bouncing back to normal functioning following stressors. 'Bouncing back' is generally viewed as a key feature of resilience (e.g. Bryan et al., 2019; Carver, 1998; Fletcher, 2019; Hill et al., 2018a, 2018b; Hosseini et al., 2016; Masten, 2014; Masten & Obradović, 2006; Pincus & Metten, 2010; Pincus et al., 2018; Scheffer et al., 2018; Smith et al., 2008; Vella & Pai, 2019). This feature is in accordance with the original meaning of the word resilience (i.e. in latin 'resilire' means 'to jump or spring back'). Understanding the bouncing back process requires a focus on the responses of an athlete's state to stressors over the course of time. This provides insights into, for instance, how quickly athletes return to their normal level following an adverse experience like a heavy defeat. Relatedly, when athletes cannot return to their normal level, or the return takes relatively long, it may be a warning signal of a resilience loss (e.g. Helmich et al., 2021; Hill et al., 2018a; Scheffer et al., 2018; Van de Leemput et al., 2014).

In the psychological sciences, other conceptualizations of resilience include maintaining wellbeing or functioning following stressors, or growing or thriving after stressors (e.g. Bryan et al., 2019; Carver, 1998; Smith et al., 2008). An example of maintaining wellbeing or functioning following stressors as a component of resilience is the absence of psychopathology after traumatic experiences (e.g. Bonanno, 2004; Bonanno et al., 2011; Luthar & Cicchetti, 2000; Luthar et al., 2000; Rutter, 1985). In the sports context, qualitative research has shown that Olympic gold medalists encountered a variety of stressors, from daily hassles to major life events (e.g. the death of a loved one). These athletes were able to withstand these stressors in the sense that they did not impact their functioning on the sports field (Fletcher & Sarkar, 2012). Accordingly, researchers have been interested in the psychological factors that protect or 'shield' athletes against the stressors they encounter (e.g. Bryan et al., 2019; Galli & Gonzalez, 2015; Sarkar & Fletcher, 2014). Fletcher and Sarkar (2012) have summarized the main protective factors as positive personality, motivation, confidence, focus, and perceived social support. For instance, positive personality traits such as adaptive perfectionism, optimism, competitiveness (i.e. the desire to win in competitive situations), would be relevant in dealing with stressors that athletes encounter (for an extensive review, see Sarkar & Fletcher, 2014).

Other psychological papers include growing or thriving after stressors in their conceptualizations of resilience. That is, people may improve following a history of stressors or adversity compared to individuals who encountered little or no adversity (e.g. Collins & MacNamara, 2012; Howells & Fletcher, 2015; Sarkar et al., 2015; Savage et al., 2017; Seery, 2011; Seery et al., 2010). In sport and exercise psychology, this process is often described across a relatively long time span (e.g. several years in a career). For instance, Sarkar et al. (2015) interviewed Olympic champions and found that they encountered various stressors in and outside their sports (e.g. deselection, injury, death of a loved one). The athletes described these stressors as essential in the development toward their gold medal. More specifically, these stressors triggered greater effort, desire, focused reflection, and learning. This fits with the idea that encountering stressors prepare individuals to deal with larger amounts of (future) adversity, and enable them to develop more adequate responses to such events (e.g. Collins & MacNamara, 2012; Hardy et al., 2017; Savage et al., 2017).

### Towards a better understanding of the bouncing back process

Although the bouncing back process has been considered as a key feature of resilience in sport and exercise psychology (e.g. Bryan et al., 2019; Fletcher & Sarkar, 2016; Galli & Vealey, 2008; Hill et al., 2018b; Mummery et al., 2004), previous studies typically relied on qualitative interviews, questionnaire data, or mixed method designs to examine stressors and protective factors in general and/or at a single time point (e.g. Cowden et al., 2016; Cowden & Meyer-Weitz, 2016; Fletcher & Sarkar, 2012; Galli & Vealey, 2008; Gucciardi et al., 2011; Martin-Krumm et al., 2003; Mummery et al., 2004). In other research, a brief resilience scale has been used to provide a 'static indicator' of individuals' self-reported ability to bounce back following stressors (e.g. Smith et al., 2008). Outside sports, however, based on time series of individuals' psychological states, researchers already successfully determined 'dynamic indicators' of resilience. For instance, Van de Leemput et al. (2014) expressed resilience in terms of the recovery rate to one's normal emotional state following stressors in daily life. They used a structured diary technique to monitor individuals' positive and negative affect several times a day, for five or six consecutive days, ending up with 50–60 measurements points. The researchers showed that a depressed state somewhere in that period was typically preceded by a so-called critical slowing down in emotions. This warning signal entails that the return to the previous (positive and typical) affective state started to slow down, which indicates a loss of psychological resilience (see also Helmich et al., 2021; Hill et al., 2018a, 2018b; Kuranova et al., 2020; Wichers et al., 2016). Building upon such insights from other domains, we argue that an important next step for research in sport and exercise psychology is to capture the dynamic bouncing back process as it occurs when people are confronted with stressors (Bryan et al., 2018; Hill et al., 2018b).

Furthermore, in previous research, associations between stressors and resilience-related variables are typically based on scores of groups of athletes, or commonalities detected in qualitative interviews with athletes (e.g. Cowden & Meyer-Weitz, 2016; Fletcher & Sarkar, 2012; Galli & Vealey, 2008). However, a model based on group data only generalizes to a model of individual processes if very specific conditions apply, which are hardly ever met in psychology and sport sciences. This issue is called the ergodicity problem (e.g. Den Hartigh et al., 2018; Fisher et al., 2018; Glazier & Mehdizadeh, 2019; Hill, Meijer, et al., 2021; Molenaar, 2004; Molenaar & Campbell, 2009; Neumann et al., 2021; Van Geert, 2014). One important condition, for instance, is stationarity. This implies that the statistical properties of a variable, such as the mean value and variance, do not change over time, which is unlikely to occur (e.g. Hill, Meijer, et al., 2021; Scheffer et al., 2018; Van de Leemput et al., 2014; Wichers & Groot, 2016). Another condition is homogeneity, meaning that the statistical model defining the relationships between variables is homogeneous across the sample of interest (e.g. Molenaar, 2004). However, athletes typically respond differently to the same stressor (cf. Hill, Kiefer, et al., 2020; Lazarus & Folkman, 1984; Neumann et al., 2021), implying that the homogeneity assumption is unlikely to be fulfilled. Indeed, recent research has shown that changes in psychological and physiological resilience variables at the group-level, do not 'generalize' to individual athletes (e.g. Hill, Meijer, et al., 2021; Neumann et al., 2021). This idea has also been emphasized in other contexts in which stress and recovery processes are relevant. In organizational psychology, for example, Sonnentag et al. (2017) indicated that it is

important to consider the individual differences, and that researchers 'should pay more attention to temporal issues and dynamic aspects of the recovery process' (p. 74).

Finally, most studies on resilience have been context- and discipline-specific, whereas 'the ability of an entity or system to return to normal condition after the occurrence of an event that disrupts its state' applies to different disciplines (Hosseini et al., 2016, p. 47; see also Scheffer et al., 2018). In particular the disciplines of psychology, physiology, and sports science have been interested in how the psychological, physical, and performance state of athletes returns to the original state following psychological and physiological stressors (e.g. Bryan et al., 2018; Gijzel et al., 2017, 2019; Heidari et al., 2019; Hill et al., 2018a, 2018b; Kellmann et al., 2018; Pincus & Metten, 2010; Seeman & Robbins, 1994). Furthermore, the discipline of data science offers the tools to integrate multimodal data, and to analyze the time series on personalized warning signals for resilience losses. Such insights, in turn, can be communicated to practitioners through online dashboards (cf., De Leeuw et al., 2021).

Hence, to better understand the bouncing back process among athletes, a multidisciplinary, dynamic and personalized perspective is needed. Accordingly, in future studies on resilience, the following ingredients should be (put) in place. First, a measurement infrastructure needs to be established to obtain data on athletes' psychological and physiological states and the stressors they encounter. Second, the infrastructure should allow a high frequency data collection (at least once a day) to conduct proper time series analysis (cf. Gijzel et al., 2017; 2020; Helmich et al., 2021; Kuranova et al., 2020; Van de Leemput et al., 2014). Third, the analysis should provide insights into whether, and when resilience losses occur in individual athletes. Given recent developments in sports research and practice, these ingredients can be accounted for. Indeed, many sports organizations already invested in measurement infrastructures to collect data on stress, or load, and recovery at a physical level (e.g. Brink et al., 2010; Cross et al., 2016; Impellizzeri et al., 2004; Jaspers et al., 2018; Lovdal et al., 2021; Van der Does et al., 2017). This can be extended with the collection of data on psychological stressors and states. With such repeated measurements in place, physical and psychological resilience can be measured based on sensor and experience sampling methods (cf. Blaauw et al., 2016; Gijzel et al., 2020). Furthermore, the field of data science and sports analytics offers robust methods to integrate and analyze those multidimensional processes (e.g. Couceiro et al., 2016; De Leeuw et al., 2021; Jaspers et al., 2018; Lovdal et al., 2021; Orie et al., 2021).

The multidisciplinary, dynamic, and personalized perspective on resilience thus integrates knowledge and challenges in sport and exercise psychology with knowledge and methodological advances from the fields of physical resilience and data science. In the next section, we will discuss the relevant aspects of physical resilience in more detail.

## Bouncing back in the physical domain

In the disciplines of physiology and sports science, the themes of physical resilience and load and recovery are typically focused on the process of bouncing back following stressors (e.g. Brink et al., 2010; Gijzel et al., 2019; Kenttä & Hassmén, 1998; Kuipers & Keizer, 1988; Rector et al., 2021; Reilly & Ekblom, 2005; Varadhan et al., 2018; Whitson et al., 2016). That is, athletes need to recover when their biopsychosocial system is perturbed by physiological stressors. Typical physiological stressors athletes are exposed to relate

to their training, and can be characterized by the frequency (number of sessions per day), intensity (relative to individual capacity), duration (minutes per session), and type of training (strength, speed or endurance). When quantifying the training stress, one can distinguish external and internal load. External load is the load prescribed by a coach in a training session, such as the distance covered. Internal load on the other hand, reflects how the body responds to that workload. This is often calculated as the combination of intensity and duration of the session (e.g. Brink et al., 2010; Impellizzeri et al., 2004; Jaspers et al., 2018). An important question that has dominated the research agenda in this discipline is how athletes respond to the load stressors (e.g. Brink et al., 2010; Heidari et al., 2019; Jaspers et al., 2017; Kellmann et al., 2018). In brief, according to the current models, when athletes are exposed to a certain training load, this initially results in fatigue and performance decrements. Subsequently, athletes may recover to the previous level following training stress (e.g. Schwellnus et al., 2016; Soligard et al., 2016).

Contrary to the domain of sport and exercise psychology, many studies on load and recovery in sports sciences already collected quantitative data across time. Stressors have been captured through sensor data, for instance based on local position measurements (LPM) or global positioning systems (GPS). Such systems can provide insights into external load information like accelerations and decelerations of athletes, distance covered, durations above certain speed thresholds, and so forth (e.g. Buchheit et al., 2014; Jaspers et al., 2017; Stevens et al., 2017). Internal load information is typically captured via heart rate measures or Ratings of Perceived Exertion (RPE). Subsequently, responses to the stressors are often measured with self-report measures on well-being (a sports questionnaire with items on muscle soreness, sleep, perceived recovery), or Total Quality of Recovery (TQR). Research using such measures has suggested, for instance, that changes in load (Cross et al., 2016) and recovery (Van der Does et al., 2017) may be indicative of a resilience loss (i.e. not bouncing back to the previous level) and precede an injury or performance decrement.

While the employed measurement infrastructure in these studies would allow an analysis of the time series in stressors and recovering back to previous levels, similar issues as in the psychological resilience literature can be identified. For instance, the great majority of research ignored individual, temporal processes by reporting relations between load and recovery aggregated across time and athletes (e.g. De Freitas Cruz et al., 2018; Debien et al., 2018; Nicolas et al., 2019; Sansone et al., 2020; Selmi et al., 2018). In line with the ergodicity issue of psychological resilience, a recent study showed that group level statistics on load, recovery, and their relationship, do not generalize to individual athletes (Neumann et al., 2021). Furthermore, Lovdal et al. (2021) demonstrated the merits of accounting for the temporal element in load and recovery research, thereby applying knowledge from data science. These authors applied a machine learning approach on load and recovery data from middle- and long-distance runners across several years. Their results suggest that the occurrence of physical problems (i.e. injuries) largely depends on acute load indicators in the previous days.

Outside sports sciences, researchers in medicine and psychophysiology already analyzed the temporal element in the process of bouncing back following stressors more explicitly. For instance, Gijzel and colleagues have studied dynamic indicators of physical resilience in geriatric patients (e.g. Gijzel et al., 2017, 2019, 2020; Rector et al., 2021). In one

of their studies, they included data on daily physical measures of heart rate and physical activity, and psychological well-being based on experience sampling. They concluded that such temporal data added significant value to understanding the physical resilience of the patients. In other research in experimental settings, the area under the curve (AUC) has been used to study psychophysiological changes before, during, and after exposure to a social stress task (e.g. Childs & de Wit, 2014; García-León et al., 2019; Gerber et al., 2017; Kudielka et al., 2004; Liu et al., 2017; Mazurka et al., 2018; see DuPont et al., 2020 for a meta-analytic review). In these studies, researchers have measured hypothalamic–pituitary–adrenal (HPA) functioning in terms of cortisol levels and/or heart rate, at different measurement points during an experiment in which participants had to give a presentation and do an arithmetic test in front of judges. Resilience was quantified by calculating the AUC on the measures before, during, and after the stress onset, which informs about the recovery rate of the psychophysiological process following the stressor based on the trapezoid formula (for more information, see Pruessner et al., 2003). Studies examining resilience in HPA functioning in other contexts also demonstrated the importance of measuring the recovery phase following stressors (e.g. DuPont et al., 2020; Seeman & Robbins, 1994; for an attempt to relate AUC outcomes to self-reported resilience in sports, see Meggs et al., 2016). Apart from such experimental studies, a recent study successfully applied AUC analysis to individual's daily affective states in order to predict changes in resilience across longer periods of time (Kuranova et al., 2020). Finally, resilience changes in motor performance have been determined based on a comparable analysis (Hill, Van Yperen, et al., 2020).

Taken together, approaches that aim to extract dynamic resilience indicators, such as the AUC and critical slowing down analyses, can be applied to different types of psychological and physiological measures (e.g. DuPont et al., 2020; Gijzel et al., 2017; Kuranova et al., 2020; Scheffer et al., 2018; Van de Leemput et al., 2014). This, in turn, can inform about response duration and return-to-normal levels after stressors that individuals are exposed to. Consequently, to better understand the bouncing back process of resilience, and to identify warning signals, collecting and analyzing temporal data is of key importance. Employing measurement infrastructures from load and recovery studies, and analytic strategies from physical resilience, therefore provide crucial ingredients of a multidisciplinary, dynamic, and personalized perspective on resilience in sports.

## Implementing a multidisciplinary, dynamic, personalized perspective

Based on the previous sections, we conclude that across the disciplines of psychology, physiology, and sports science, resilience can be considered as a dynamic and athlete-specific process, with an important focus on the return to normal functioning following stressors. To better understand and improve the resilience of athletes, we therefore advocate for a perspective that operationalizes resilience in a way that these aspects are taken into account. More specifically, in order to implement a multidisciplinary, dynamic, and personalized perspective in the sports field, the following steps need to be taken. First, informed by theoretical insights from the fields of psychology, physiology, and sports science, define the factors to be monitored, employ the measurement infrastructure at the sports organization to assess these factors, and determine the frequency at which

they need to be measured (see subsection 'Variables to monitor'). Second, using knowledge from data science, conduct analyses that account for the fluctuations in the individual, temporal process in order to determine resilience and detect warning signals of resilience losses (see section 'Using knowledge from data science'). Third, based on this information, provide 'data-driven guidance' (i.e. concrete feedback) to practitioners in the sports field, who can then apply personalized interventions if necessary (see section 'Practical implementation').

## Variables to monitor

In accordance with the multidisciplinary, dynamic, and personalized perspective, the monitoring system should allow for the measurement of the stressors, as well as the psychological and physiological responses to stressors of individual athletes over time. Based on existing literature in the field of sports, we will next elaborate on possible factors that could be monitored.

### Monitoring stressors

There is a myriad of psychosocial stressors that can be encountered (Sarkar & Fletcher, 2014). Yet, athletes may regularly be perturbed by unenjoyable practice sessions and bad performances, which may be assessed on a daily basis. Furthermore, at lower frequency other (life) events may occur, which may be less usual but also need to be assessed (Sarkar & Fletcher, 2013). For instance, COVID-19 has led to various stressors for athletes across different sports and countries (see Gupta & McCarthy, 2021). Assessing their perturbing influences on the responses of athletes (see next section) can be particularly relevant in such a period. Therefore, athletes should also be given the opportunity to point out, through self-report, the types of significant stressors they experienced, including their contexts (cf. Gupta & McCarthy, 2021; Ivarsson et al., 2014; Sarkar & Fletcher, 2014; Van Der Sluis et al., 2019).

On the physiological level, defining stressors experienced by athletes can be relatively straightforward. Recent developments in micro sensor technologies are increasingly implemented to monitor individual athletes in training sessions (see 'Bouncing back in the physical domain' section). Sport clubs and organizations that have access to these technologies can thus accurately measure external loads of athletes on a daily basis (e.g. Jaspers et al., 2018; Lovdal et al., 2021). In addition, Heart rate and the RPE can be assessed to determine the internal load. After a training session, ideally within 30 min, athletes can report their RPE that is multiplied by the session duration to get the session-RPE, which provides a typical estimation of training load (Foster et al., 2001, 2021). The RPE report is increasingly assessed using an online application (filling out the question on a smartphone or tablet, e.g. Menaspà et al., 2018). To facilitate the multidisciplinary data collection, items about the daily psychosocial stressors (e.g. related to the enjoyability and self-rated performance) need to be added.

### Monitoring responses to stressors

In order to monitor the responses to the stressors, detailed insights can be gained when collecting the psychological and physiological measures that are descriptive of the resilience process (cf. Den Hartigh et al., 2014; Gernigon et al., 2010; Hill et al., 2018a; Pol et al.,

2019, 2020; Scheffer et al., 2018; Van de Leemput et al., 2014). This means that, perhaps counterintuitively, measuring many different variables is not necessarily better. The key is to determine the (higher order) factors that can signal when athletes perform well and stay healthy while encountering stressors, and when resilience starts to break down (e.g. Fonseca et al., 2020; Hill et al., 2018a). This is in accordance with the support for 'a definition of resilience that is scalable across levels of analysis and suitable for communication across disciplines' (Masten et al., 2021, p. 532). Relatedly, the proposed scalable measurement approach provides a resilience measure reflecting how athletes respond to stressors they typically encounter in the sport setting, which is asked for in the field of sport psychology (e.g. Galli & Gonzalez, 2015; Gucciardi et al., 2011; Sarkar & Fletcher, 2013).

The factors to be assessed may be found at the affective, cognitive, behavioral, and physiological level (e.g. Gernigon et al., 2010). In line with previous research examining temporal processes of resilience-related variables (e.g. Van de Leemput et al., 2014), the focus should be on the warning signals, which are expressed in the fluctuations of variables and dynamic relations between variables before a resilience loss occurs (e.g. Helmich et al., 2021; Kuranova et al., 2020; Scheffer et al., 2009, 2018; Van de Leemput et al., 2014; Wichers et al., 2016). In the study by Van de Leemput et al. (2014), the focus was on temporal fluctuations in emotional variables, as this would provide information on resilience in the mood state of people. Across different domains, such a focus can tell researchers and practitioners more about *when* there is a problem with the resilience of the system under study and therefore signal when an intervention is needed (Scheffer et al., 2018; see section 'Using knowledge from data science'). Note that the prospect of measuring relatively few variables also makes the monitoring process easier to implement and interpret for practitioners in the sports field.

To give an illustration in the sport psychological domain, mood, motivation, and self-efficacy are key variables related to resilience and sport performance (e.g. Fletcher & Sarkar, 2012; Galli & Vealey, 2008; Gernigon et al., 2010; Lundqvist & Kenttä, 2010; Sarkar & Fletcher, 2014; Sève et al., 2007). Mood is a state of mind, reflecting the way athletes are feeling at a particular moment. In addition to mood, self-efficacy and motivation may be measured in a straightforward way, just by asking how confident athletes are in their abilities to perform, and how motivated they are at that moment (cf., Den Hartigh et al., 2016, 2020; Vallerand et al., 1988). These variables can be measured at a relatively high frequency (e.g. at the start of every training day), to see how they respond to stressors that athletes encounter (e.g. related to life events as well as training sessions, matches, etc. on the previous day(s)).

On a physiological level, Total Quality of Recovery (TQR, Kenttä & Hassmén, 1998) may be administered. This higher-order measure consists of one item measuring how well an athlete is recovered. Typically, the TQR is measured on training days, and is related to external and internal load indicators to determine the relationship between load and recovery for athletes (e.g. Brink et al., 2010; Hartwig et al., 2009; Kellmann et al., 2018). When the time to return to the normal level of the psychological and/or physiological measures increases, this could be predictive of a resilience loss on the psychological and/or physiological level (see the section 'Using knowledge from data science'). As with the stressors, the psychological and physiological responses to stressors can be measured on a daily basis using an online application.

### Monitoring protective factors

As discussed in the previous subsection, resilience can be determined based on temporal processes in psychological and physiological measures (e.g. Gijzel et al., 2020; Hill et al., 2018a, 2018b; Scheffer et al., 2018). Yet, in line with earlier research on resilience, protective factors may moderate the resilience process (e.g. Galli & Pagano, 2018; Ristolainen et al., 2014). In other words, measuring protective factors may provide information about who is generally more resilient when encountering stressors (Sarkar & Fletcher, 2014; cf. Verhagen et al., 2018). We will therefore briefly tap into these factors as well. In the psychological domain, Fletcher and Sarkar (2012) proposed different kinds of protective factors, summarized as positive personality, motivation, confidence, focus, and perceived social support. Such factors likely remain more stable across time and could be relevant to measure at a lower frequency (e.g. one or two times in a season). As an illustration, personality factors or the motivation to perform well at the Olympic Games likely does not undergo significant changes from day-to-day. Nevertheless, personality or the motivation for a distant goal may moderate the negative effects of daily stressors, and thereby the resilience of athletes (Fletcher & Sarkar, 2012). The same goes for relatively stable characteristics or capacities like anthropometric characteristics, VO2max, neuromuscular control, which may moderate resilience losses in the physical domain. Such data can also be included in the analytic model, because data science (machine learning) models can account for multimodal data that is collected at different frequencies.

## Using knowledge from data science

To understand the bouncing back process of resilience, the temporal data on stressors and responses to stressors should be properly analyzed. This means that patterns should be detected in multimodal dynamic processes. For this purpose, machine learning is a promising application and a logical fit with the perspective on resilience outlined in this paper. Specifically, machine learning is an approach to data analysis where 'models' can be 'trained'. A model is a set of operations that can be applied to input data to predict a target. For example, when proceeding from the conceptualization of resilience as a dynamic process including psychological and physiological responses to different types of stressors, an athlete's resilience score may be predicted based on the stressors and responses in the previous days. Training a model implies a continued improvement over time. In this modeling process, new data points will continue to update the 'trained' model. This modeling process has a strong focus on predicting *when* the target variable (e.g. motivation or physical recovery) will have a specific value. The *why* question on the other hand is more challenging to answer, which is in line with the notion that the study of resilience warrants a dynamic and personalized approach. Indeed, the *why* might change over time and is likely to be different for different individuals. The *when* question has more practical value, and directly fits with the theoretical conceptualization of resilience as a dynamic process (e.g. Hill et al., 2018a, 2018b; Masten et al., 2021; Scheffer et al., 2018).

To facilitate evidence-based practice, data science experiments are conducted to examine the robustness of patterns in the data. These experiments test whether a trained model is not 'overfitted', that is, incorrectly assuming that a pattern in the data

generalizes beyond the given data. The (combination of) factors that are used to predict resilience losses are the so-called features of the model, and can be derived from the previous stressor and subsequent recovery data of the athlete in question (e.g. Lovdal et al., 2021; Rossi et al., 2018). This idea fits with the assumption that warning signals can be detected in information prior to a resilience loss. Such features are constructed from the raw data collected on the sports field (e.g. psychosocial stressors, motivation scores, sensor data, physical recovery scores). These raw data, in turn, could come from different modalities and may be measured at different frequencies. By analyzing the data over time, where the previous data points have an inherent influence on the next data point, it becomes possible to develop a multidimensional model that captures the resilience of individual athletes over time. These data-driven models can provide the basis for personalized model-based interventions (cf., De Leeuw et al., 2021; Kent et al., 2018; Schork, 2015).

## Determining the target

In the process of finding the optimal machine learning model of resilience, a 'target' needs to be determined based on the domain expertise of psychology, physiology, and sports science. The target is the variable (or concept) that the model should learn to predict. In the context of resilience research, the target would ideally be how resilient someone is on a numerical scale. As indicated previously, we conceptualize resilience as the process of returning to normal functioning after the occurrence of a stressor (e.g. Carver, 1998; Hill et al., 2018b; Hosseini et al., 2016; Scheffer et al., 2018; Seeman & Robbins, 1994). Figure 1 visualizes this idea, where the area of normal functioning is highlighted in green. The figure also illustrates that quantifying the target takes into account (1) the disruption after a stressor (dashed red arrow), and (2) subsequent return to normal (solid green arrow). If the relation between the disruption and the return is 'abnormal', this can be considered as a resilience loss. We have visualized
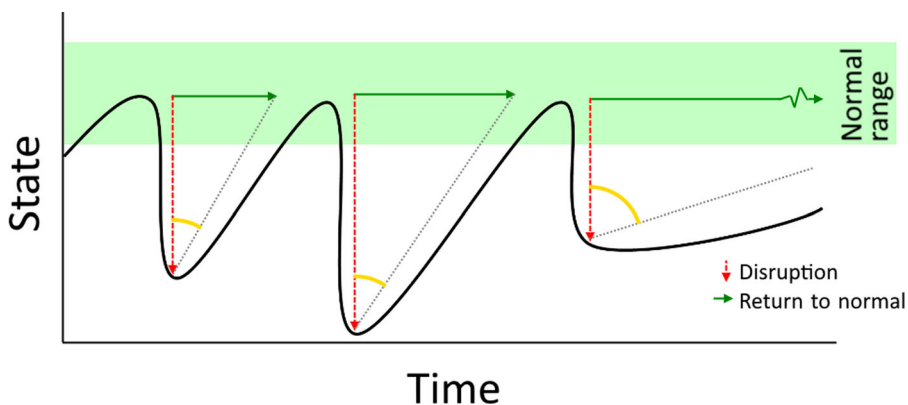


**Figure 1.** Hypothetical time series of an athlete's state which drops after a given stressor (dashed red arrow), and returns (solid green arrow) within the normal range for the individual (highlighted in green). The relation between the disruption and the return as visualized by the return angle captures how resilient the athlete is at that moment. In this hypothetical example, a resilience loss would be an abnormal angle indicating that the individual does not return quickly enough.

this relationship as the 'return angle' (in yellow).[1] The first two returns are within the 'normal range', thereby reflecting a normal return period for that particular athlete given those particular stressors. The return angle in the third episode is larger than normal, and accordingly reflects a resilience loss. The 'normal' relationship can, for instance, be modeled using a regression approach. With this model, the *predicted* return can be compared to the *actual* return, yielding a numerical estimation of resilience that can be used as a target.

In the domains of psychology, physiology, and sports science there are multiple metrics that can be used to represent the resilience process, that is, the stressor and the return. It is therefore important to reiterate that the process displayed in Figure 1 can pertain to psychological as well as physiological processes. Hence, losses in resilience can be detected in psychological variables, physiological variables, or a combination of these. Like in other disciplines (e.g. Helmich et al., 2021; Scheffer et al., 2009, 2018; Van de Leemput et al., 2014; Wichers et al., 2016), it is important to focus on the fluctuations in variables that are relevant to resilience and sports performance (see the subsection on 'Variables to Monitor'). As a simple example on the physical side, an athlete's measure of training load on a particular day can be considered as a stressor-score. The next day, before the training, the recovery can be determined. In a normal situation, the player can recover within one day to the normal (previous) recovery score. If after two training sessions the recovery becomes slower, as expressed by a comparable training load followed by a slower return to the normal range, the return angle has increased. This can provide an indication of a resilience loss. Consequently, failing to act on this resilience loss (e.g. by changing the intensity of the next training day for that athlete) may result in maladaptive outcomes such as nonfunctional overreaching or an injury (Heidari et al., 2019; Kellmann et al., 2018; Meeusen et al., 2013). A similar approach can be taken when mood or motivation is the variable of interest, for instance. Losing matches and/or tough training sessions may have a (temporary) disruptive impact on the mood of an athlete. A series of such stressors may trigger a resilience loss on which sports practitioners need to act. Whether the defined variable is more of a physiological or psychological nature, a resilience loss is likely the result of an individual biopsychosocial process that can be captured by the 'features' that are defined (see below).

Having chosen the target, machine learning is used to train a model that can predict this target. As input for the model, features should be included that encompass the multidimensional measures taken of the individual athletes. More specifically, from a theoretical point of view, the features should include the psychosocial and physiological stressors of individual athletes, as well as the temporal processes of psychological and physiological variables. Finally, if an effective model has been trained, it can be used for real-time predictions of future resilience scores and -losses. That is, these predictions allow to infer *when* a resilience loss might occur. A coach or sport psychologist may subsequently use the predicted resilience score as an additional source of information to determine whether or not to intervene. In order to ultimately accomplish this, it is necessary that there is a complete, well-functioning pipeline in place, which covers the entire process from data collection to machine learning applications and feedback to the coach or sport psychologist (see next section).

## Practical implementation

As can be inferred from the previous sections, a close collaboration between psychologists, sports scientists, and data scientists is needed to improve our understanding of the dynamic resilience process. In addition, there needs to be a strong connection with sports practitioners to facilitate data collection, and to apply the knowledge in practice. Two possible barriers for successful implementation of our perspective concern, first, the measurement infrastructure and, second, response bias of the athletes. First, an important requirement is that there is a proper infrastructure that includes the entire pipeline – from data collection to scientific analysis and feedback – in order to better understand and improve the resilience of athletes (see Figure 2). On the side of sports practice (left part of the figure), a structured routine of data collection should be in place that includes physiological and psychological measures. Ideally, in interaction with psychologists and sports scientists, the content of the variables to be measured are determined, and embedded scientists and practitioners assist in the structured data collection. On a soccer field, for instance, psychological data – including stressors, mood, motivation, see subsection 'Variables to monitor' – can be collected through an application that connects with a database where the data are stored. This app can also be used to collect the perceived recovery and exertion data of athletes before and after training sessions, respectively. Other physiological data such as external load can be collected through wearables of the players (e.g. Jaspers et al., 2018).

Second, to minimize the risk of response bias the protocol of data collection is crucial (cf. Bergen & Labonté, 2020). If athletes, for instance, sense that their data can be used for the purpose of making selection decisions, there is a risk of socially desirable responses to
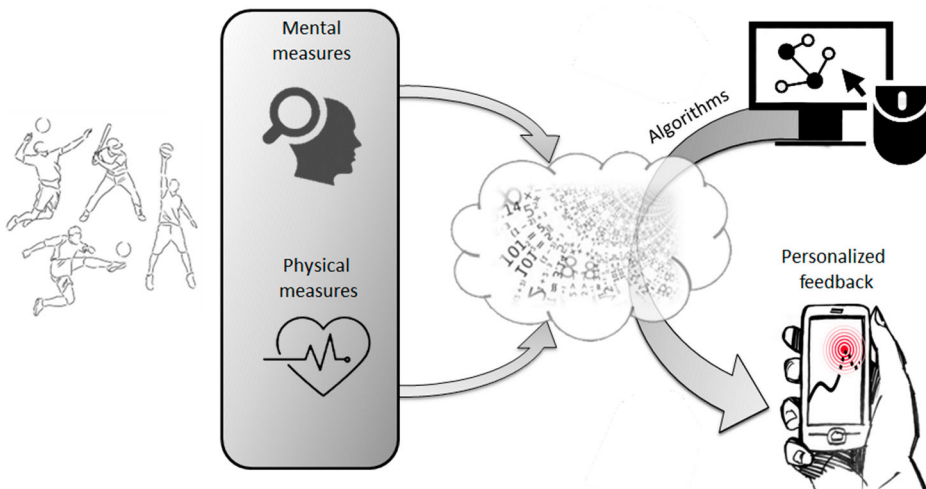


**Figure 2.** The pipeline from data collection to feedback, tailored to a multidisciplinary, dynamic, and personalized perspective on resilience (https://project-ris.nl/english/index.html). Psychological and physiological data collected through an app and sensors are pushed to a data platform, where they are securely stored for each athlete individually. Algorithms to detect warning signals in the psychological and physiological data are (automatically) run on the data yielding descriptive and analytic outcomes of each athlete which can be graphically displayed in the dashboard.

the resilience-related questions. Therefore, implementing the monitoring as part of the daily routine on the sports field is important. Relatedly, athletes need to be made aware of the fact that the monitoring, analysis, and feedback are part of the data-driven guidance to optimize the health and performance of the athletes for longer periods of time.

To let the data scientists apply their analytic models, a fast and secure flow from the psychological and physiological data to the database should be established (middle part of Figure 2). In an ideal scenario, this happens in an online, synchronized fashion. If apps and sensors are used from external companies, it is often possible to collect the (raw) data through application programming interfaces (APIs), and structure them as required. After 'cleaning' the data in the database, data scientists can define the features in the data and predict the defined target (see section 'Using knowledge from data science'). Such a fast and systematic approach to data collection and analysis has been up and coming in the past decade, primarily in the fields of eHealth and personalized medicine (e.g. Blaauw et al., 2016; Blaauw & Emerencia, 2015; Emerencia et al., 2013; Van der Krieke et al., 2017). However, with the rapidly developing advances in technology and data science in the sports field, applications to the sports context are currently rising (e.g. Couceiro et al., 2016; De Leeuw et al., 2021; Goes et al., 2021; Jaspers et al., 2018; Knobbe et al., 2017; Lovdal et al., 2021).

Given that machine learning approaches can 'get to know' the individual athletes, personalized insights and interventions are possible (e.g. De Leeuw et al., 2021). Ideally, the app that is used to collect the responses of athletes, also serves as a dashboard for feedback (right part of Figure 2). In the field of sports, feedback dashboards are already employed by professional organizations. Yet, dashboards in which data-driven warning signals can be added to the descriptive graphs are lacking, but can be very useful. Currently, whether or not an athlete is considered to be in the 'danger zone' to loose resilience, incur an injury, or develop a mental problem is often based on the evaluation of an expert in the field, such as a coach. When the pipeline – psychological and physiological data collection, automated data analysis, feedback dashboard – is in place, the model-based warning signals will provide the expert with additional information on the individual athletes. Such a personalized approach has been up and coming in the medical sciences in terms of 'Personalized Medicine' (e.g. Hamburg & Collins, 2010; Joyner & Paneth, 2015; Kent et al., 2018; Schork, 2015). It can be valuable to coaches and other experts in sports practice such as a sport psychologist, as it allows them to implement a tailored, effective intervention when a psychological and/or physiological resilience loss is predicted.

In line with the personalized approach, recommended interventions should be specific to the situation of the athlete. Examples are physiological- and/or psychological stress management interventions, such as adjusting the training schedule for the athlete and/or providing Mindfulness Acceptance Commitment training (e.g. Gervis & Goldman, 2020; for reviews on various possible interventions, see Brown & Fletcher, 2017; Gledhill et al., 2018). Hence, when the necessary investments in the pipeline have been made, based on a collaboration between psychologists, sports scientists, data scientists, and sports practitioners, novel scientific and practical insights can be gained in an efficient way. Long lasting collaborations of this kind may, in turn, contribute to better health and performance of athletes for longer periods of time.

## Summary and conclusion

Based on a review of the segmented literatures on resilience in psychology, physical resilience, and load and recovery in physiology and sports science, we proposed a multidisciplinary, dynamic, and personalized perspective to better understand how athletes bounce back following stressors. In order to detect resilience losses, out of the many biopsychosocial data that can be collected from athletes on a daily basis, data science provides an important contribution to determine warning signals. Furthermore, interpretable insights on the state of individual athletes, and possible resilience losses in the near future, can be presented to coaches and other experts through a dashboard. This is only possible when psychologists, physiologists, sports scientists, data scientists, and sports practitioners closely collaborate. This collaboration provides the foundation for a pipeline – from data collection on the sports field to personalized feedback – that can revolutionize the study and improvement of athletes' resilience.

## Note

1. Note that the return angle is a quantification of resilience based on the perspective presented in this article. Alternative quantifications one may think of are the earlier mentioned area under the curve, critical slowing down, or other dynamic resilience indicators depending on the measurement design and collected data.

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