"Finding Indicators of Resilience Losses in Time Series of Psychological Parameters in Youth Soccer Players."

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Master Thesis – Talent, Development and Creativity

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June 2022
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Preface

In front of you is my master's thesis for the master Talent, Development and Creativity at the University of Groningen. The study I conducted investigated warning signals of resilience losses in youth soccer players. The thesis is written as part of my graduation of the Master Psychology and is part of a bigger Resilience Project (Den Hartigh et al., 2022), in which different researchers conduct studies about various parts of resilience in athletes. Together with my supervisors Niklas Neumann and Ruud den Hartigh, I worked on this thesis from October 2021 till June 2022. I was able to expand my knowledge about talent, development, and creativity in the domain of sport psychology, for which I am very thankful.

First, I really want to thank Niklas and Ruud for their helpful guidance during my graduation year. During the research they were always ready to answers my questions and provide my study with some feedback. Thanks to that, I was able to improve the quality of my thesis. Second, I really want to thank the organization I collaborated with. They shared their data, knowledge, and organization with me and approved me with the opportunity to conduct this research. Without them, this would not have been possible. Finally, I want to thank my family and friends for their motivational and loving support during the writing process, which helped me to keep going. Especially, I want to thank my brother Jasper Ottens for his help with Excel. His knowledge and expertise of this program caused that I could rapidly perform my analysis in Excel.

I hope you enjoy reading my master's thesis.

Mariëlle Ottens

Groningen, June 2022

Abstract

Resilience is an important concept in the development of youth elite athletes. It is a dynamical process which entails athletes' bouncing back to their previous level of functioning after exposure to a stressor (Hill, et al., 2018). Resilience will be approached as an individual-specific process that unfolds over time. In this current research, different statistical indicators of resilience losses were explored in time series data of psychological parameters (i.e., self-efficacy and self-rated performance) of youth soccer players. These indicators are changes in mean, the slope, autocorrelation, and fluctuations, which are measured in time series data of self-efficacy and self-rated performance. The sample consists of 18 male youth players of a professional soccer academy in The Netherlands. The players completed some single-item self-report questions about physical and psychological aspects (i.e., self-efficacy, self-rated performance, and life-events) on a tablet in the locker room before and after their training or match. This data has been analyzed by means of a Changepoint analysis. The focus was on changepoints in statistical indicators, prior to a decrease in mean, to investigate which changepoints are occurring before a resilience loss. The study reveals that in 50% of the cases of self-efficacy and 61% of the cases of self-rated performance, a specific pattern of indicators occurs prior to a drop in self-efficacy and self-rated performance, which can be seen as a warning signal of a resilience loss. In specific, if multiple indicators occur together, this is often a warning signal for a possible decrease in the resilience of a player. This finding can be valuable for soccer organizations because this could mean that we can see and potentially avoid resilience losses in practice, for example by a timely intervention by a sport psychologist or coach.

Keywords: resilience losses, self-efficacy, soccer, changepoints, warning signals.

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Finding Indicators of Resilience Losses in Time Series of Psychological Parameters in Youth Soccer Players

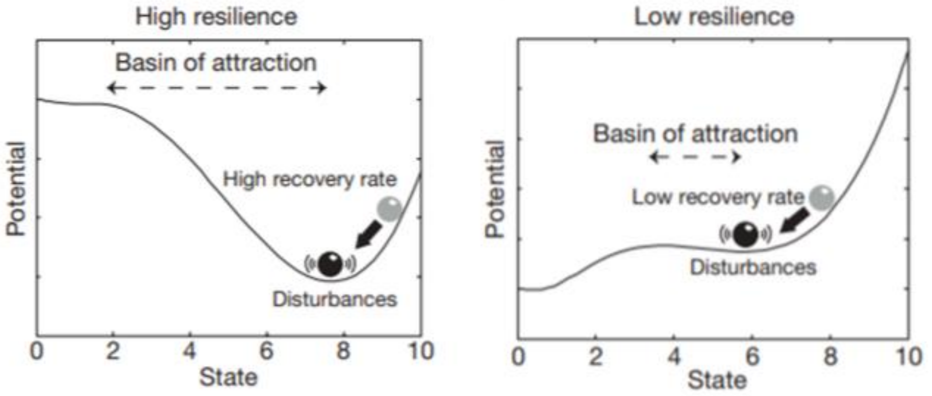
In December 2019, Memphis Depay tore his cruciate ligament during a match with Olympique Lyon. This injury costed him his participation at the European Championships and required several months of recovery (AD, 2019). After these setbacks, he did not give up his career and recovered from his injury by training a lot. He was able to get back to his previous level of functioning, after which he thrived and received a dream transfer to FC Barcelona in June 2021 (ESPN, 2021). In sport psychology, we would say that Memphis Depay was resilient, because he was able to bounce back to his previous level of functioning after his injury (Hill et al., 2018).

Resilience is also an important concept in the development of youth athletes. It is a dynamical process which entails athletes' bouncing back to their previous level of functioning after a stressor (Hill, et al., 2018). Resilience can be seen as a process that emerges from the interaction between various components within the person and stressors from the environment (e.g., Hill et al., 2018; Fletcher & Sarkar, 2013; Egeland et al., 1993). The complex dynamical system theory supposes that every individual will be exposed to some natural disturbances from the environment. Most of these disturbances are small and have little or no influence on the system, whereby the system can quite easily return to its previous state. In other cases, however, when an individual is not resilient at that particular moment, a disturbance can have a negative influence on the individual, such as a declining well-being or decreasing performance (Gijzel, 2020). Disturbances are mostly called stressors. In other words, the negative internal or environmental stimuli to which an individual is exposed (Fletcher, Hanton & Mellalieu, 2006). For athletes, these stressors can be further distinguished in competitive stressors (e.g., injuries, pressure or expectations; Fletcher & Sarkar, 2013), organizational stressors (e.g., leadership issues or the attitude of the coach; Arnold & Fletcher, 2012), and personal stressors (e.g., relationship problems or the death of a family member; Gould et al., 1993; McKay et al, 2008).

Figure 1 displays a visualization of high and low resilience as a landscape metaphor. The shape of the landscape determines how resilient the system is. When the slope of the landscape is steep, the black ball (current state of the system) can deal with big disturbances and can quite easily return to the previous stable state of functioning (i.e., the basin of attraction). This characterizes a high resilient system (left picture of figure 1). Only when a disturbance is of influential size, the black ball gets a large push over the tipping point. A tipping point is a critical threshold, after which the system makes a critical transition by shifting from one state to another (Gijzel, 2020). The recovery rate of a high resilient system is typically high, which means that the system can recover fast to its previous state after a disturbance. When the slope of the landscape is flatter (right picture of figure 1), a smaller disturbance can push the black ball more easily over a tipping point. The recovery time for this system is reduced because the capacity of the system to return back to the previous system is diminished (e.g., Scheffer et al., 2009; Gijzel, 2020). When the recovery time of a system is increasing, this process is called critical slowing down, which can be an indication of a transition towards a lower level of resilience (Gijzel, 2020).

Figure 1

The Visualization of Resilience of a Dynamical System. The slope of the landscape has an influence on the recovery rate of the system. The steeper the slope, the higher the recovery rate. This is a characteristic of a more resilient system.



Note. Taken from Early-warning signals for critical transitions, by Scheffer and colleagues (2009), p. 54.

To decide if an athlete is high or low resilient at a specific moment in time, daily monitoring of psychological parameters can be used. The purpose is to monitor the parameters in which resilience indicators can be assessed. Resilience indicators are statistical indicators within psychological parameters that can reveal changes in the level of resilience (Gijzel, 2020). Changes in these indicators can be monitored in time series of psychological parameters (e.g., Scheffer et al., 2009). For instance, if recovery time after a stressor increases for consecutive days, this is a warning signal of critical slowing down, which may lead to mental dips, a declining wellbeing or diminished performance in the long term (e.g., Gijzel et al., 2020; Hill et al., 2018; Scheffer et al., 2015). In the current study, the aim is to detect these indicators of resilience losses, based on time series data of relevant psychological and performance parameters in the context of soccer.

Monitoring psychological parameters

Den Hartigh et al. (2022) proposed some parameters that are important in the context of the sport performance, including self-efficacy and self-rated performance. In the current study, I will therefore examine self-efficacy and self-rated performance of athletes over time in order to detect resilience indicators in these parameters.

Self-efficacy is someone's perception about their own capabilities to execute different steps of an action to achieve a performance goal (Bandura, 1997; Ryan & Moller, 2017). People have their own comfort zone, in which they perform with confidence. Outside of their comfort zone, they can experience feelings of insecurity (Galli & Vealey, 2008). This means that when an athlete experiences a lot of confidence, this makes it easier to handle stress and pressure in a competitive sport (Sarkar & Fletcher, 2014). On the other hand, athletes who experience a lower self-efficacy worry more about - for example - an injury and give up sooner when they get exposed to a stressor or failure (Feltz et al., 2007). In other words, when self-efficacy is experienced as high, someone is more resilient to stressors and can perform better. Therefore, it is important that self-efficacy recovers every day, so the athlete feels confident to perform. A resilience loss can thus be observed in time series of self-efficacy.

Self-rated performance is a psychological construct in which someone rates their own experienced performance. As mentioned earlier, stressors can have a positive or negative influence on performance and the experience of performance (Gijzel, 2020), causing that experienced performance, among other things, depends on how someone manages adversity. If an athlete is less resilient, someone is not able to easily bounce back to the previous level of functioning, causing a decrease in performance. Since stressors can suddenly arise, the self-rated performance can also vary a lot. However, being psychologically resilient can have a positive effect on the performance and well-being of an athlete (e.g., Rutter, 2012; Denckla et al., 2020; Luthar et al., 2000). On the other hand, if an athlete rates his own performance lower than normal, this could mean that the athlete was less resilient at that specific moment (Carver, 1998). In short, the level of resilience can be observed in time series on how someone experiences his own performance.

Life events, such as the death of a loved one or family problems, can function as stressors, and can thus lead to a decline in performance if the athlete is not resilient enough (Hill et al., 2018). In sports, these stressors can come from different domains and can be distinguished into organizational, personal, or competitive stressors (Sarkar & Fletcher, 2014). The stressors may lead to a reduction in the level of resilience (e.g., Fletcher & Sarkar 2013, Fletcher & Sarkar, 2012). Because of this, it is important to take these into account during the monitoring of resilience losses.

Taken together, the psychological parameters of resilience (i.e., self-efficacy and self-rated performance), the life events, and injury data used in this current study must be analyzed to detect resilience losses. Changes in level of the psychological parameters can thus be an indicator of a change in resilience, which can be observed in these time series data.

Individual monitoring

As has become clear from the previous section, there are a lot of different aspects that can influence how resilient someone is in specific situations, for example a stressor such as an injury or multiple rejections in a row (e.g., Bhatnagar, 2021). The way an athlete responds to a stressor and how the resilience process will look like is different for various athletes (e.g., Hill et al., 2021; Bhatnagar, 2021). Therefore, it is important to monitor each athlete individually and to get familiar with each individual resilience pattern of responses to a stressful event.

The importance of focusing on individual athletes was demonstrated earlier in a study among soccer players of a professional soccer academy (Neumann et al., 2021). The authors investigated the process of load (physiological stress) and recovery, which shows great resemblance to the resilience process. Both contexts focus on soccer players and their response to a stressor (i.e., psychological and physiological), namely whether a person is able to recover from this stressor by bouncing back to his previous level of functioning. The researchers found in their study that statistical indicators (i.e., variance and relations between load and recovery) on group level could not be generalized to individual players in that group. As such, they demonstrated the importance of individual monitoring in the context of soccer.

Warning signals of resilience

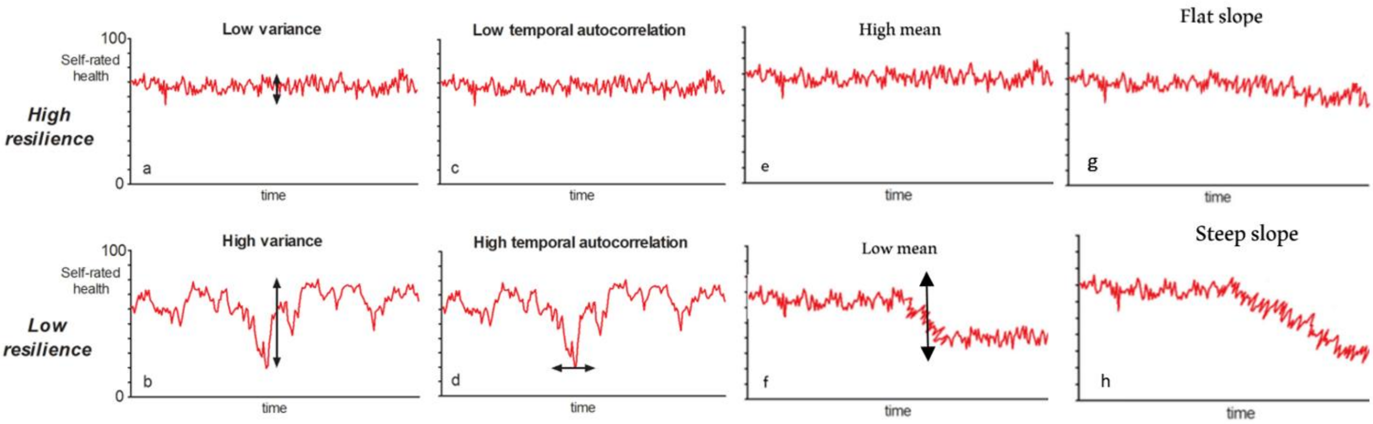
To better understand the resilience of athletes, it is important to understand what kind of deviations in statistical indicators of psychological parameters (i.e., self-efficacy and self-rated performance) are meaningful, and can thus be considered as an indicator of resilience losses. One can imagine that all athletes experience days in which they do not feel very confident to perform maximally, for example because of fatigue, no optimal recovery, or a lack of team spirit. However, if this day is followed by a recovery of self-efficacy on the next day, there is no problem with the athletes' resilience. Statistically speaking, this means that an outlier of a day is not immediately considered as a warning signal. According to the literature, it is more important to focus on a multi-day reduction of scores of a variable, which not immediately recovers to its previous level (e.g., a slumbering decrease in the mean of self-efficacy). This process is called the process of critical slowing down (Gijzel, 2020), meaning that the system recovers more slowly from a disturbance (slower recovery rate). This process can cause a tipping point. If anyone goes beyond this tipping point, this may lead to consequences such as mental issues or performance problems (e.g., Gijzel et al., 2020; Hill et al., 2018; Scheffer et al., 2015).

To identify a resilience loss, researchers have distinguished different resilience indicators. First of all, fluctuations (i.e., variance) and autocorrelation have been designated as resilience indicators (e.g., Ives, 1995; Gijzel, 2020; Robertson et al., 2017). Besides, in research on psychopathology about indicators and critical transitions, Helmich and colleagues (2021) found that rises in skewness of the score (i.e., the slope) can also be an indicator of resilience loss. Furthermore, according to research of De Jonckheere and colleagues (2019), focusing on simple statistics, such as changes in mean, may work equally well as indicator, compared to the advanced warning signals explained above. These indicators – also called early warning signals – can be a precursor for a transition to another state (e.g., Scheffer et al., 2009; Gijzel, 2020; Helmich et al., 2021). Therefore, it is necessary to analyze various time series of psychological parameters from individuals to examine different kind of meaningful resilience indicators.

A hypothetical illustration of different resilience indicators is shown in *Figure 2*. Someone who is high resilient typically shows a lower variance, meaning there is a little fluctuation in scores, in other words a stable pattern (a vs. b). Besides, a high resilient person shows a low temporal autocorrelation, which means that a disturbance has little influence on the next event (c vs. d). Third, a resilient person shows a stable high mean, meaning the mean of the scores on the psychological parameter is constantly high, compared to a period with a constantly lower score on for example self-efficacy. Finally, a high resilient person shows a flat slope with low skewness, meaning the slope of the scores are flat. Changes in these resilience indicators may be seen as an early warning signal of a resilience loss (e.g., Gijzel, 2020).

Figure 2

Hypothetical illustration of resilience indicators.



Note. Hypothetically made graphics. Graphics from variance and autocorrelation are taken from Bouncing back: Using a complex dynamical systems approach to measure physical resilience in older adults, by Gijzel (2020), p. 64.

To observe meaningful indicators in the data, the most fitting window of interest must be explored. The research of Carey and colleagues (2016) shows great resemblance with resilience and can therefore be used in psychology, because in a high-performance setting like the sport context, athletes must recover not only physiologically, but also mentally. They found that a window of interest from 7 and 28 days is the most accurate window for a reliable prediction. Hasselman and Bosman (2020) mentioned in their research that a window can also be determined by theoretical and empirical knowledge about the process, where a window is formed that makes sense for practice. For practice, this means that the buildup of a training scheme can be used in the decision about what window fits best. In soccer, a training scheme is built up containing 4 weeks of 7 days or 28 individual days of training. The window of 7 and 28 days used by Carey and colleagues (2016), could therefore possibly be used in this study to analyze the time series data, because this makes sense in the soccer context.

The current study

In this master thesis research, I will take a novel step by analyzing time series of self-efficacy and self-rated performance from individual soccer players at a professional youth soccer academy in the Netherlands. I will take a closer look at changes in resilience indicators, more specifically autocorrelation (Ives, 1995), fluctuations (e.g., Gijzel, 2020; Robertson et al., 2017), changes in mean (DeJonckheere et al., 2019) and changes in the slope (Helmich et al, 2019). In this research I will take a novel step by analyzing various individual time series of psychological and physiological data, to explore if the occurrence of statistical indicators in time series can act as warning signals of resilience losses. In order to answer that question, I make use of an infrastructure that was developed in the soccer field.

Methods

Participants

A total of 18 male youth soccer players were included for the current study. These players are member of the youth academy of a professional soccer club in The Netherlands. The soccer players are competing for the under 18 (U-18), meaning they are 16 or 17 years old. The U-18 team competes in the second division of the football league in The Netherlands. They have 6 to 8 training sessions a week, consisting of 2 strength training sessions on Tuesday and Thursday. Besides, the players train daily on the field for 5 times a week, mainly in the morning.

The original dataset consisted of time series data of 29 players over a whole season with 37 weeks of soccer activity. Research by Amiri and Jensen (2016) suggests that, if more than 30% of the values in a data set is missing, this is too damaging for useful results. For this reason, in the current study is chosen to exclude players from the sample who missed more than 30% of their values. Because of this criterion, eventually 18 players were retained for analysis. The specific demographic data of these players cannot be shared, for the sake of privacy.

Procedure and Measurements

The present study was conducted according to the requirements of the Declaration of Helsinki and was approved by the ethics committee of the Faculty of Behavioral and Social Sciences of the University of Groningen (The Netherlands, research code project: PSY-1819-S-0308).

During the whole season, the soccer players have completed single-item self-report questions on a tablet in the locker room before and after their training or match. In case of training at home for a longer period (i.e., because of the government measures during the corona pandemic), the players received an SMS to fill in the questions at home. Filling in these questions, took about 2-5 minutes per day. The questions were asked in Dutch or English, depending on the native language of each player.

From research it is known that measuring a construct through one question is reliable, valid, and viable in athlete monitoring (e.g., Abdel-Khalek et al., 2006; Duignan et al, 2020). For that reason, it was chosen to measure self-efficacy and self-rated performance through a single-item self-report question. The question about life-events consists of a yes/no question and some follow-up questions when the athlete answered the first questions with 'yes'.

Self-efficacy. Self-efficacy is questioned before every training session by means of "How confident are you that you can perform maximally today?". To answer the question, the athlete must slide a dot on the scale from 0 ("not at all confident") to 100 ("very confident").

Self-rated performance. After the last training session of the day, the athlete answers a question about their self-rated performance by means of "How well did you perform today?". This is answered by sliding a dot on a scale from 0 ("very bad (far below my capabilities)") to 100 ("maximally (to the best of my capabilities)").

Life events. Once a week, athletes answer a question about possibly experienced life events over the last week. The athlete answers the question "Did something important happen in the last week?", by selecting the dot of "yes" or "no". In case of "yes", some follow up questions show up. These consist of a question "How positive or negative was this event?" on a scale of 0-100 (0 = very negative, 100 = very positive) and "What was this event related to?" (1 = myself, 2 = home-situation/close family/significant others, 3 = friends/other family/acquaintances, 4 = school, 5 = society/news, 6 = public space/stranger, 7 = club/team, 8 = other, namely…).

Data Analysis

The answers to all the questions mentioned above, come together in a dashboard in an app, where an overview arises of time series data over a whole season. During the season, some answers were missing, because of for example illness or technical problems. The missing values of the remaining 18 players were replaced by means of the nearest neighbor technique. This method simply predicts the missing values, by calculating the mean of the available values that are in the proximity of the missing value. The missing value is then replaced by this calculated average (e.g., Amiri & Jensen, 2016; Wasito & Mirkin, 2005).

After this, the time series data was transferred to Excel, in which the score patterns were analyzed. During the analysis, a rolling window of 28 days was implemented (Carey et al., 2016; Hasselman & Bosman, 2020). The time series data was analyzed in Excel, by means of autocorrelation (e.g., Ives, 1995; Gijzel, 2020), fluctuations (e.g., Gijzel, 2020; Robertson et al., 2017), changes in mean (DeJonckheere et al, 2019) and slope (Helmich et al, 2019).

Autocorrelation. Autocorrelation gives information about how influential a score of today is on the score of the next day. When a stressor causes for example a lower self-efficacy and the autocorrelation is high, this means that the score of tomorrow is probably also lower, which is an indicator of a lower level of resilience (e.g., Gijzel, 2020; Zach, 2020). It is known that if the autocorrelation increases, a particular state becomes more correlated with a state on another moment. This means that there is sort of a spillover effect from one variable on itself to another day. On the long term, an increase in autocorrelation signifies that someone will recover more slowly from a dip, in other words an increase in the recovery rate, which is an indicator of a decline in resilience (Scheffer et al., 2009; Ives, 1995; Held & Kleinen, 2004). In Excel we calculate autocorrelation to measure the degree of similarity between the current values and the historical values, in other words the current values and the lagged version of itself over a specific time interval. Because of this, we can predict future scores by referring the past values (Zach, 2020). Therefore, we use the lag 1 autocorrelation, with which the occurrence of transitions to a lower level can be predicted (e.g., Scheffer et al., 2012; Van de Leemput et al., 2014; Clements & Ozgul, 2016). Autocorrelation is calculated by means of the formula mentioned below (Zach, 2020), in which X = value of the indicator and n = a moment in the time series.

$$Autocorrelation = (SUMPRODUCT(X_n{:}X_{total(n-2)} - AVERAGE(X_1{:}X_n), X_{n+2} - (AVERAGE(X_1{:}X_n)) / COUNT\ (X_1{:}X_n)) / VAR.P\ (X_1{:}X_n) \quad (1)$$

If the autocorrelation increases before a transition, this can be seen as an early warning signal for transitions in the level of resilience (Scheffer et al., 2009).

MASD. The MASD stands for the Mean of Absolute Successive Difference of the data sequence. This method is a simplified version of the commonly used Mean Squared Successive Difference (S. Kunnen, personal communication, 18th November 2021). The MASD computes the variability based on the absolute difference between each two points, instead of the squared difference. Important to mention is that the absolute mean is always positive because the difference between two values is measured, whereby direction is not taken into account. To use MASD in practice, the first step is to calculate the absolute difference between two scores of a psychological parameter.

$$ABSOLUTE\ DIFFERENCE = ABS(X_n - X_{n-1}) \quad (2)$$

Second, the mean of these absolute differences is computed, using a rolling window of 28 days. The MASD is calculated by means of the formula mentioned below:

$$MASD = AVERAGE(X_{ABS(Xn)} : X_{ABS(Xn+28)}) \quad (3)$$

An increase in the MASD is an indicator of increased variability, in other words, more instability of the variable (Von Neumann et al., 1941). More instability in scores, in other words an increase in the quantity of fluctuation and the MASD, can be seen as an indicator of a resilience loss (e.g., Gijzel, 2020; Scheffer et al., 2009).

Changes in mean. The mean is the weighted sum of values, which describes the distribution of scores (Von Mises, 1964). Changes in mean give information about the change in distribution of scores on a specific parameter. If the mean of self-efficacy or self-rated performance is high, this can be an indicator for a high resilient athlete at that particular moment (e.g., Fletcher & Sarkar, 2012; Sarkar & Fletcher, 2014). In the current study, we have a closer look at changes in mean, which can function as an indicator of a change in resilience. When the mean changes to a lower level, this can be seen as an indicator for a change in the level of resilience or a resilience loss. Therefore, changes in mean can be used as an indicator of resilience loss during analyzing time series data.

Changes in slope. The slope can be seen as another indicator of a resilience loss. When the slope rises and the line becomes more skewed, the system shows more instability (Guttal & Jayaprakash, 2008), which is an indicator of critical slowing down (Helmich et al., 2021). Besides, the slope is used to take variation in autoregression into account, to estimate the temporal autocorrelation (Gijzel, 2020). Therefore, when the slope becomes steeper, this can be seen as an indicator of a decrease in the level of resilience. On the other hand, if the slope becomes flatter, this can be seen as an indicator of a more stable level of resilience. Changes in slope can thus be seen as an indicator of a change in level of resilience.

Changepoint analysis

A changepoint analysis in R is used to detect multiple changes within a given time series (Killick & Eckley, 2014). This will give further insight into when meaningful changes in resilience indicators occur for each athlete. For the changepoint analysis in R, the package 'TSMCP' of Li and Yin (2018) will be used.

After the changepoint analyses, a closer look is necessary at the period prior to a changepoint in mean. To do so, the changepoints were implemented as lines in the time series data consisting of the raw scores on the psychological parameters. This creates a total overview of the scores on the parameters over a whole season, including the changepoints of the resilience indicators. To specifically focus on resilience losses, special attention is paid to the changepoints prior to a changepoint in mean to a lower level.

Results

First, the results for self-efficacy will be shown, containing graphics with changepoints in resilience indicators. Second, the results for self-rated performance are displayed the same way as for self-efficacy. The figures for both self-efficacy and self-rated performance consist of the raw data for each variable and the changepoints in the resilience indicators. The changepoints in the indicators are visualized as lines with different colors, which are successively changes in mean (black line), slope (green line), MASD (orange line) and autocorrelation (yellow line). The results of the changepoint analysis for each resilience indicator for both parameters are shown in *table 1* (i.e., self-efficacy) and *table 2* (i.e., self-rated performance).

Changepoints of resilience indicators for self-efficacy

The figures 3, 5 and 7 contain the raw data of self-efficacy over a whole season for one soccer player. To see a resilience loss coming, special attention is paid to the different changepoints prior to a changepoint in mean, to see if the change in the mean can be explained by the occurrence of changepoints in resilience indicators before the resilience loss. This means that a changepoint in mean before a change to a lower level, is comparable with a resilience loss, where the other indicators function as early warning signals for this resilience loss. An elaboration of all the graphics of self-efficacy is included in *Appendix I*.

What stands out in these figures is that two or three changepoints in different resilience indicators precede a changepoint in mean (black line). This is mostly followed by a drop in self-efficacy. The changepoints in indicators, followed by a changepoint in mean to a lower level, can been seen as a resilience loss. In 50% of the cases (9 of the 18 analyzed players) of self-efficacy, we can find this pattern of two or three changepoints in resilience indicators that precede a changepoint in mean. This pattern is also found for player 1, 7, 11, 13, 14, 17, 21, 27 and 29.

Table 2

ChangePoints in Resilience Indicators in Self-Efficacy (window of 28 days).

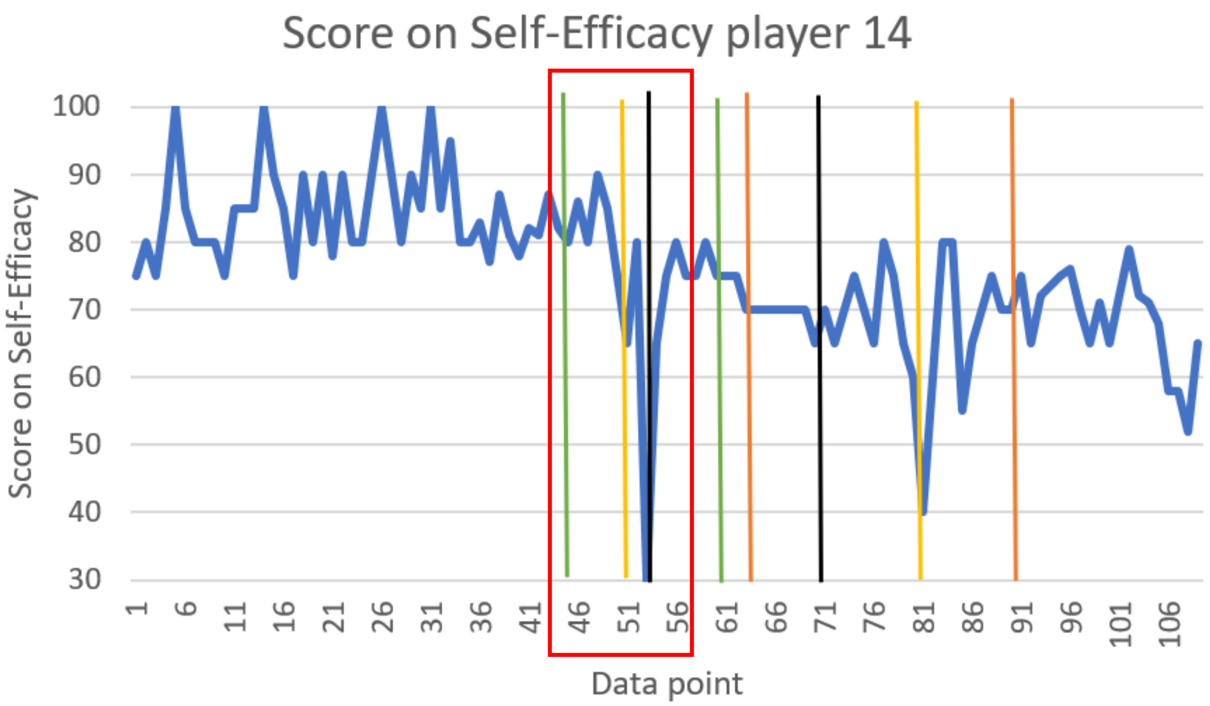
Player	Self-Efficacy mean	Self-Efficacy MASD	Self-Efficacy Slope	Self-Efficacy Autocorrelation
1	36; 75; 113; 131.	15; 100; 119.	54; 112; 136.	33; 61; 100; 112.
3	18; 43; 100.	21; 53; 88.	21; 87.	21; 65; 80.
4	27; 55; 106.	55.	42; 61; 99.	15; 72.
6	45; 73; 106.	40; 73; 114; 130.	25; 93; 123.	47; 122.
7	40; 79; 127.	47; 75; 101.	17; 71; 125; 141.	8; 64; 86; 126.
11	23; 48; 88; 120.	8; 78; 112.	25; 103.	24; 49.
13	24; 83; 95; 124.	19; 121.	50; 91; 108.	37; 72; 92.
14	26; 43.	37; 63.	17; 33.	23; 53.
16	27; 56; 118.	56; 118.	25; 41; 56; 135.	55; 76; 145.

17	45; 70; 102; 130.	23; 69; 101; 129.	47; 126.	37; 76; 100.
18	34; 93.	63; 91.	47; 86; 103.	34; 63; 117.
19	31; 115.	42; 87.	10.	40; 58; 97; 116.
20	63; 81; 97.	20.	26; 77; 114.	29; 94.
21	33; 59; 96; 114.	14; 76; 93; 121.	13; 84; 116.	53; 138.
24	29; 57; 87.	10; 74; 146.	41.	23; 90; 145.
25	47; 87; 129.	43; 86; 129.	51; 76; 95; 143.	30; 92.
27	39; 54; 86.	21; 52; 68; 97.	30; 70.	19; 46; 69; 98.
29	29; 74; 112.	68; 111.	10; 56; 142.	8; 57; 105.

Note. The yellow marked changepoints occur almost together. In the most cases, two or more changepoints in various indicators precede a changepoint in mean, meaning they can function as a warning signal for a resilience loss.

Figure 3.

Raw data with changepoints in resilience indicators for self-efficacy of player 14.



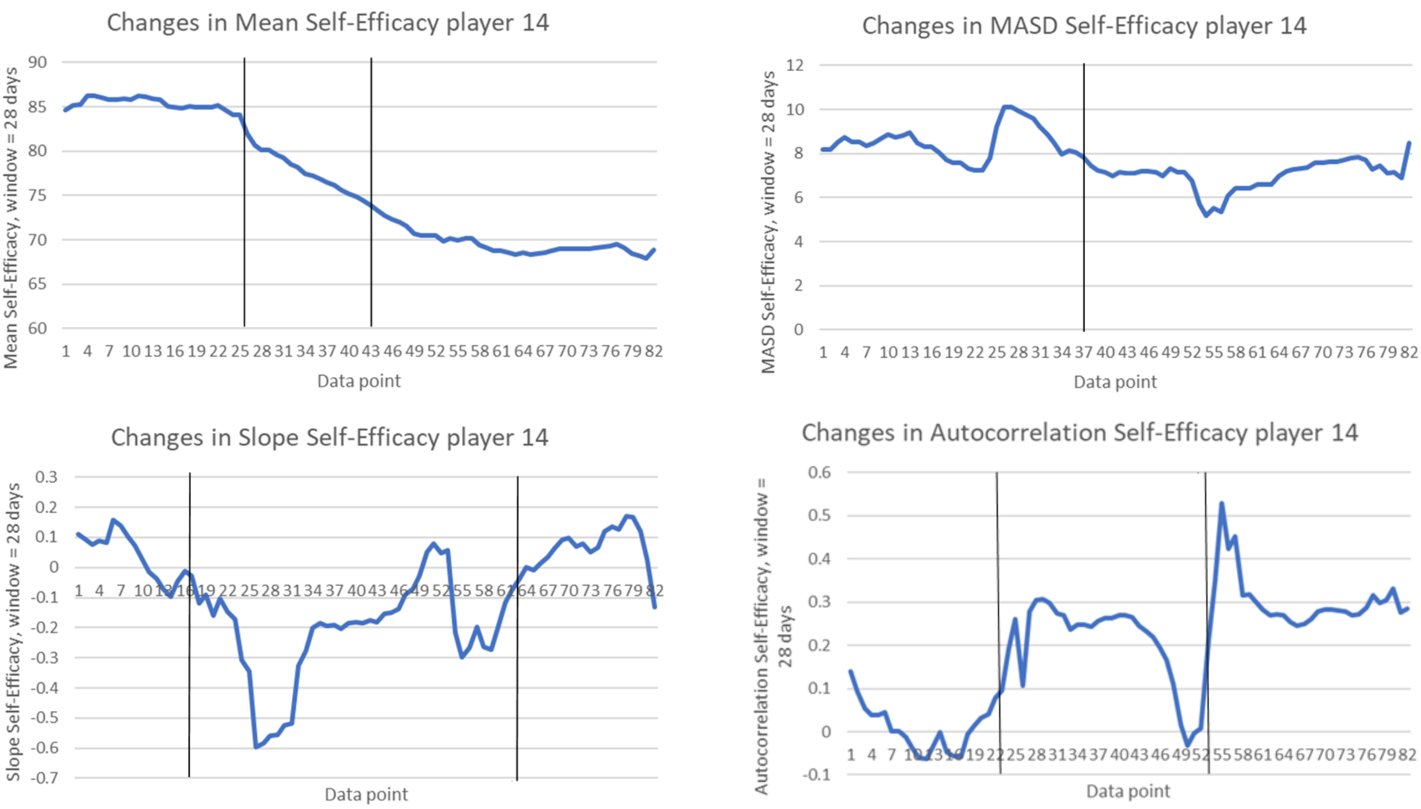
Note. Change in mean = black, change in slope = green, change in MASD = orange and change in autocorrelation = yellow. The red square indicates the moment of a resilience loss, pictured by a loss in self-efficacy.

As shown in figure 3, several changepoints in resilience indicators can be noticed. Between datapoint 48 and 54 (i.e., the red square), an abrupt decline from about 80 to a score of 0 at self-efficacy can be observed. This is denoted by a changepoint in mean at datapoint 54. This changepoint in mean is preceded by a changepoint in slope at datapoint 45 and a changepoint in autocorrelation at datapoint 51. Later in the course of self-efficacy, a similar pattern can be noticed. First, the line of self-efficacy increases, after which the line further declines to another changepoint in mean at datapoint 71. Again, this changepoint is preceded by two changepoints in other resilience indicators, successively a change in slope at datapoint 61 and changepoint in MASD at datapoint 65.

In figure 4, the individual courses of the four resilience indicators are pictured over a whole season, successively the mean, the slope, autocorrelation and MASD. These patterns are based on a window of interest of 28 days, so the data points in figure 3 and 4 are not comparable. For that reason, a datapoint in figure 3 corresponds to a datapoint in figure 4 that is 28 days earlier, taken the window of interest into account. This means for example that in figure 4 and table 1, a changepoint in mean at datapoint 26, corresponds to a changepoint in mean at datapoint 54 (i.e. datapoint or changepoint + 28 days) in figure 3. By this method, a correct comparison can be made between the raw data and the data of resilience indicators with a window of 28 days.

Figure 4.

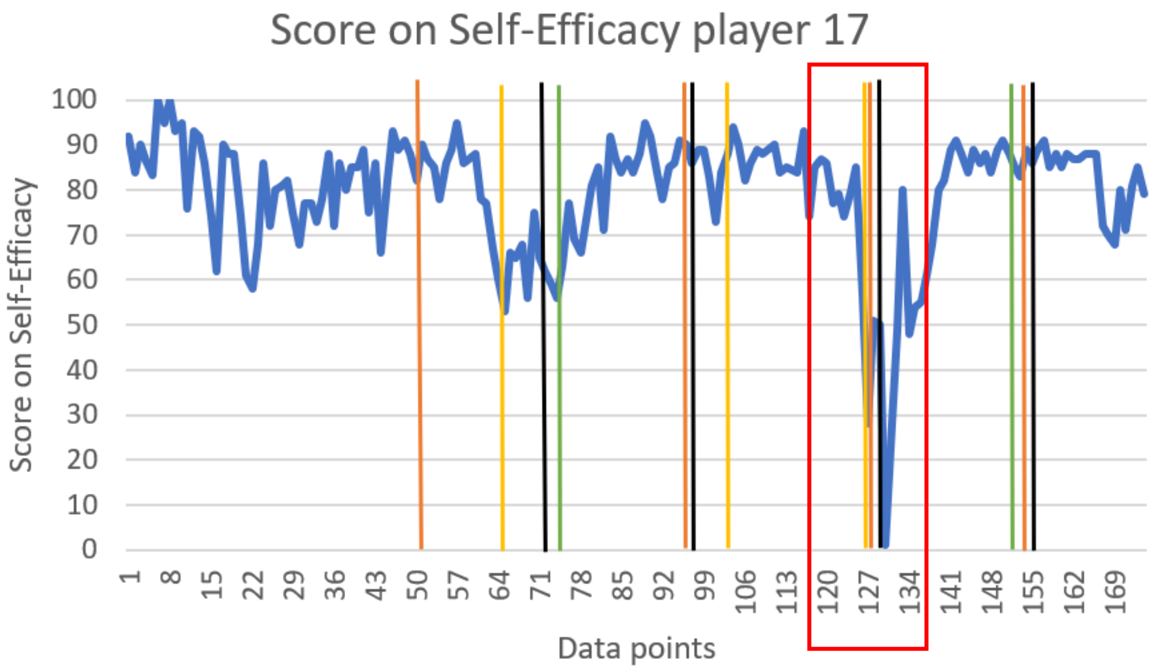
Individual graphs of resilience indicators for self-efficacy of player 14 including the changepoint.



In figure 4 is shown that the first decrease of the level of self-efficacy is characterized by a decrease in mean, a decrease in slope and an increase in autocorrelation. The second decrease of the level of self-efficacy is characterized by a decrease in mean, an increase in slope and a decrease in MASD. Again, the most remarkable observation is the pattern in which two or three changepoint in resilience indicators precede a changepoint in mean. The occurrence of these changepoints close together is mostly followed by a drop in mean is also found for player 1, 7, 11, 13, 17, 21, 25, 27 and 29. Player 17 is further visualized in figure 5, while the others are included in *Appendix I*.

Figure 5.

Raw data with changepoints in resilience indicators for self-efficacy of player 17.



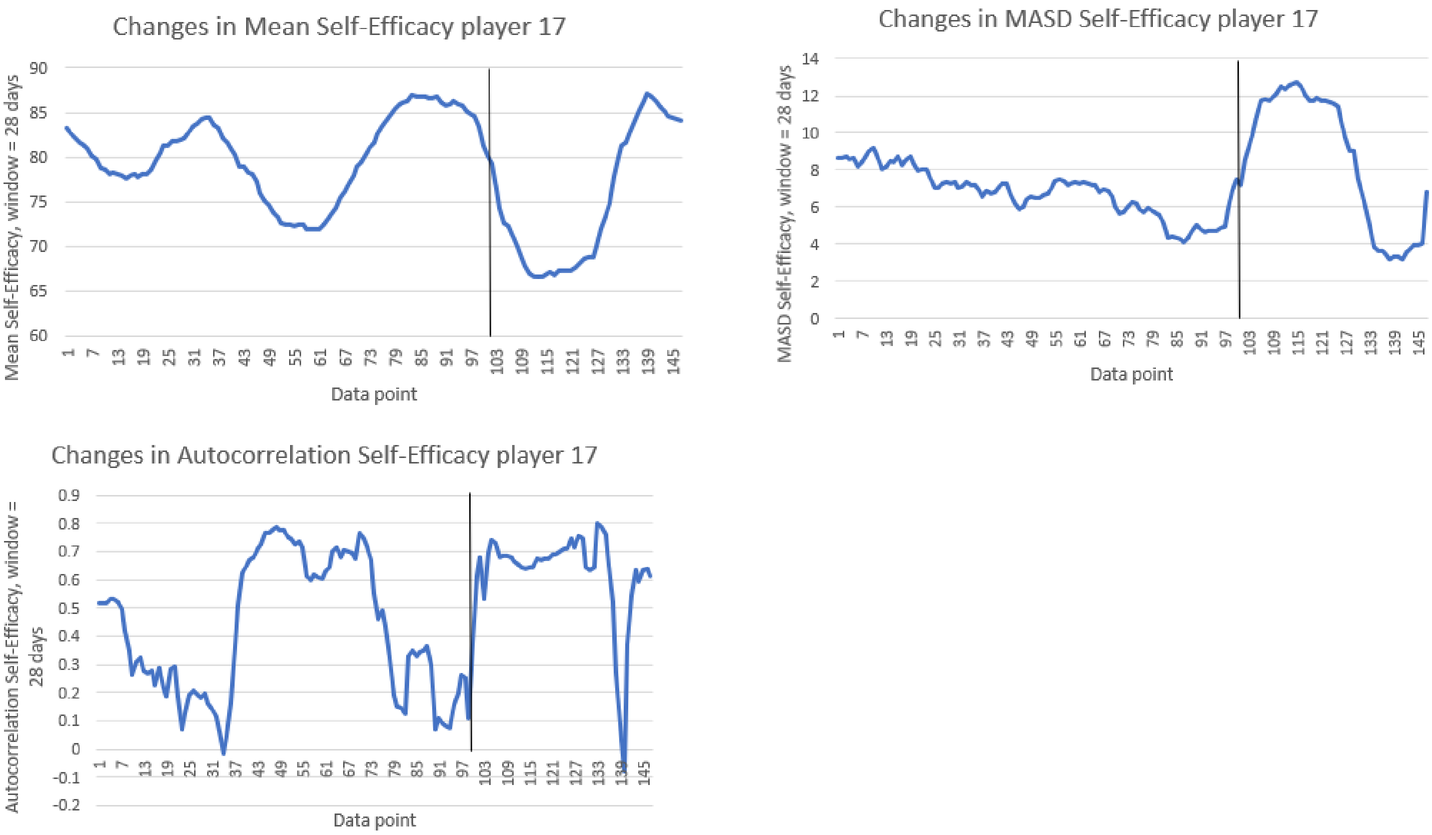
Note. Change in mean = black, change in slope = green, change in MASD = orange and change in autocorrelation = yellow. The red square indicates the moment of a resilience loss, pictured by a loss in self-efficacy.

As shown in figure 5, several changepoints in resilience indicators can be noticed. At datapoint 129 (i.e., the red square), a clear reduction of the level of self-efficacy is observable, which can be an indicators of resilience loss. The drop in self-efficacy is characterized by three changepoints in resilience indicators. At first a changepoint in autocorrelation at datapoint 128, followed by a changepoint in MASD at datapoint 129 and finally a changepoint in mean at datapoint 130.

In figure 6, the individual graphs of the resilience indicators are pictured for over a whole season. Here, the black line acts as the changepoint that occurs within the red square. The graphs represent successively the mean, autocorrelation and MASD. Because of different windows, a changepoint in mean at datapoint 130 in figure 5 corresponds to datapoint 102 in figure 6, the changepoint in MASD at datapoint 129 in figure 5 corresponds to datapoint 101 in figure 6, and the changepoint in autocorrelation at datapoint 128 in figure 5 corresponds to datapoint 100 in figure 6, taken the window of interest into account.

Figure 6.

Individual graphs of resilience indicators for self-efficacy of player 17 including the changepoints.



In figure 6 is shown that prior to the huge decrease in the level of self-efficacy, a decrease in mean, an increase in autocorrelation and a decrease in MASD is observable. Again, the changepoint in mean is preceded by two changepoints in other resilience indicators, which can be an indicator of resilience loss.

Changepoints of resilience indicators for self-rated performance

Just like self-efficacy, the focus on self-rated performance also applies to the changepoints prior to a changepoint in mean, to see if these changes in the mean can be explained by the occurrence of changepoints before the resilience loss. This leads to the revelation that the pattern that was earlier observed for self-efficacy, was also observable for self-rated performance. This was the case for player 1, 4, 6, 7, 16, 18, 19, 20, 24, 25 and 29. This means that in 61% of the cases (11 of the 18 players) of self-rated performance, players show the pattern of two or three changepoints in resilience indicators that precede a changepoint in mean (black line), which is followed by a decline in the level of self-rated performance. Two of these players are further visualized in figures 7 and 9, while the others are included in *Appendix II*.

Figure 7.

Raw data with changepoints in resilience indicators for self-rated performance of player 1.

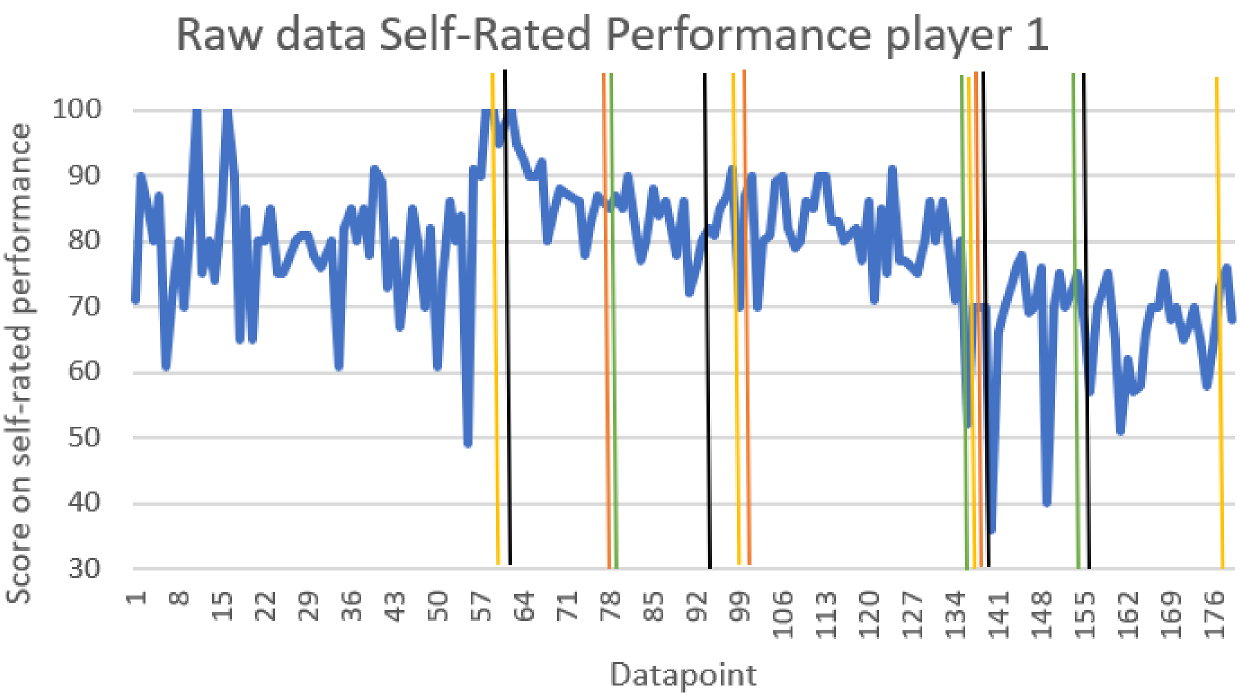


Table 2

ChangePoints in Resilience Indicators in Self-Rated Performance (window of 28 days).

Player	SR_Performance Mean	SR_Performance MASD	SR_Performance Slope	SR_Performance Autocorrelation
1	34; 65; 112; 128.	49; 72; 111.	51; 108; 126.	33; 71; 109; 149.
3	17; 42; 87; 104.	36; 73; 85; 101.	23; 62.	23; 88.
4	29; 58; 108.	43.	39; 100.	43; 98.
6	24; 61; 90; 118.	18; 74; 113.	87; 109; 120.	18; 74; 87; 117.
7	9; 78; 128.	14; 71; 120.	15; 118.	15; 45; 81; 116.
11	50.	8; 68; 120.	42; 62; 94; 109.	28; 60; 88; 115.
13	41; 90; 145.	14; 89; 115.	46; 61; 110; 129.	73.
14	44; 54.	6; 55.	20; 60.	34.
16	45; 66; 96; 110.	52; 73; 101; 131.	52; 109; 99.	110.
17	34; 133.	73; 97; 125.	47; 126.	35; 62; 99; 136.
18	23; 57; 90; 115.	57; 92.	15; 85; 103.	15; 57.
19	31; 52; 106.	28; 60; 103.	14; 52; 143.	52; 87; 140.
20	9; 80; 94; 108.	58; 94; 107.	30; 75; 107.	53; 80.

21	34; 72; 95; 124.	15; 124.	20; 94.	23; 44; 95.
24	54; 89; 117.	52; 136.	53; 105; 115.	55; 86; 113.
25	58; 68; 85.	19; 92; 102.	49; 73; 102.	51; 73.
27	42; 63; 90.	19; 47; 100.	47.	66; 95.
29	8; 75; 110.	21; 53; 80; 107.	24; 110; 82.	81; 54; 111.

Note. The yellow marked changepoints occur almost together. In the most cases, two or more changepoints in various indicators precede a changepoint in mean, meaning they can function as a warning signal for a resilience loss.

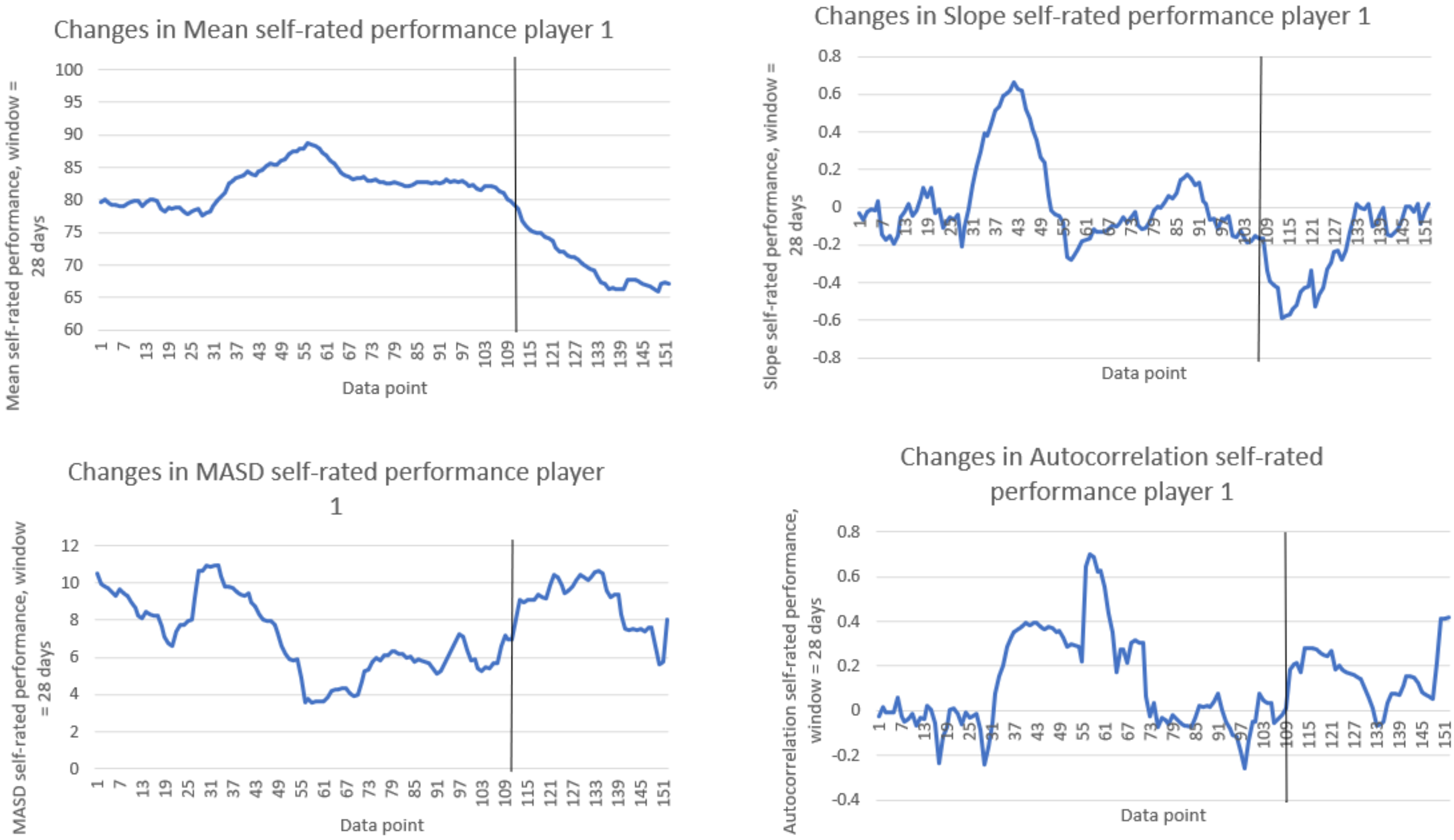
Note. Change in mean = black, change in slope = green, change in MASD = orange and change in autocorrelation = yellow. The red square indicates the moment of a resilience loss, pictured by a loss in self-rated performance.

In figure 7, the fluctuating course of self-rated performance for player 1 is pictured, containing various changepoints in each resilience indicator. At datapoint 140, there is a clear reduction in the level of self-rated performance observable, which seems to be a more deviating reduction than usual fluctuation for this player. This decrease in the level of self-rated performance can be seen as a resilience loss, which is preserved by a changepoint in slope at datapoint 136, a changepoint in autocorrelation at datapoint 137 and a changepoint in MASD at datapoint 139, after which the changepoint in mean at datapoint 140 is observable.

In figure 8, the individual courses of the four resilience indicators over a whole season are pictured. These figures were used for a closer look at the changepoints within a specific resilience indicator. A changepoint in figure 8 correspond to the datapoint in figure 7, but 28 days later (i.e. datapoint or changepoint + 28 days). For that reason, the changepoint in mean at datapoint 140 in figure 7 corresponds to datapoint 112 in figure 8, the changepoint in slope at datapoint 136 in figure 7 corresponds to datapoint 108 in figure 8, the changepoint in MASD at datapoint 139 in figure 7 corresponds to datapoint 111 in figure 8 and the changepoint in autocorrelation at datapoint 137 corresponds to datapoint 109 in figure 7, taken the window of interest into account.

Figure 8.

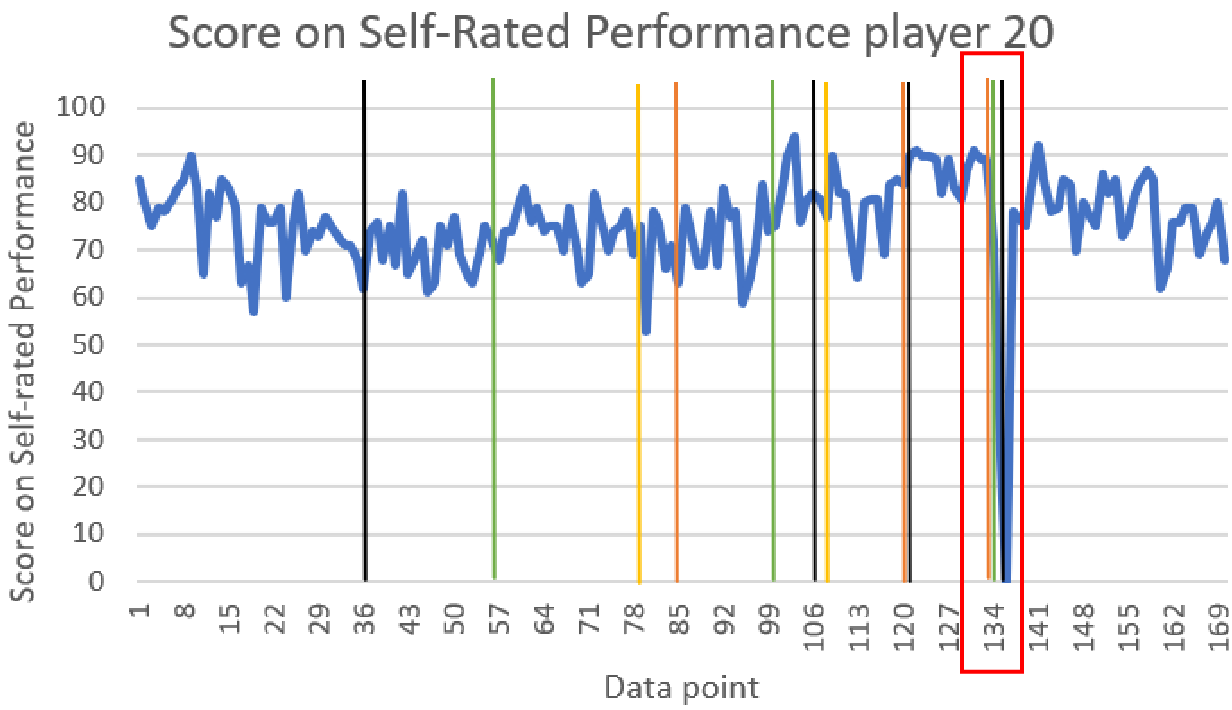
Individual graphs of resilience indicators for self-rated performance of player 1 including the changepoints.



In figure 8 is shown that the decrease in the level of self-rated performance is accompanied by changepoints in different resilience indicators. These are successively a decrease in mean, a decrease in slope, an increase in MASD and an increase in autocorrelation. The changepoint in mean is therefore preceded by three changepoints in other resilience indicators (i.e., the black line). This drop in the mean of self-rated performance can be an indicator of resilience loss. This pattern of various resilience indicators preceding the changepoint in mean, is also found for player 20, whose course of self-rated performance for a whole season is pictured in figure 9.

Figure 9.

Raw data with changepoints in resilience indicators for self-performance of player 20.



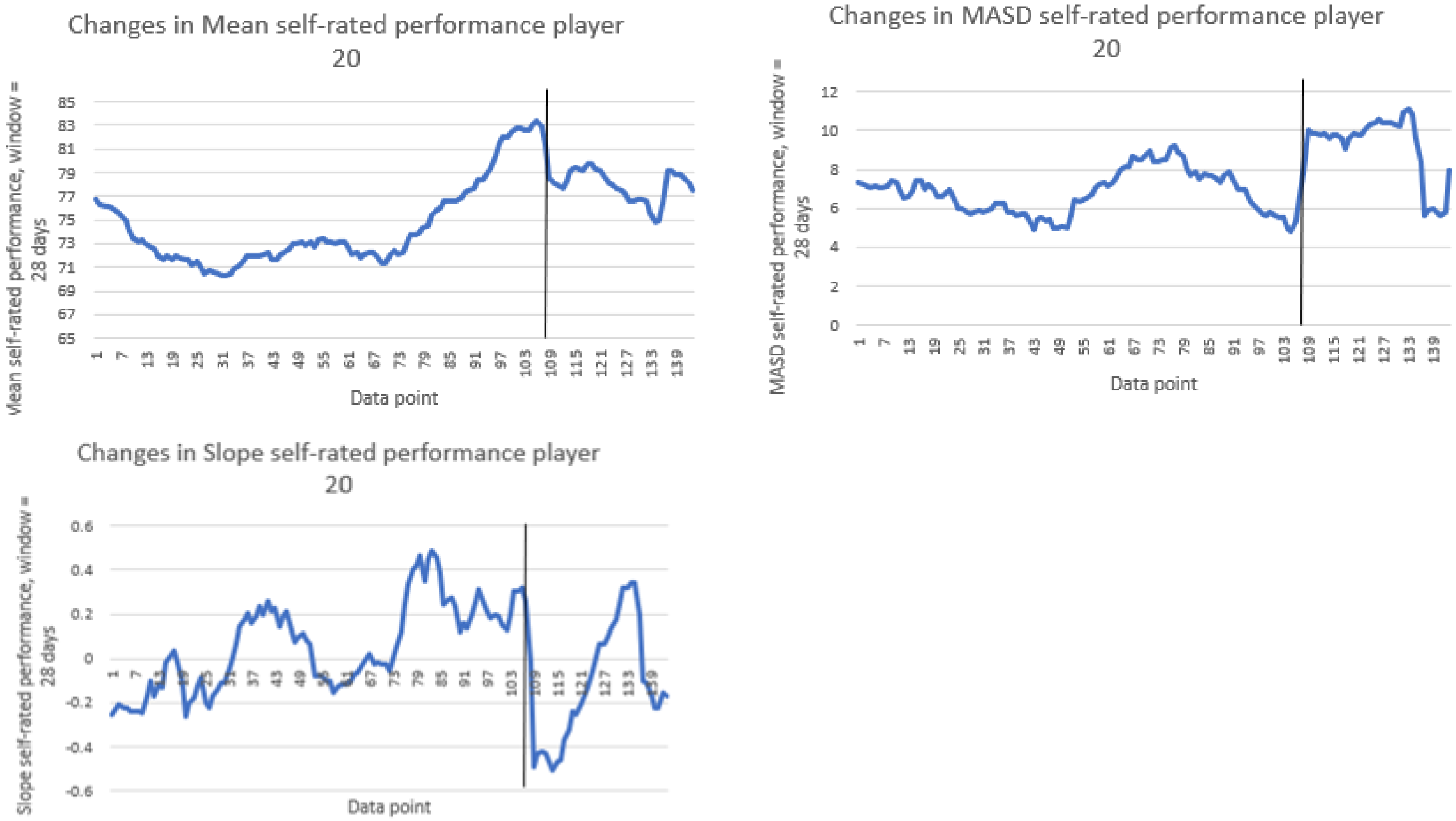
Note. Change in mean = black, change in slope = green, change in MASD = orange and change in autocorrelation = yellow. The red square indicates the moment of a resilience loss, pictured by a loss in self-rated performance.

Player 20 shows a quite stable pattern that fluctuates between a score of 55 and 90, except for datapoint 136, where a huge decrease in self-rated performance is observable. This decline is preceded by a changepoint in MASD at datapoint 135, a changepoint in slope at datapoint 135 and a changepoint in mean at datapoint 136.

To have a closer look at the changepoints within the resilience indicators, the individual courses of the three resilience indicators over a whole season are pictured in figure 10. The changepoint in mean at datapoint 136 in figure 9 corresponds to datapoint 108 in figure 10, the changepoint in slope at datapoint 135 in figure 9 corresponds to datapoint 107 in figure 10 and finally, the changepoint in MASD at datapoint 135 in figure 9 corresponds to datapoint 107 in figure 10, taken the different window of interest into account.

Figure 10.

Individual graphs of resilience indicators for self-rated performance of player 20 including the changepoints.



At datapoint 136 in figure 9, there is a huge decrease in the level of self-rated performance, which can seen as a resilience loss. Figure 10 shows that this decrease is characterized by a decrease in the mean and slope, but an increase in MASD. The changepoint in mean is preceded by a changepoint in the slope and MASD. As said before, the same pattern that was found for player 1 and 20, is also observable for other players. This applies to player 1, 4, 6, 7, 16, 18, 19, 20, 24, 25 and 29, which are included in *Appendix II*.

Discussion

The aim of the current study was to explore different statistical indicators of resilience losses (i.e., changes in mean, slope, fluctuations, and autocorrelations) in time series data of psychological parameters (i.e., self-efficacy and self-rated performance) of youth soccer players. This research showed that a resilience loss for 50-61% of the players is preceded by two or three changepoints in different resilience indicators in a short period prior to a decline of the mean of a psychological parameter.

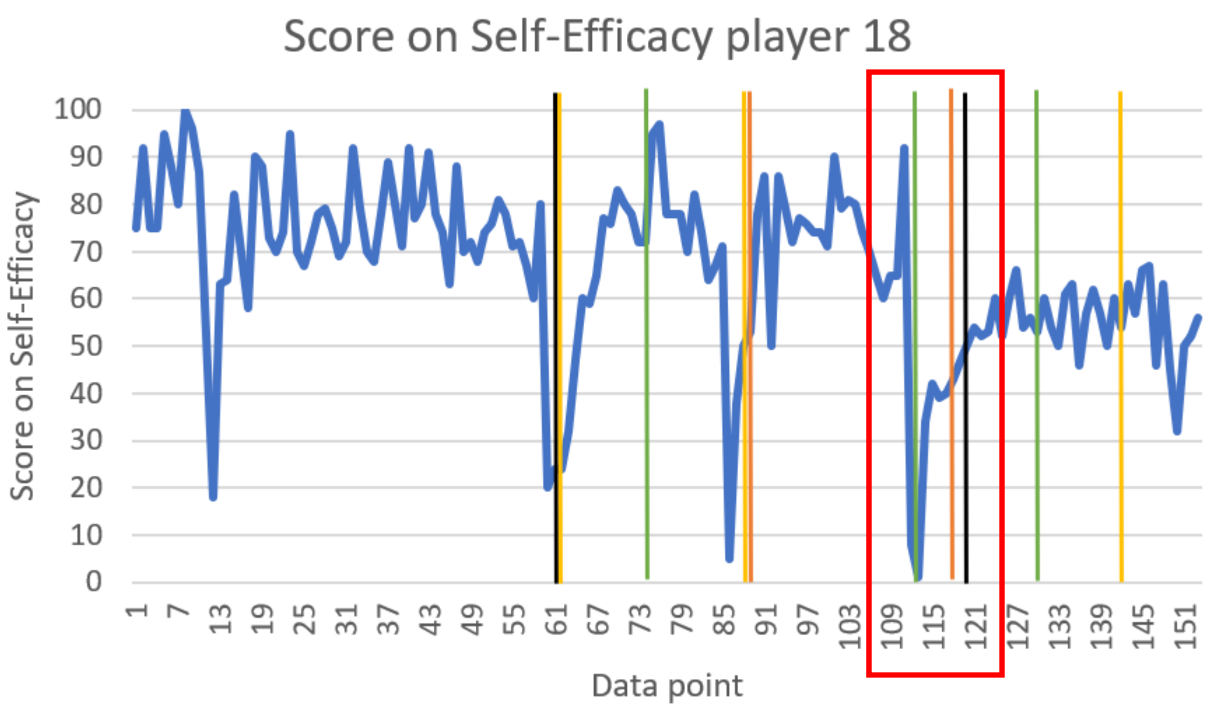
In the current study, a changepoint analysis in R has been conducted to identify the location and timing of various changepoints within the time series (Killick & Eckley, 2014). This showed that the sequence and frequency of changepoints differed per athlete. This is in line with the literature, which has shown before that each athlete responds differently to stressors, whereby the resilience process will look different for various athletes (e.g., Hill et al., 2021; Bhatnagar, S., 2021). There is no such thing as a 'one-size-fits-all' pattern of indicators, meaning that each individual shows different indicators that act as their warning signals (Scheffer et al., 2009). This again proves that it is important to monitor each athlete individually, because this also means that different resilience indicators and changepoints can be important for different athletes.

After inserting the changepoints into graphics of the raw data, a striking observation becomes visible. Before a resilience loss, multiple changepoints in resilience indicators occurred together. This observation is visible for both self-efficacy (50% of the cases (9 of the 18 analyzed players)) and self-rated performance (61% of the cases (11 of the 18 analyzed players)). We cannot say a lot about how convincing these percentages are, because comparable research is lacking, but the finding of a recurring observation, offers support for the idea that there are players for whom we can see a resilience loss coming because of the occurrence of warning signals. That means that indicators can function as warning signals for a possible decrease in the level of resilience, which was proven in earlier research (e.g., Scheffer et al., 2009; Gijzel, 2020; Helmich et al., 2021). In this situation, it can be defined as the occurrence of different changepoints in resilience indicators at the same time.

When looking at the percentages of the findings, this means that in the other cases, a different pattern or even missing pattern was observed, even though a resilience loss occurred. In figure 13 an example is shown of a player who experienced a resilience loss, but for whom the pattern of warning signals that was observed in this study was missing.

Figure 13.

Raw data with changepoints in resilience indicators for Self-Efficacy of player 18.



Note. Change in mean = black, change in slope = green, change in MASD = orange and change in autocorrelation = yellow.

When we have a closer look at the pictured red square in the graphic, a big drop in self-efficacy is observable. This time, the loss of self-efficacy is not preceeded by the occurance of multiple resilience indicators at the same time, prior to the changepoint in mean. First of all, the resilience indicators in this study are based on research of Scheffer and colleagues (2009). They suggested different indicators of resilience loss in the context of critical slowing down. This could mean that these indicators are, on the other hand, not applicable to abrupt changes, for example an abrupt injury in a match. For exploratory purposes, I therefore looked at the injury and life-event data, to see if this could be a possible hypothesis. For player 18, it turned out that he experienced an abrupt injury at datapoint 112. The fact that this is an abrupt event, could be a possible explanation for the missing warning signals. In 8 of the 18 cases of self-efficacy (44.4%) and 2 of the 18 cases of self-rated performance (11.1%), a drop in resilience was observed, which was not preceded by a warning signal. When abrupt events occur, you cannot see them coming and statistical indicators do not show up as a warning signal.

This hypothetical explanation for the finding about abrupt life-events and injuries can be connected to research of Lipsitz & Goldberger (1992). Their research was conducted in the field of geriatrics, in which resilience is also an important topic. When people are aging, they experience less complexity, which can be defined as the manner to which someone uses various interactions of inner control systems, to respond and adapt to pertubations and stressors. This decrease in complexity can be caused by a loss or impairment of functional components and cause that people cannot adapt effectively to stressors. When transfering this idea to athletes, this loss of psychological complexity can also be the case when athletes experience an injury. An injury is associated with a functional decline and being less adaptive to stress, which leads in the end to a less resilient person (Zhou et al., 2017; Lipsitz, 2004). An injury that is accompanied by a declined functional complexity, can thus be associated with a lower level of resilience and being less adaptive to stressors. Therefore, it would be very interesting for future research to investigate if this association is also the reason why the pattern found in this research is not applicable to abrupt injuries and life-events.

However, the findings in the current study are in line with previous research of Dai and colleagues (2015). They showed that a variation in performance is determined by how a system responds to different changes. When multiple things change simultaneously, the system becomes less stable and can therefore show critical slowing down to a resilience loss. This can be an explanation for the pattern in this current study. When multiple changepoints in different indicators occur in the same short period of time, the athlete becomes less stable and therefore loses resilience.

There is also different research in psychopathology that provides support for the finding that different indicators occur in the short period prior to a critical transition (Van de Leemput et al., 2014; Wichers & Groot, 2016). In this research there was found support for the hypothesis that multiple indicators occur at the same time as a precursor of a critical transition in a parameter of resilience. The occurrence of these indicators within a short period of time led to a destabilization of the system, causing a transition in a parameter. As such, the occurrence of these indicators in a short period of time can function as warning signals that reveal a resilience loss in the proximity of a tipping point (Van de Leemput et al., 2014).

Practical implementation

Stressors may lead to a decline in performance, if the player is not resilient at that particular moment (Hill et al., 2018). To decide if an athlete is high or low resilient at a specific moment in time, daily monitoring of psychological parameters can be used. The use of resilience indicators in the psychological monitoring of players is a novel step in the context of sports, because if a sports organization is able to recognize specific indicators for each player, they can probably see resilience losses coming and become influential in the prevention of these losses. For the prevention of worse consequences, such as mental dips, a declining wellbeing or diminished performance (e.g., Gijzel, 2020), it is important to intervene with psychological support to an athlete. From health psychology is known that perceived and available social support may lead to a decline in stress which can prevent this decline in performance (Lam, 2019). A sports organization can provide this mental support to a player who needs it, for example through conversations with the sports psychologist. The use of daily monitoring can cause an initial separation between players who need a conversation with the sport psychologist and players who appear to be resilient based on the monitoring.

Limitations and Future Directions

First of all, this study has been conducted based on self-reported data of youth soccer players of 16 and 17 years old. Berg and Rapaport (1954) have shown that self-report data don’t always yield evident quality. This could be because of faking in a high-stake situation (Niessen et al., 2016; Griffin & Wilson, 2012), meaning that people have the tendency to fake their answers in a performance situation. In practice, this means that athletes fill in their self-report scores less extreme, because of their fear being disadvantaged because of lower scores (e.g., not being drafted in a match). To prevent this situation from happening, the players were ensured before the start of the research, that the coach had no insight into the answers. Only the sport psychologist and sport scientist could view the answers, to provide any help if necessary. Nevertheless, complete honesty can never be guaranteed, but only stimulated through the guarantee of confidentiality. Also, this way of measuring psychological parameters ensures a continuous flow of psychological information over a longer period of time, which is necessary for continious research.

Another debatable point in the current study is the size of the dataset, which consisted of 18 youth soccer players only and can therefore be considered as a small sample. A disadvantage of a small sample size is the limit to generalize the results (Hackshaw, 2008). Neumann and colleagues (2021) already showed that statistical indicators (i.e., variance and relations between load and recovery) on the group level, could not be generalized to the individual players of that group. Therefore, the generalizability in this current study was not the most important aspect. Besides, Hackshaw (2008) mentioned that it is often better to test the research in a smaller sample, after which the sample can be broadened. An advantage of the small sample in this current study, was that the time for conducting the study was limited, whereby a small sample causes that exploration could be addressed in this relative short period of time. Moreover, small samples can inform better decisions than larger samples (Fiedler & Kareev, 2006). Therefore can be concluded that in this particular context, a small sample size was not problematic.

Third, the window of interest that is used in research has a significant influence on the outcome (Carey et al., 2017). Hasselman and Bosman (2020) advocated the use of a reasonable window that estimated practice. In the current study, a window of 28 days is used, but this can also be for example 7 days, when looking at patterns within one week of training. In future research it is therefore important to explore other windows to investigate if the same pattern can be found using other windows.

Finally, to support the findings in the current study, it is also important to investigate the absence of the occurence of multiple changepoints in indicators prior to a resilience loss. Therefore, I advice to investigate the relation between life-events and injury data with the time series data of psychological parameters of resilience. In the current study, there were found some players who experienced a resilience loss, which was not preceeded by the occurence of multiple changepoints in indicators. It turned out that some players experienced an abrupt injury. Abrupt injuries or life-events are not predictable and therefore, indicators do not show up as warning signals. This interesting finding should be further investigated in future research.

Conclusion

This current study has shown that some resilience indicators (i.e., autocorrelation, slope, mean and fluctuations) can function as warning signals for a resilience loss of young male soccer players. In 50% of the cases of self-efficacy and 61% of the cases of self-rated performance, a particular pattern of resilience indicators occurred prior to a drop in self-efficacy and self-rated performance. This pattern consisted of multiple resilience indicators that occurred together, before a changepoint in mean to a lower level, in other words a resilience loss. This means that if multiple indicators occur together, this is often a warning signal for a possible decrease in the level of resilience. Going forward, this could mean that we can see and potentially avoid resilience losses in practice, for example by an intervention of a sport psychologist or coach, when a pattern of multiple changepoints in resilience indicators occurs. However, these results must be handled with care because there were also players who did not show this pattern while experiencing a resilience loss. In the current study were found some players who showed a resilience loss at the moment of an abrupt injury, which was not preceded by multiple changepoints before the resilience loss. A possible follow-up research may therefore be to investigate if the absence of this pattern is due to abrupt injuries or life-events, because in those cases we cannot see resilience losses coming. Also, future research is necessary to investigate whether this pattern is generalizable to other sports, domains, genders, and ages.

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Appendix I

Raw data with changepoints in resilience indicators for self-efficacy.

Figure 1.

Raw data with changepoints in resilience indicators for self-efficacy of player 1.

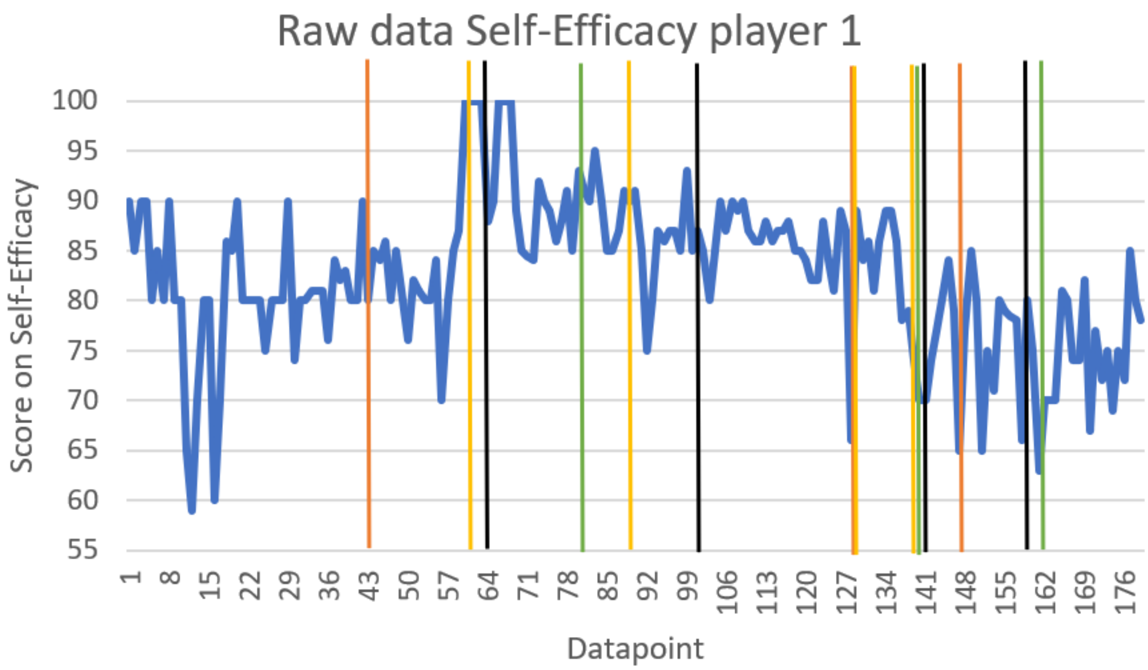


Figure 2

Raw data with changepoints in resilience indicators for self-efficacy of player 3.

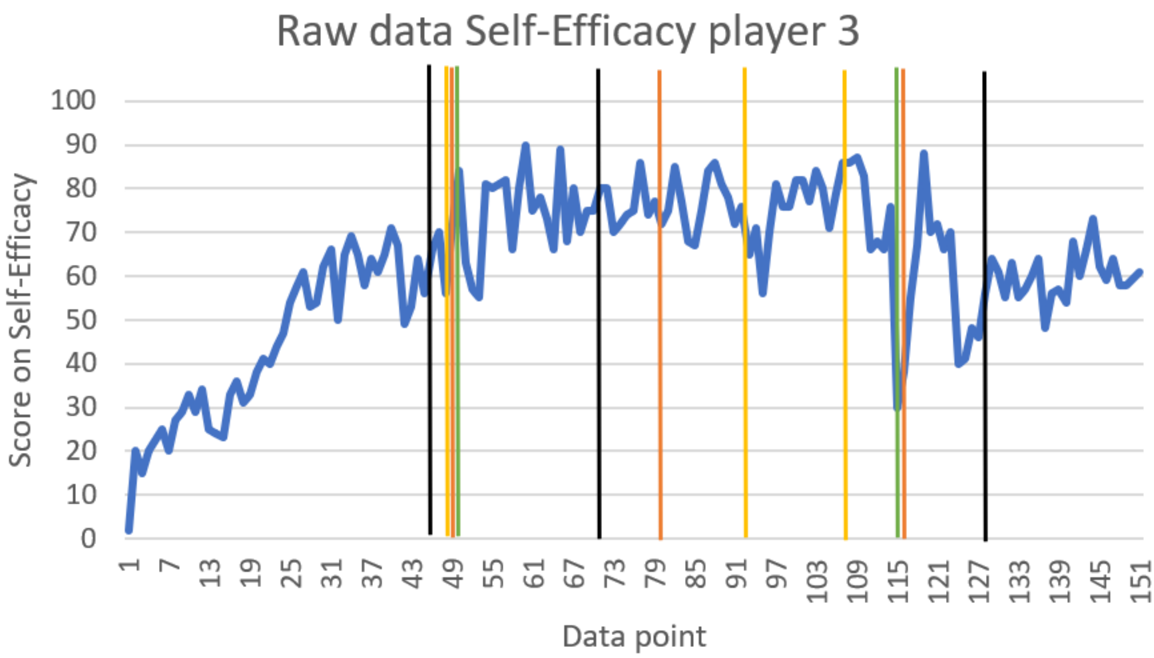


Figure 3

Raw data with changepoints in resilience indicators for self-efficacy of player 4.

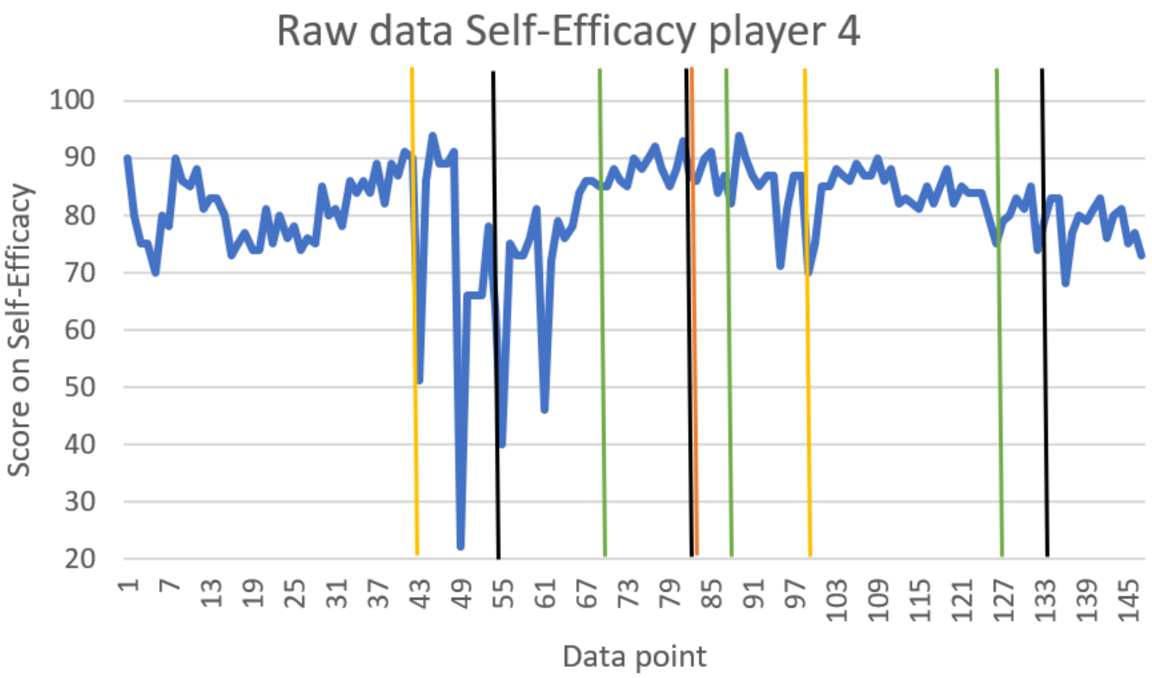


Figure 4

Raw data with changepoints in resilience indicators for self-efficacy of player 6.

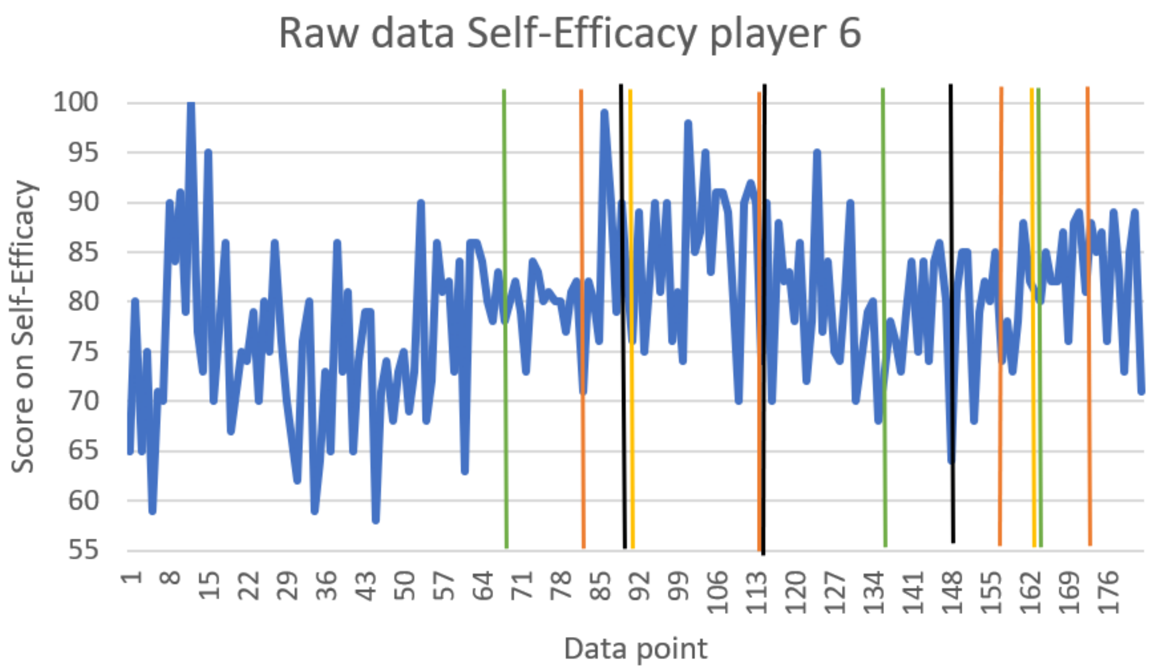


Figure 5

Raw data with changepoints in resilience indicators for self-efficacy of player 7.

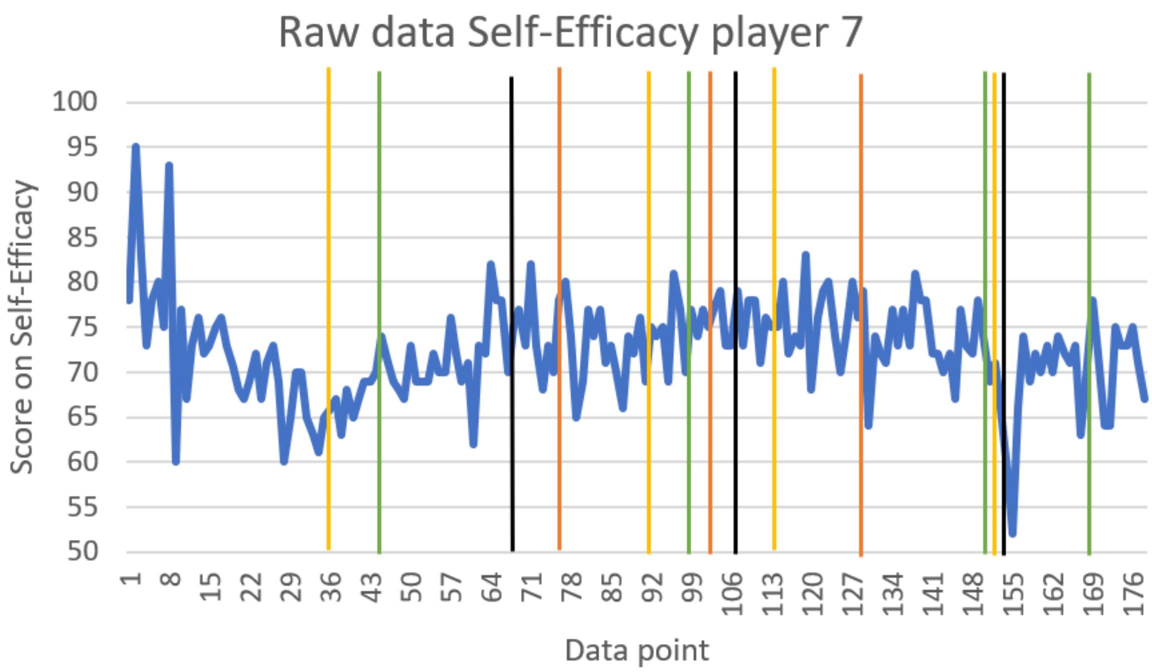


Figure 6

Raw data with changepoints in resilience indicators for self-efficacy of player 11.

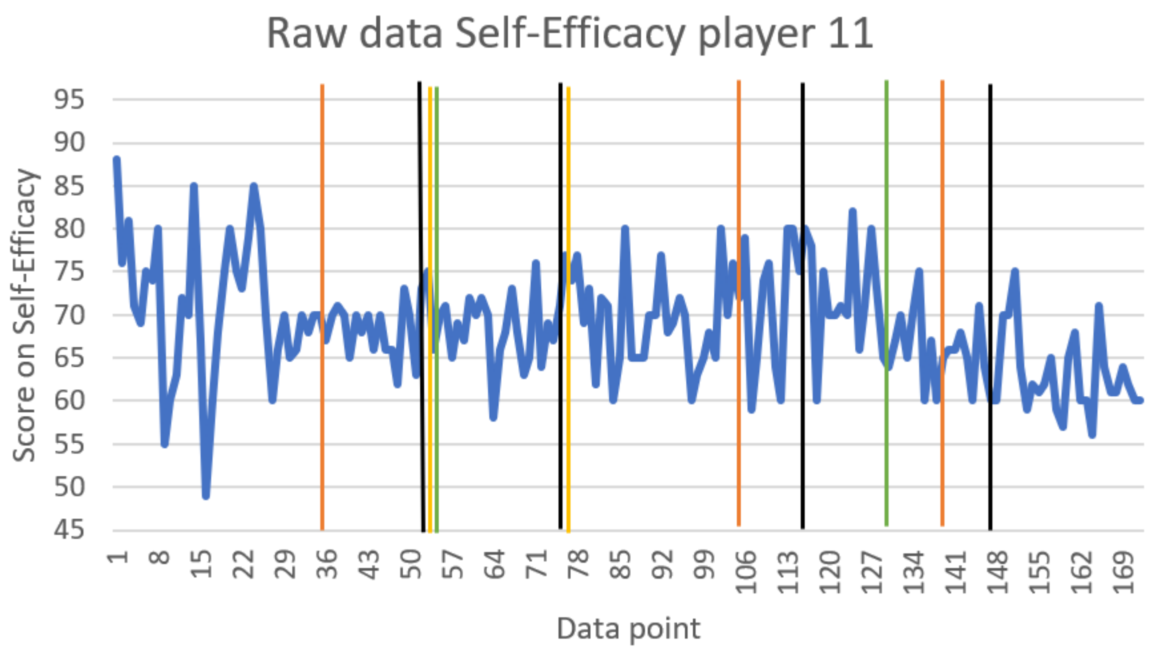


Figure 7

Raw data with changepoints in resilience indicators for self-efficacy of player 13.

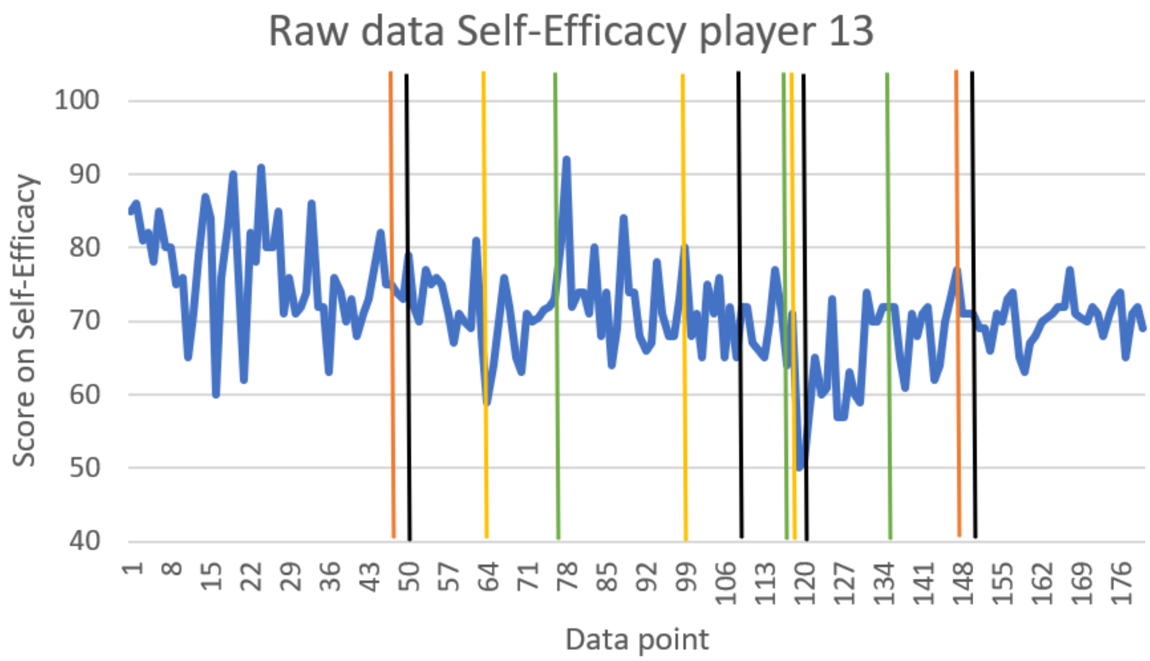


Figure 8

Raw data with changepoints in resilience indicators for self-efficacy of player 14.

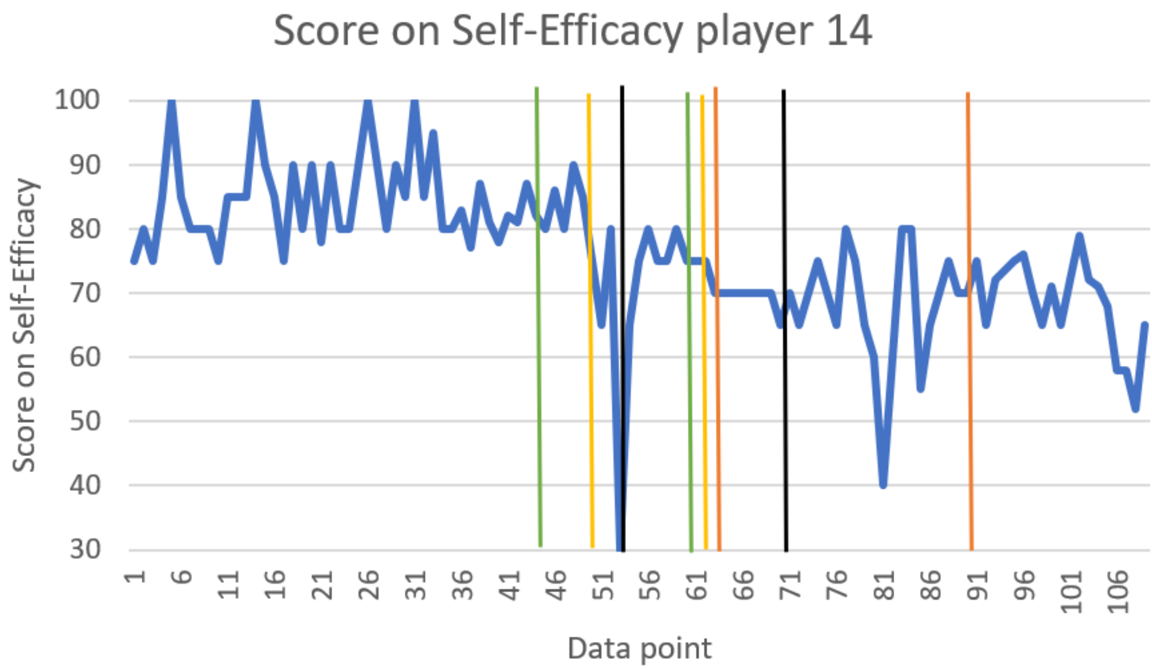


Figure 9

Raw data with changepoints in resilience indicators for self-efficacy of player 16.

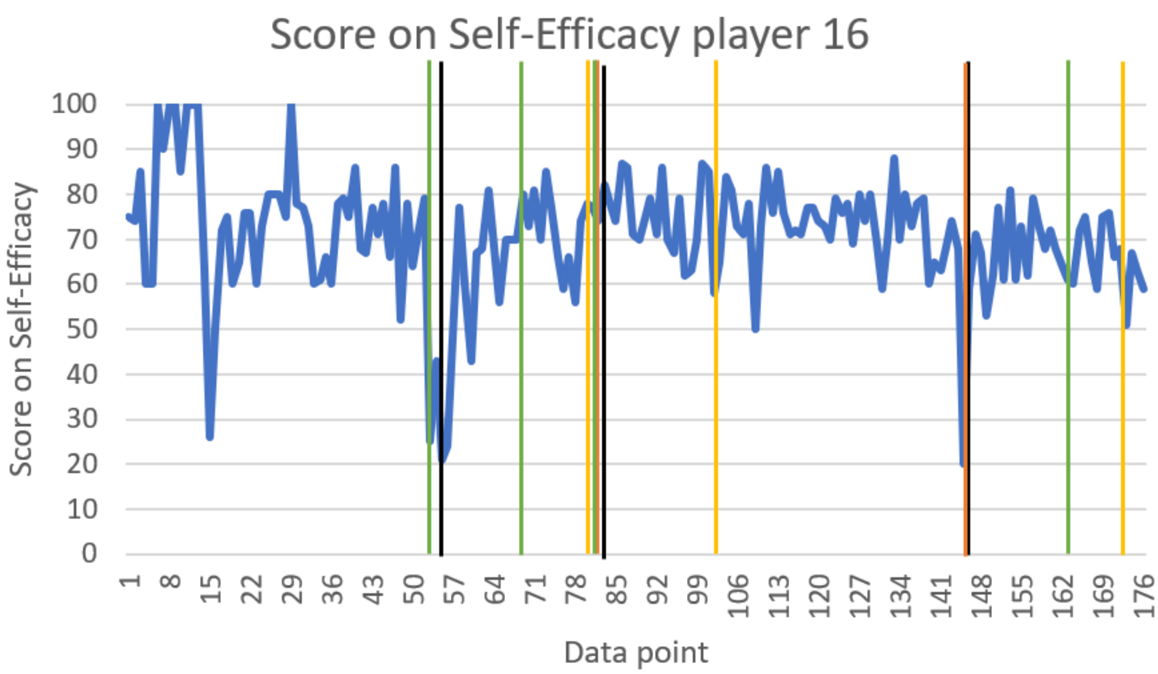


Figure 10

Raw data with changepoints in resilience indicators for self-efficacy of player 17.

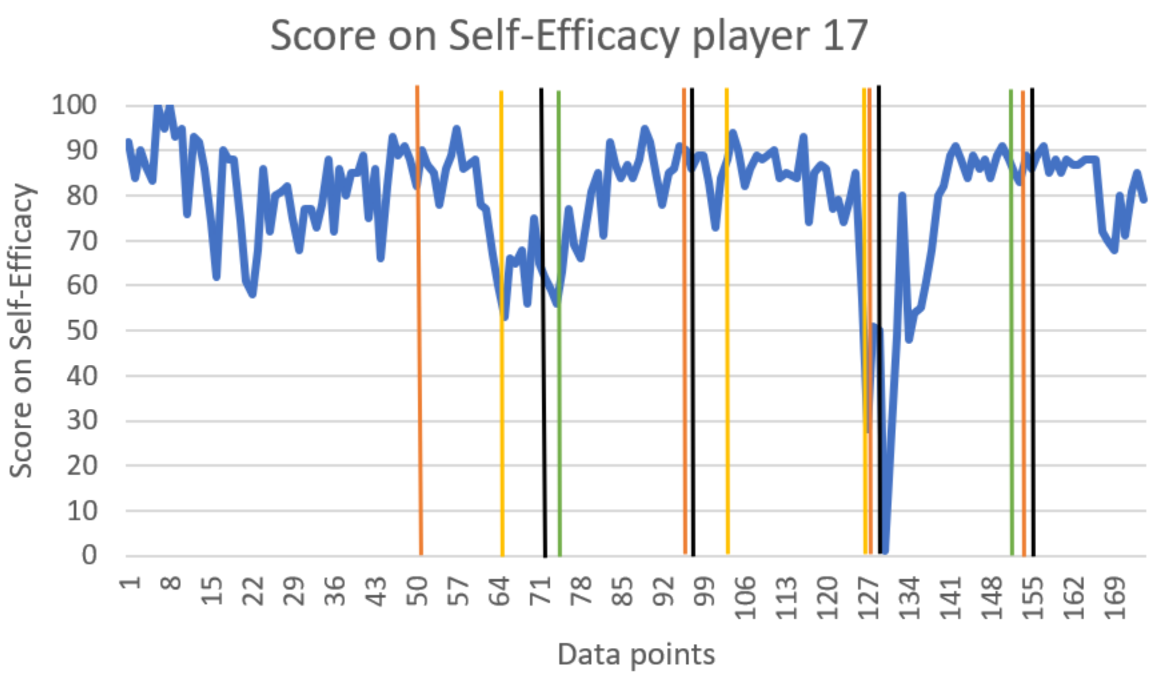


Figure 11

Raw data with changepoints in resilience indicators for self-efficacy of player 18.

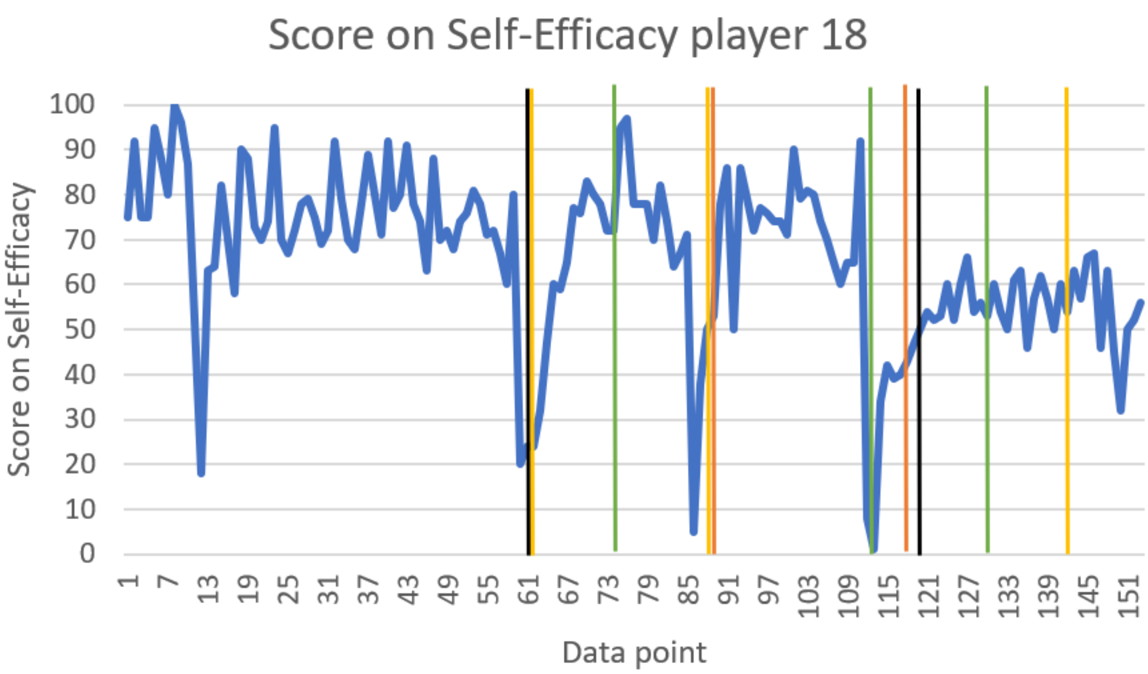


Figure 12

Raw data with changepoints in resilience indicators for self-efficacy of player 19.

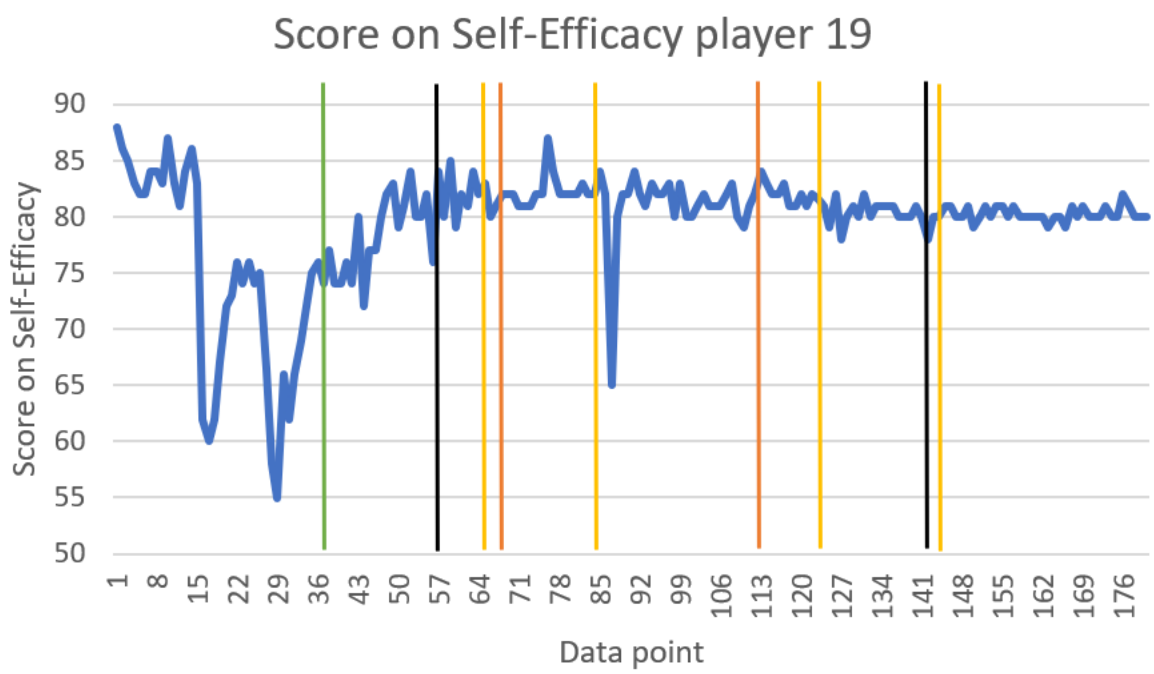


Figure 13

Raw data with changepoints in resilience indicators for self-efficacy of player 20.

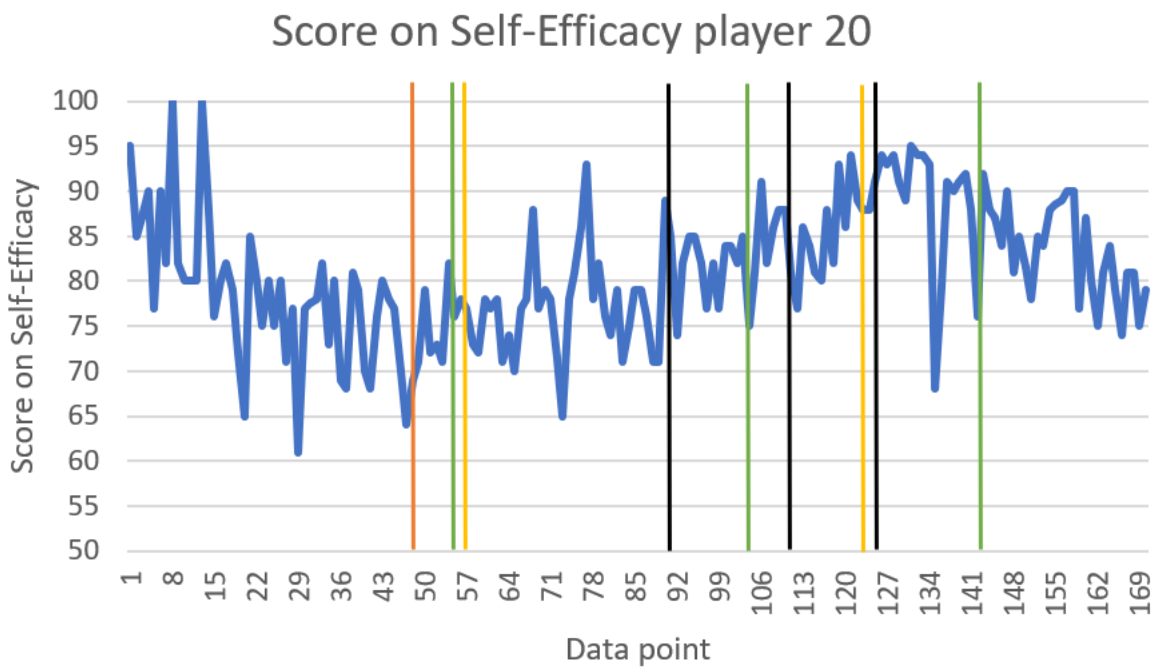


Figure 14

Raw data with changepoints in resilience indicators for self-efficacy of player 21.

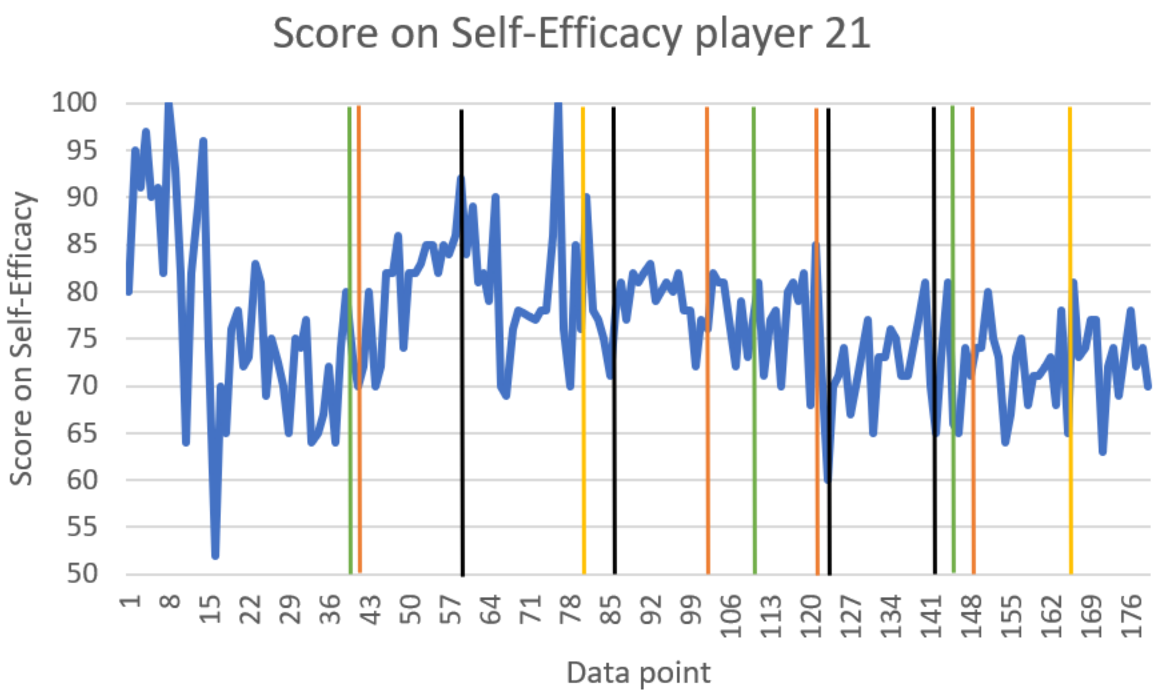


Figure 15

Raw data with changepoints in resilience indicators for self-efficacy of player 24.

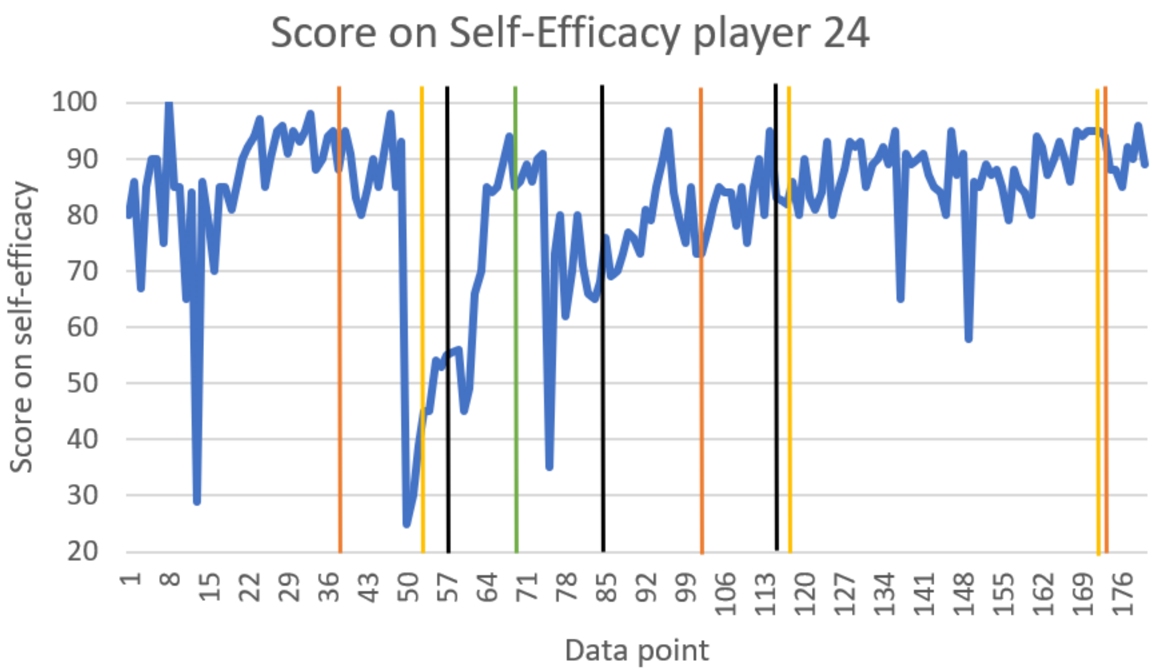


Figure 16

Raw data with changepoints in resilience indicators for self-efficacy of player 25.

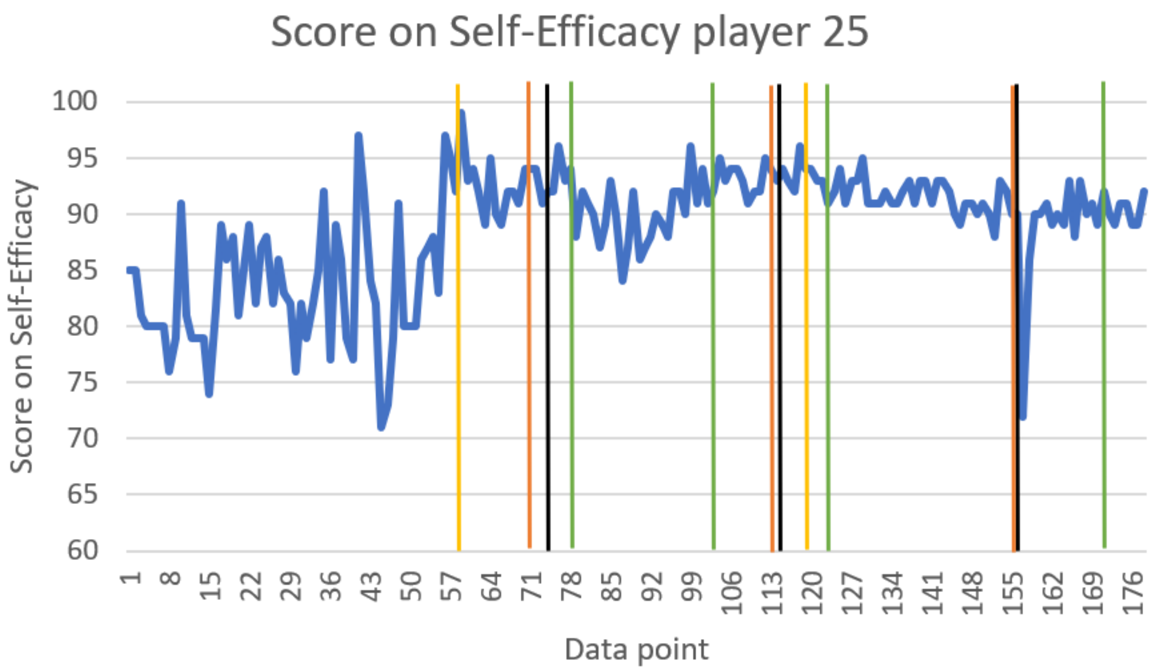


Figure 17

Raw data with changepoints in resilience indicators for self-efficacy of player 27.

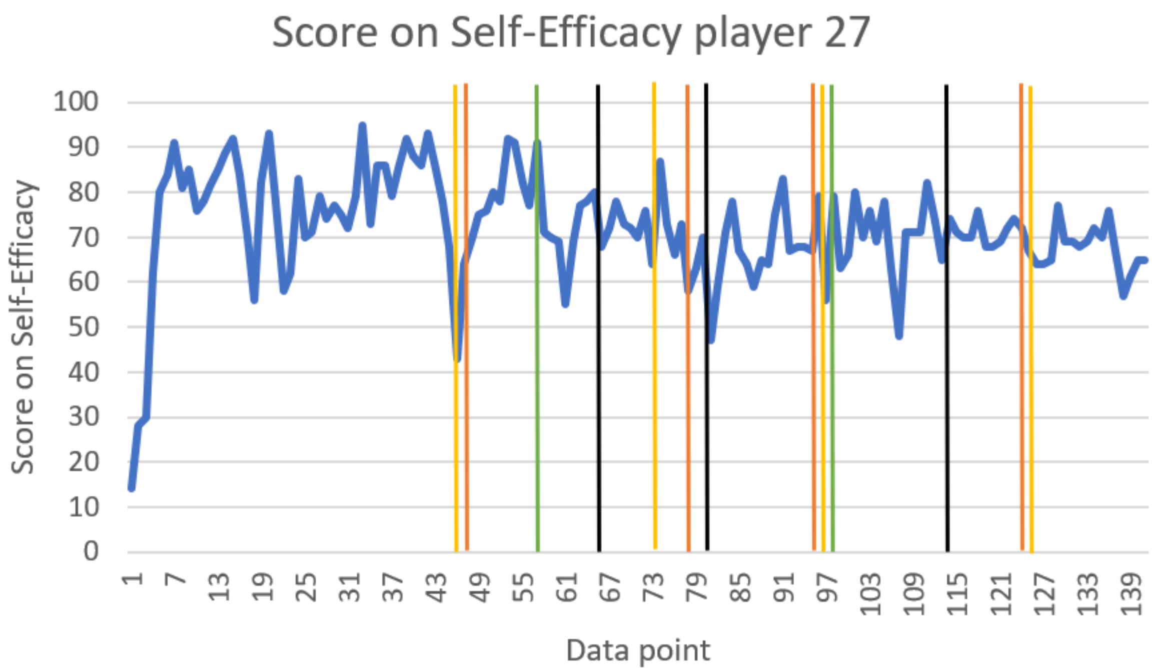
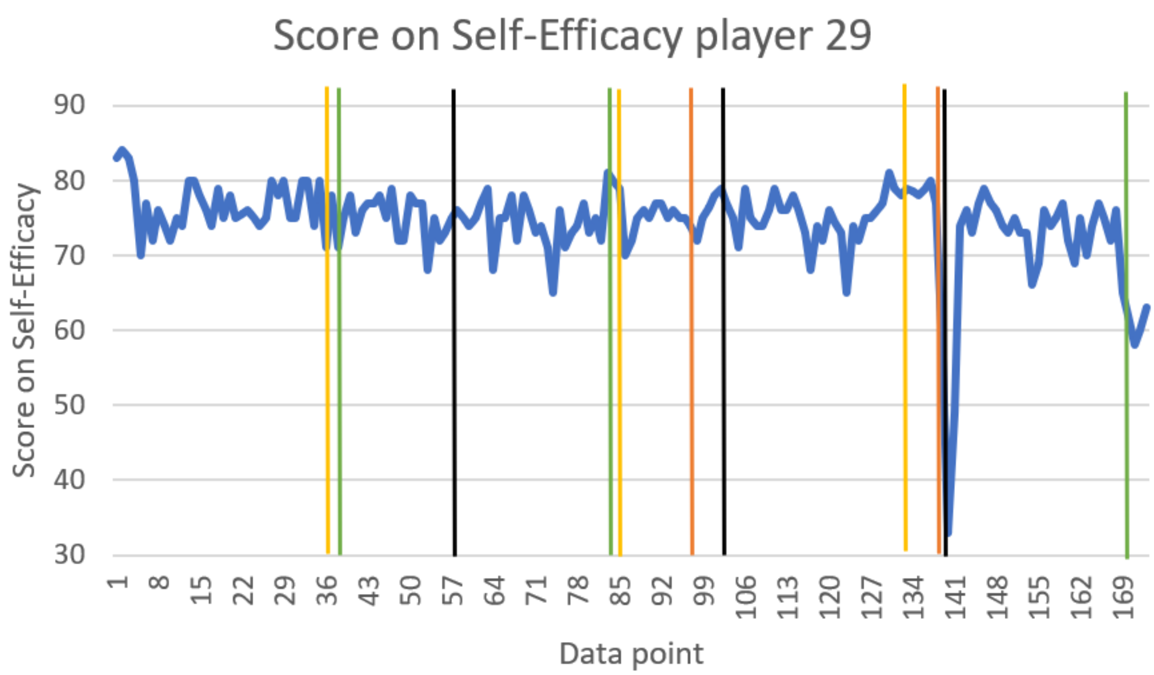


Figure 18

Raw data with changepoints in resilience indicators for self-efficacy of player 29.



Appendix II

Raw data with changepoints in resilience indicators for self-rated performance.

Figure 1

Raw data with changepoints in resilience indicators for self-rated performance of player 1.

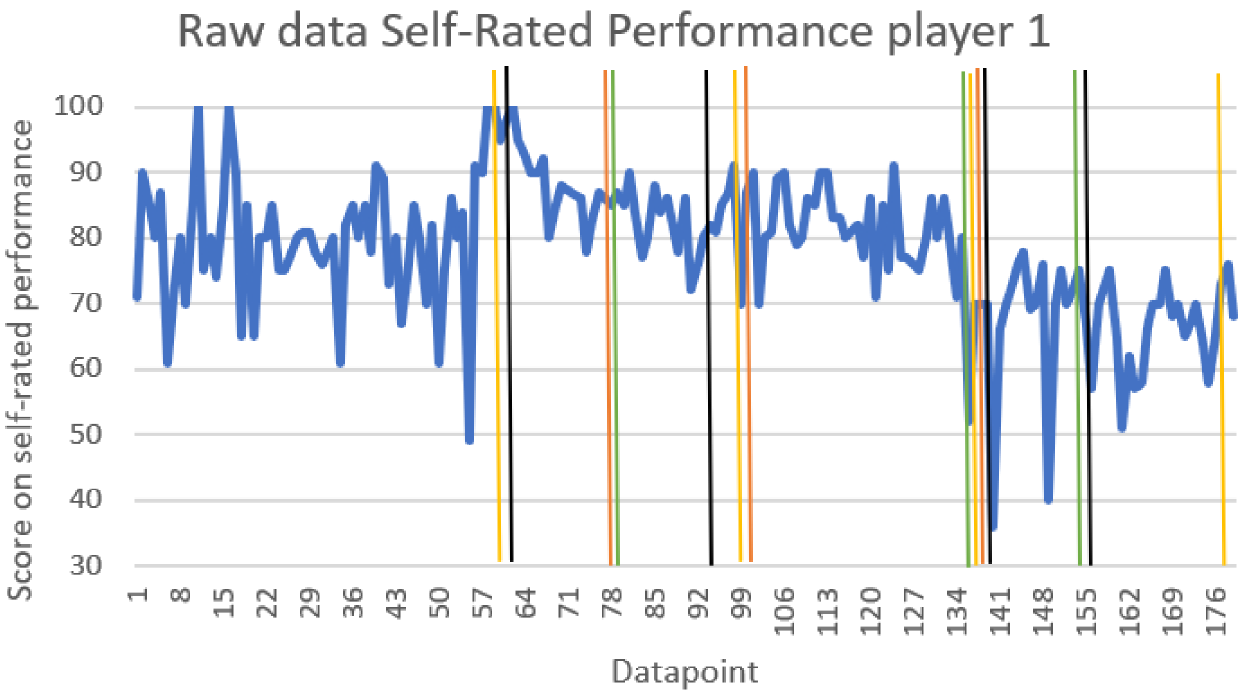


Figure 2

Raw data with changepoints in resilience indicators for self-rated performance of player 3.

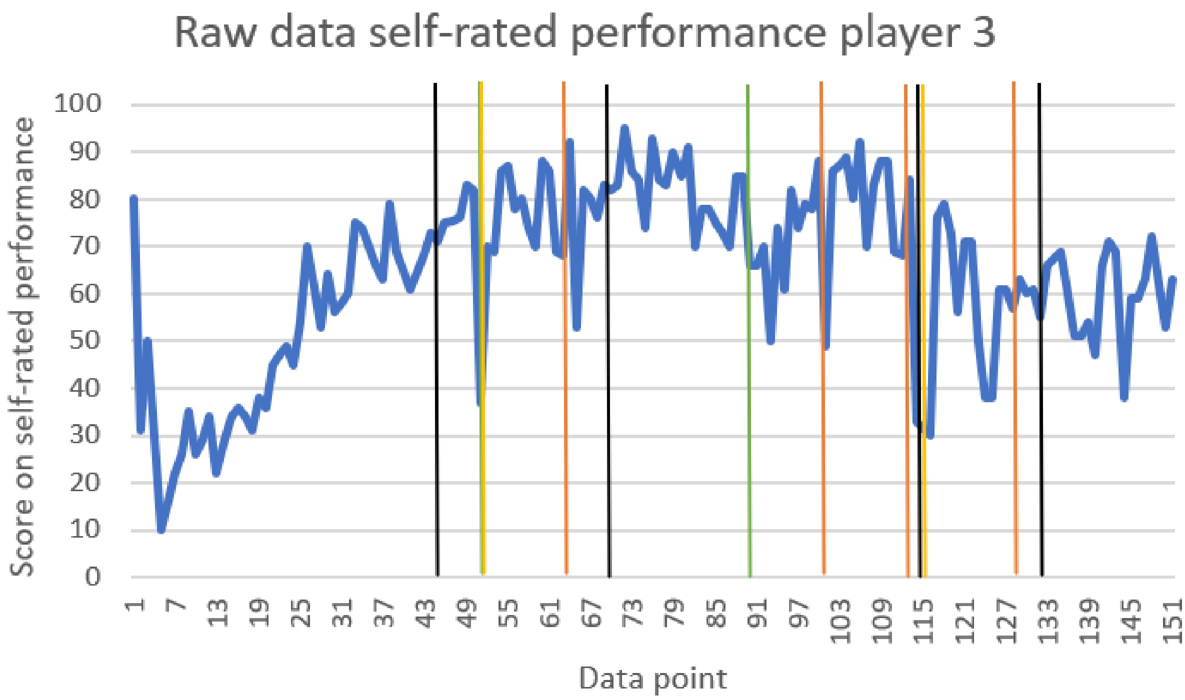


Figure 3

Raw data with changepoints in resilience indicators for self-rated performance of player 4.

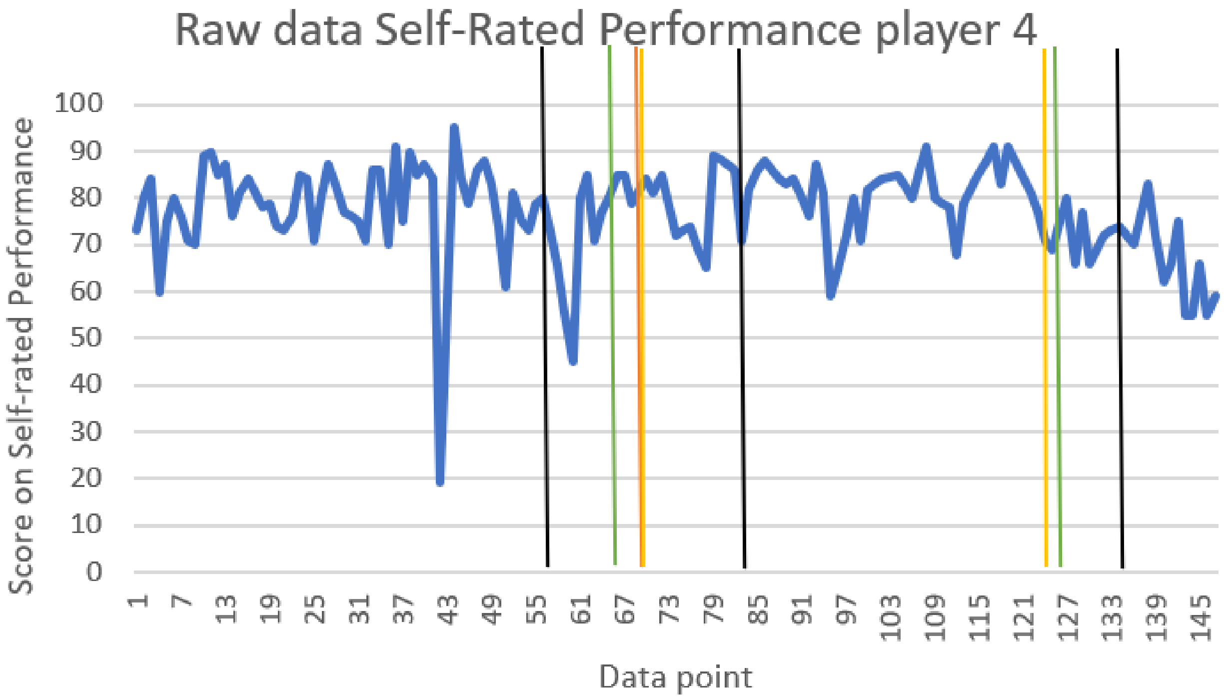


Figure 4

Raw data with changepoints in resilience indicators for self-rated performance of player 6.

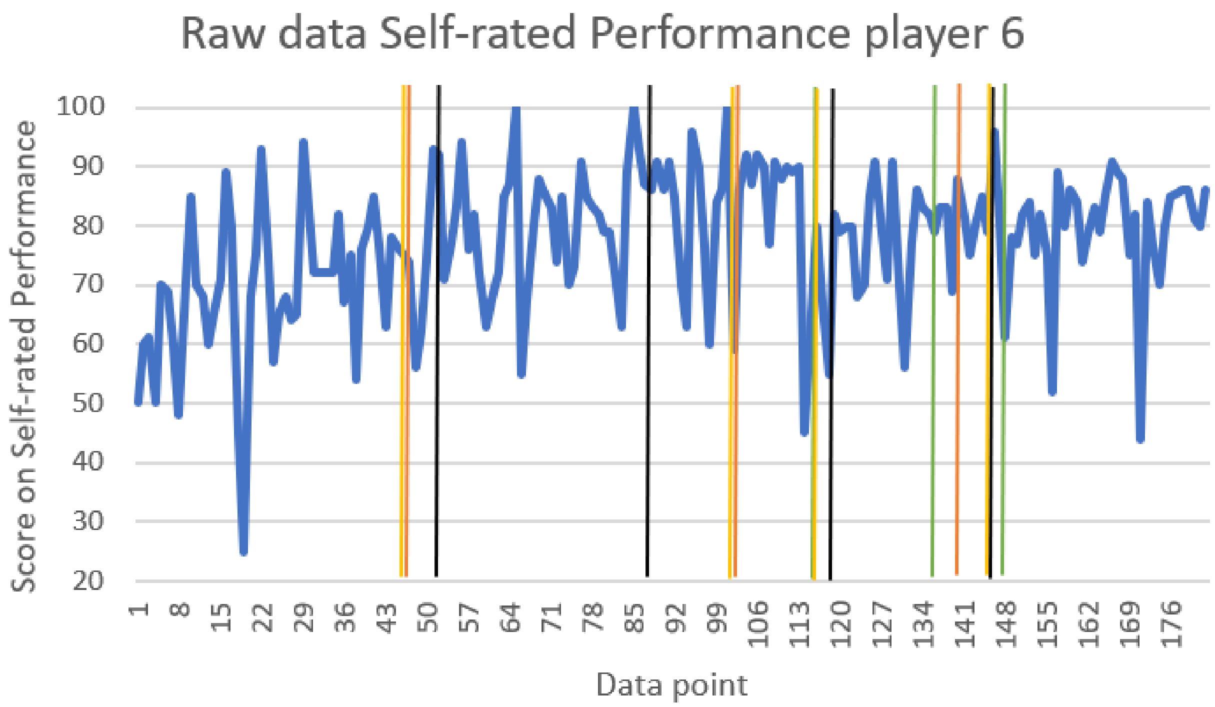


Figure 5

Raw data with changepoints in resilience indicators for self-rated performance of player 7.

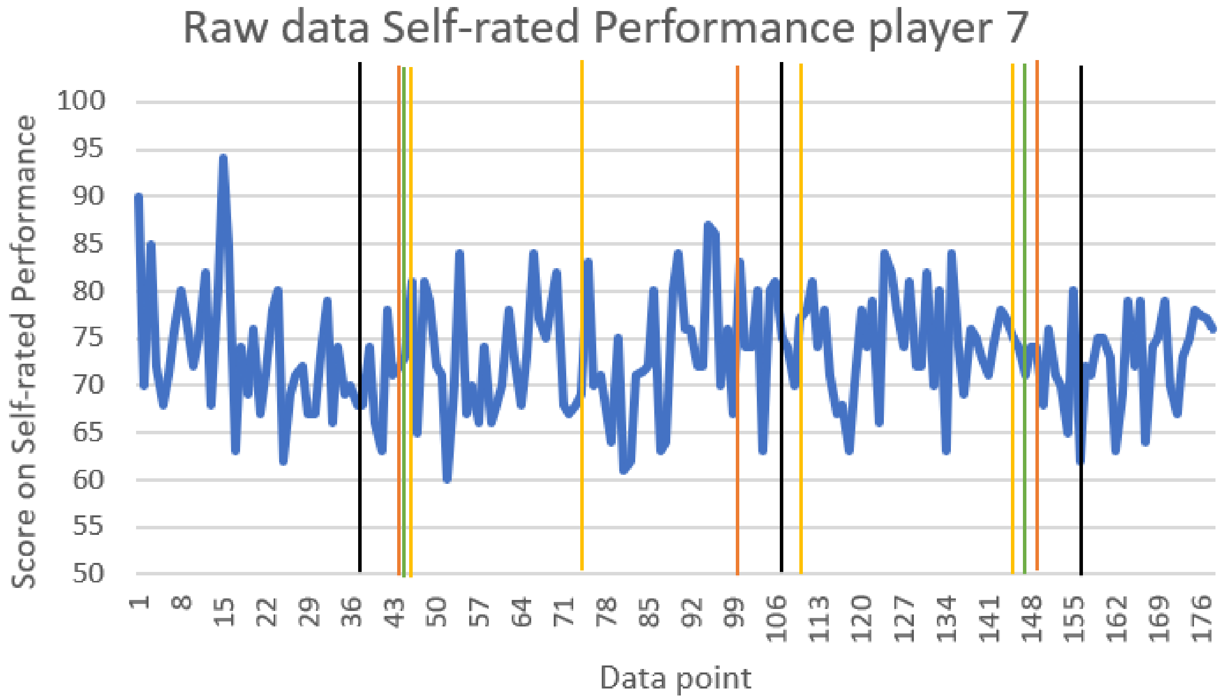


Figure 6

Raw data with changepoints in resilience indicators for self-rated performance of player 11.

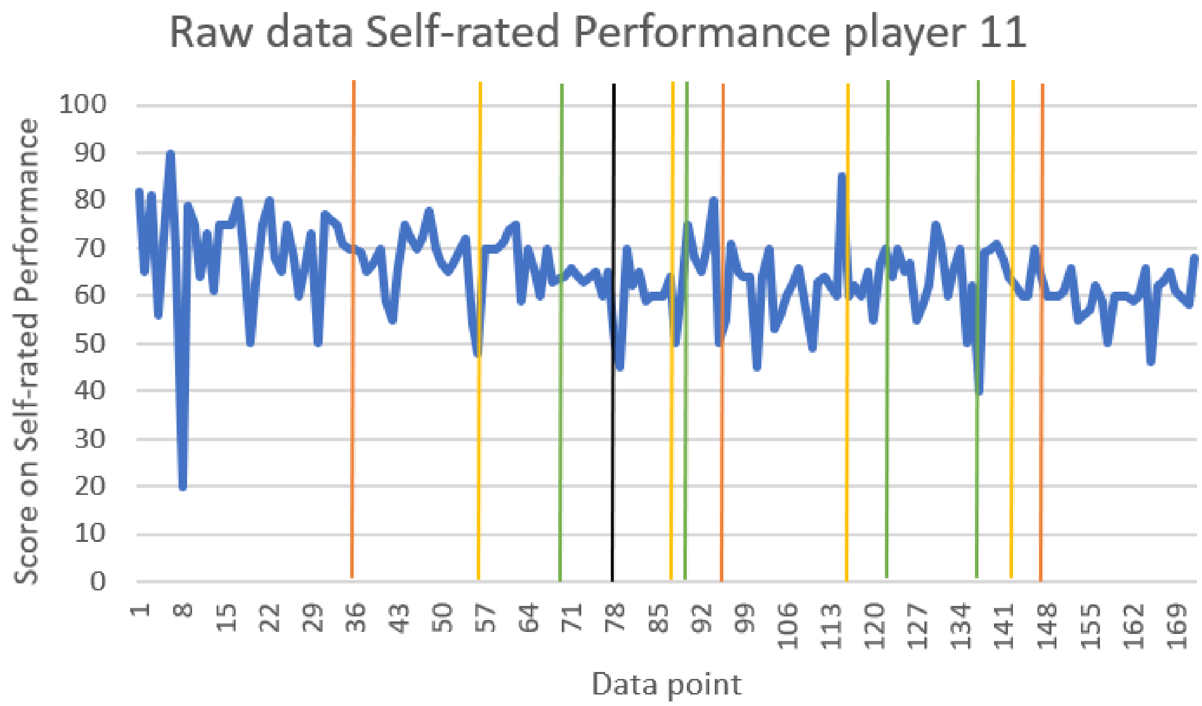


Figure 7

Raw data with changepoints in resilience indicators for self-rated performance of player 13.

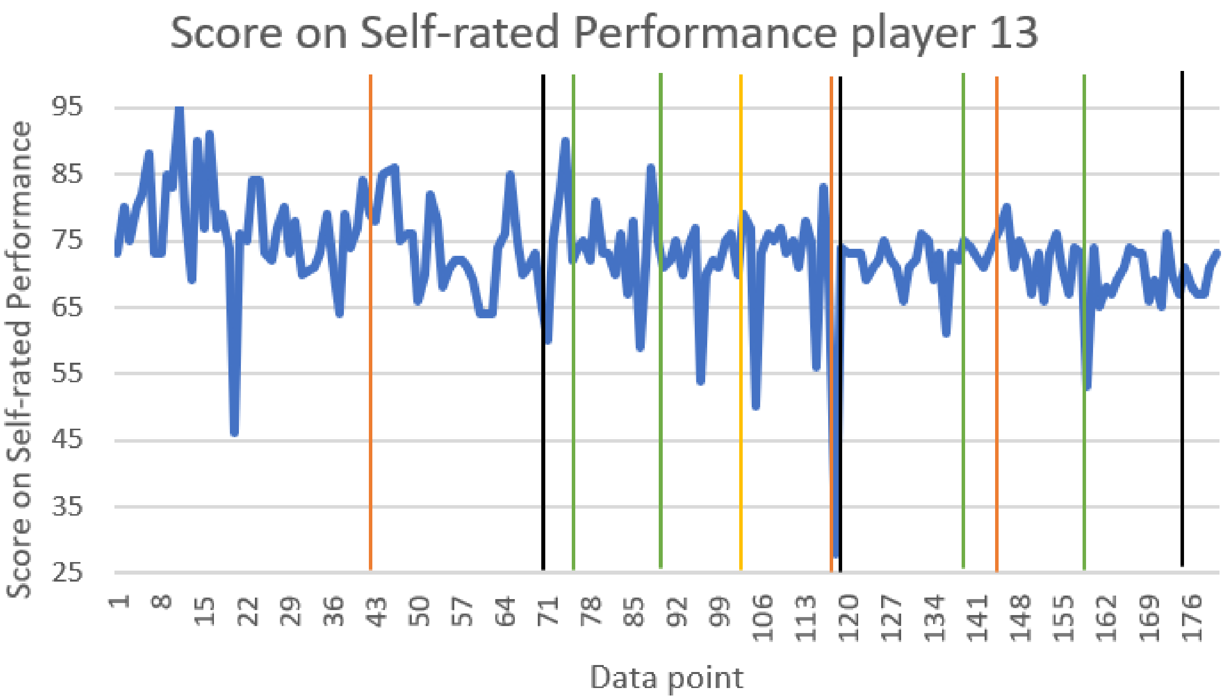


Figure 8

Raw data with changepoints in resilience indicators for self-rated performance of player 14.

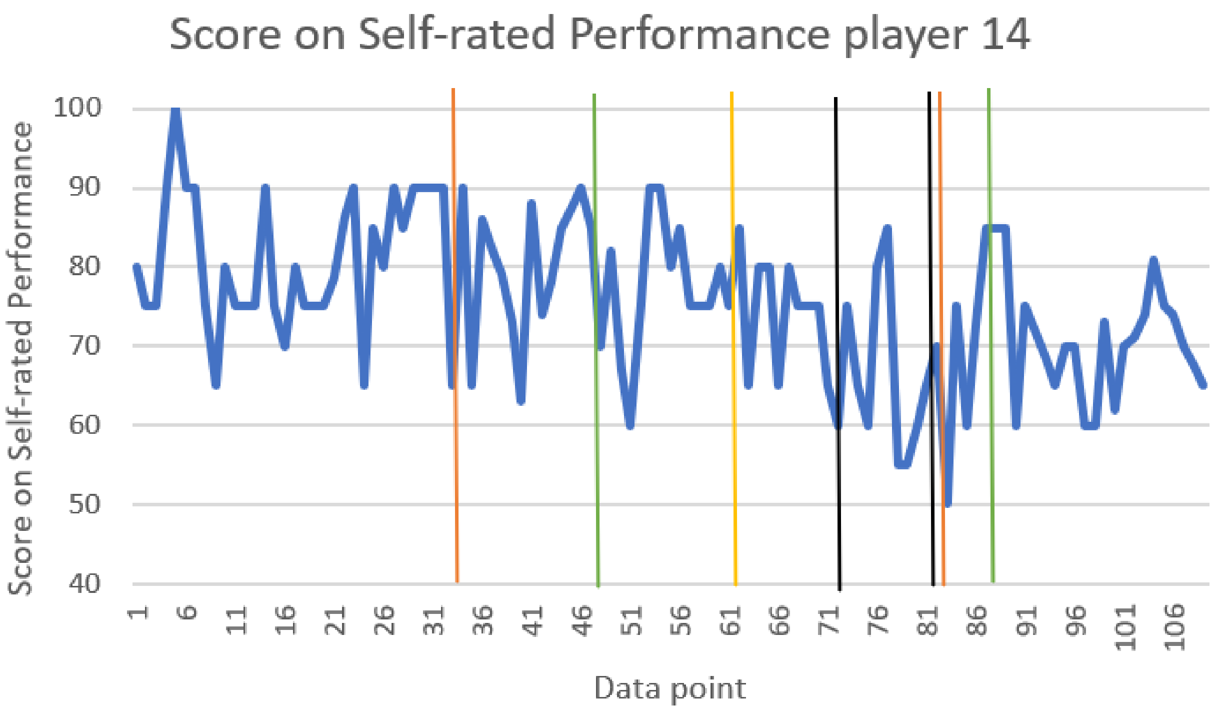


Figure 9

Raw data with changepoints in resilience indicators for self-rated performance of player 16.

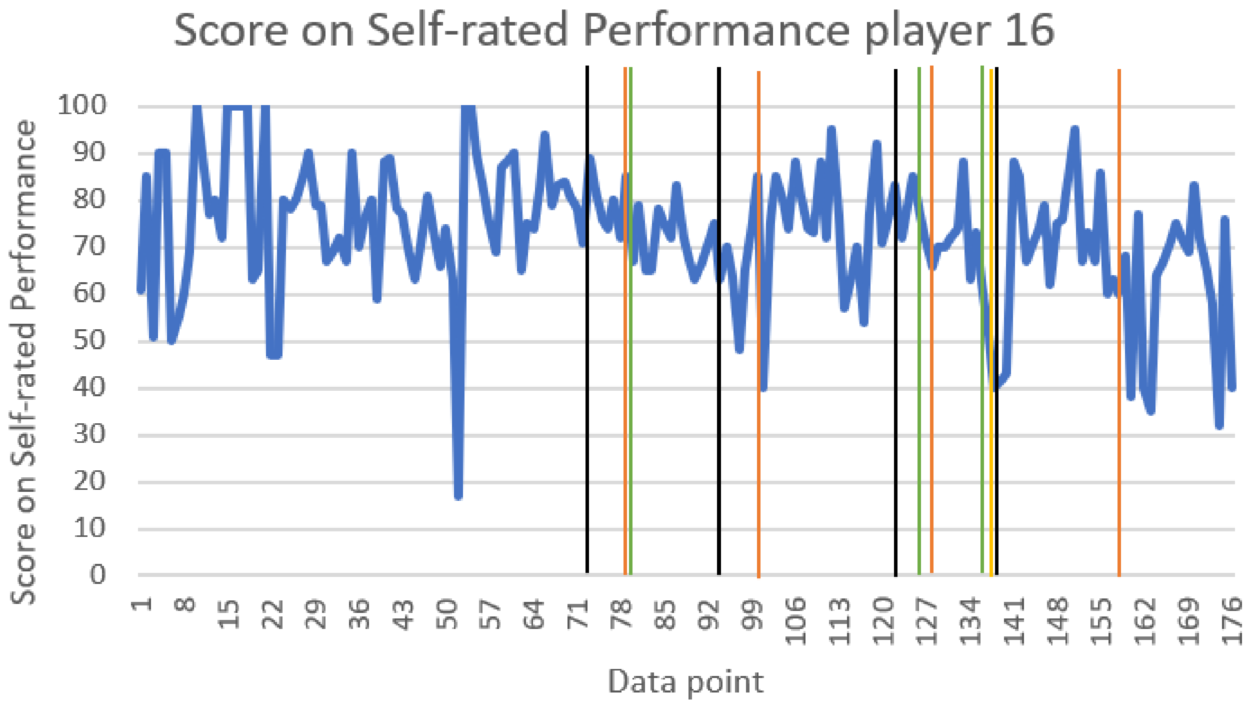


Figure 10

Raw data with changepoints in resilience indicators for self-rated performance of player 17.

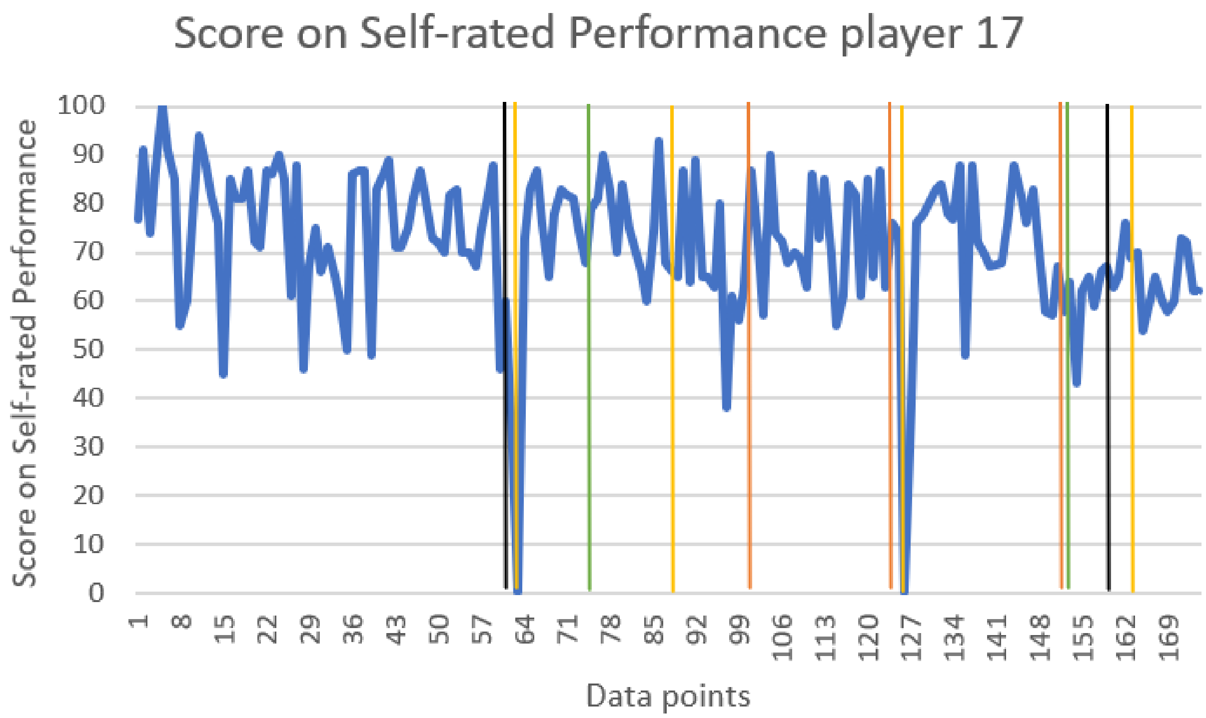


Figure 11

Raw data with changepoints in resilience indicators for self-rated performance of player 18.

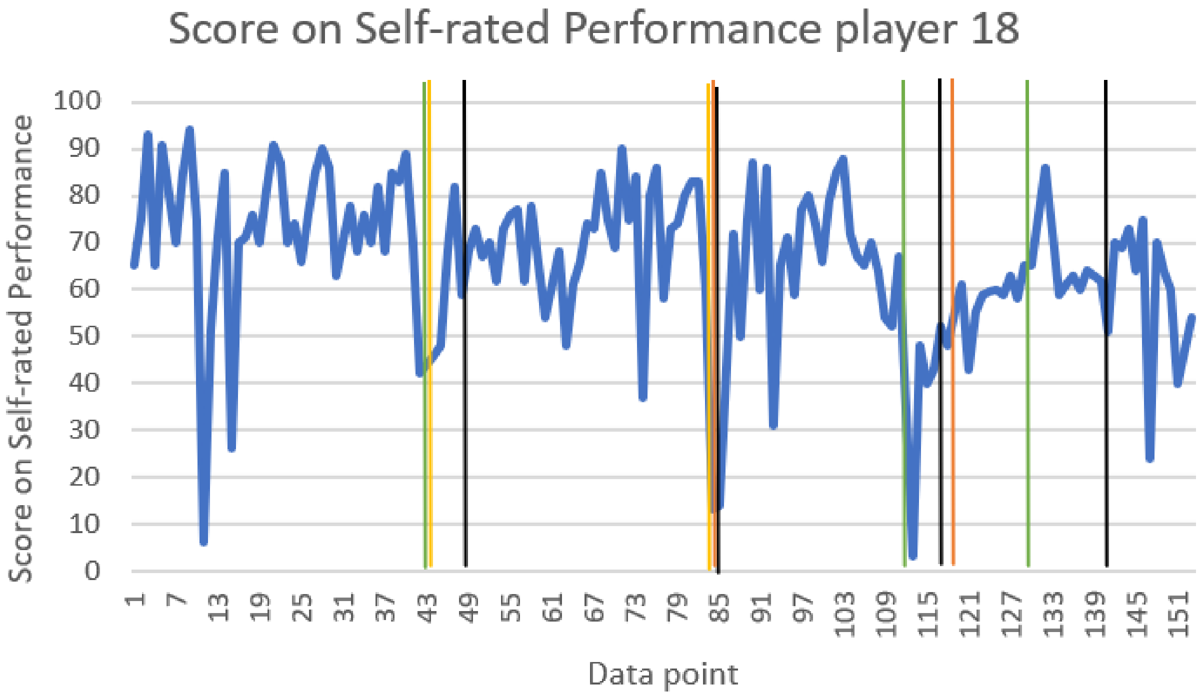


Figure 12

Raw data with changepoints in resilience indicators for self-rated performance of player 19.

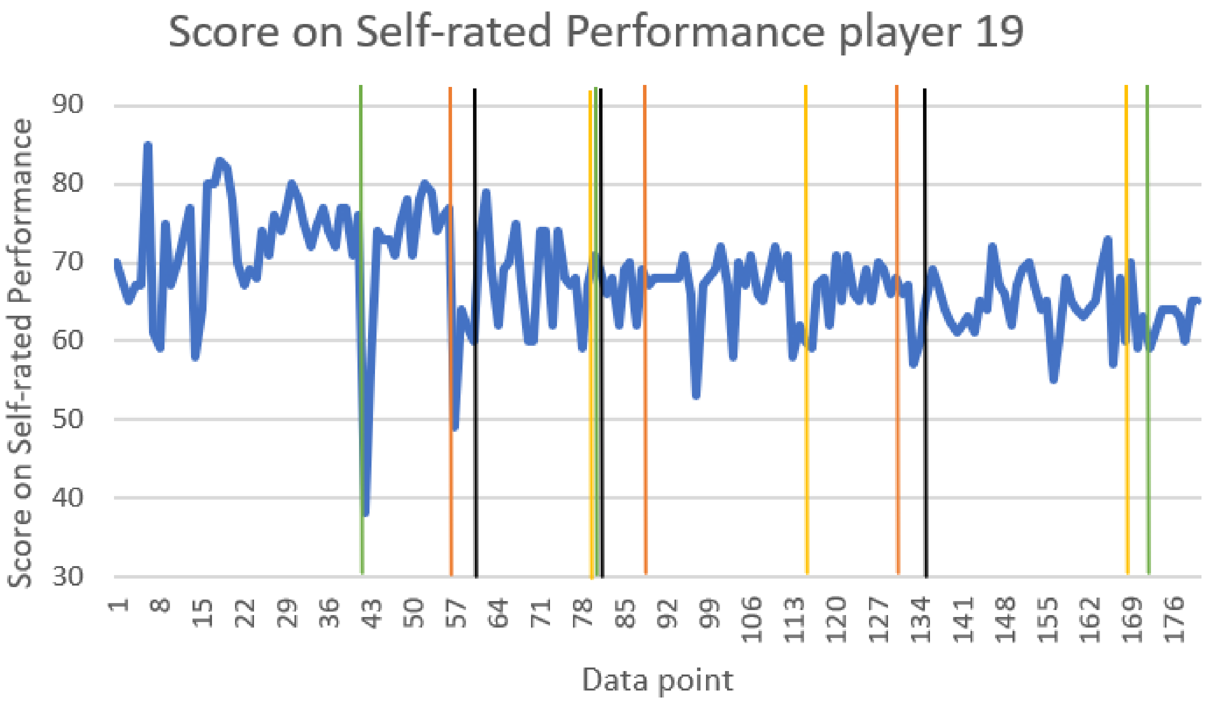


Figure 13

Raw data with changepoints in resilience indicators for self-rated performance of player 20.

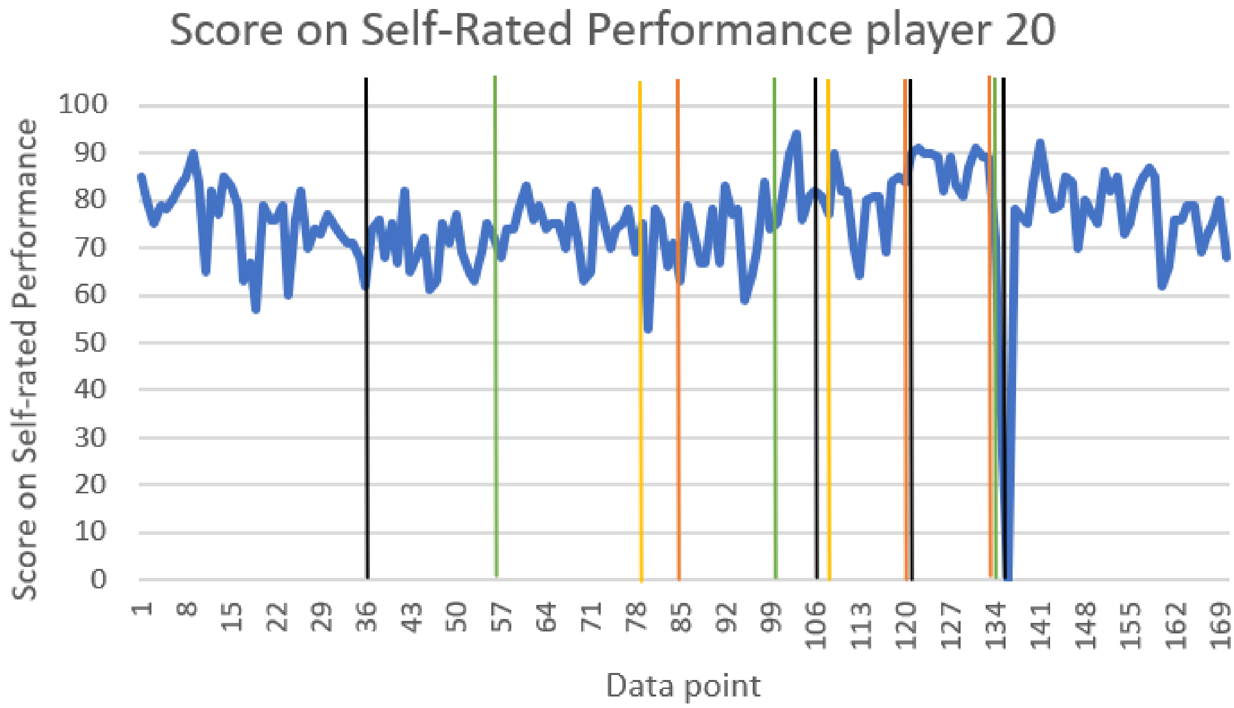


Figure 14

Raw data with changepoints in resilience indicators for self-rated performance of player 21.

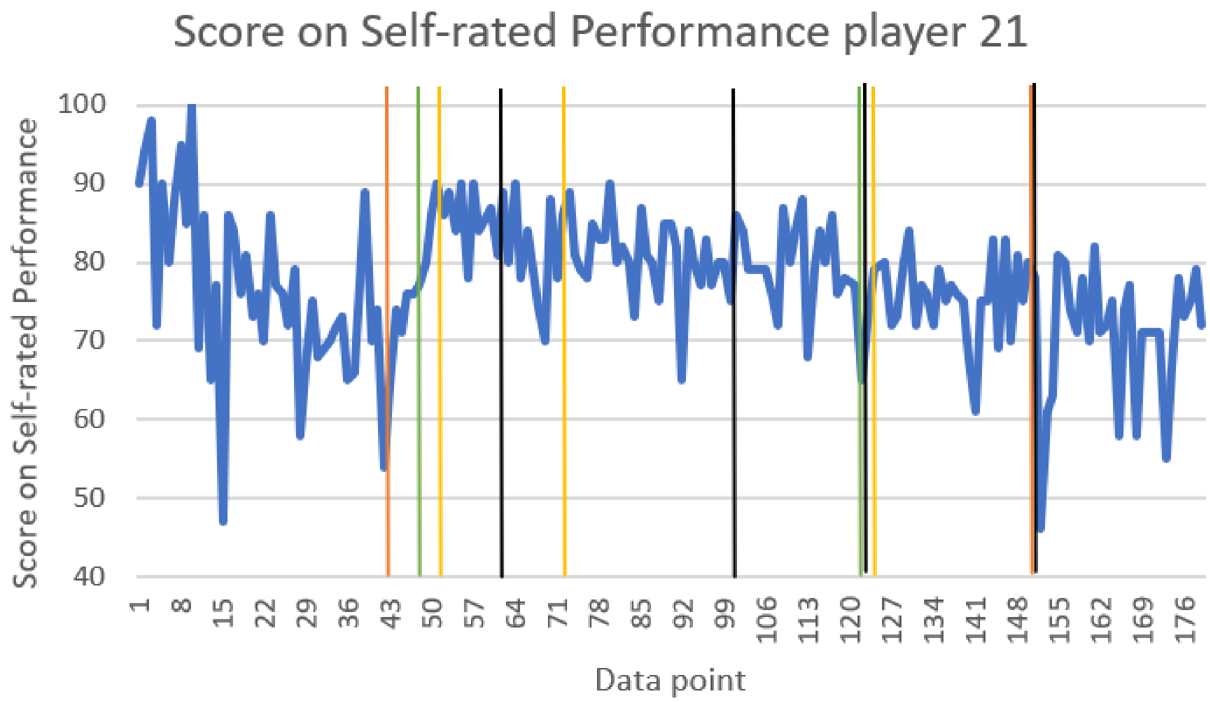


Figure 15

Raw data with changepoints in resilience indicators for self-rated performance of player 24.

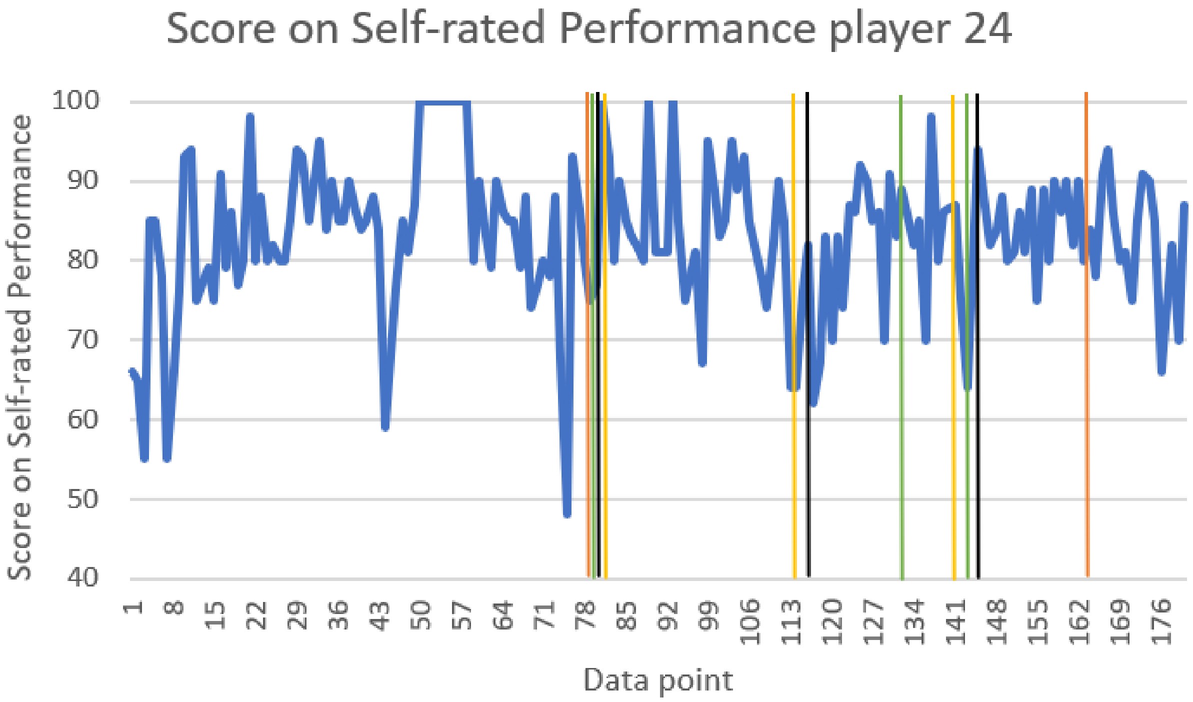


Figure 16

Raw data with changepoints in resilience indicators for self-rated performance of player 25.

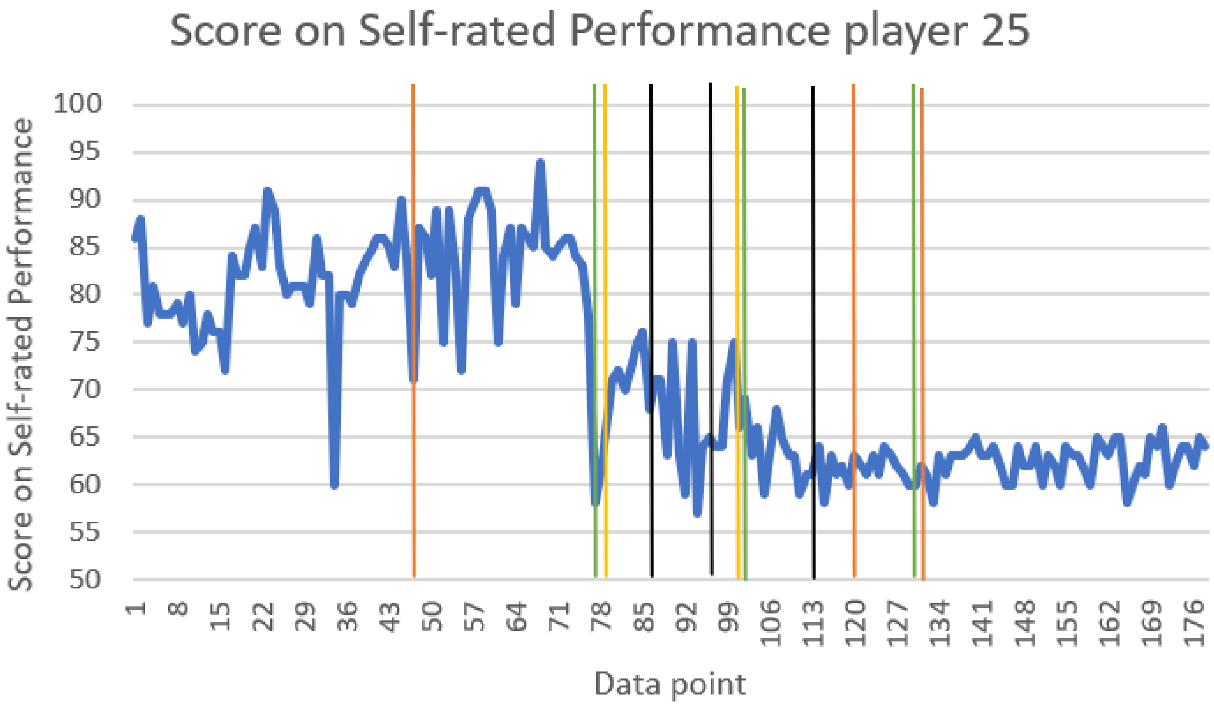


Figure 17

Raw data with changepoints in resilience indicators for self-rated performance of player 27.

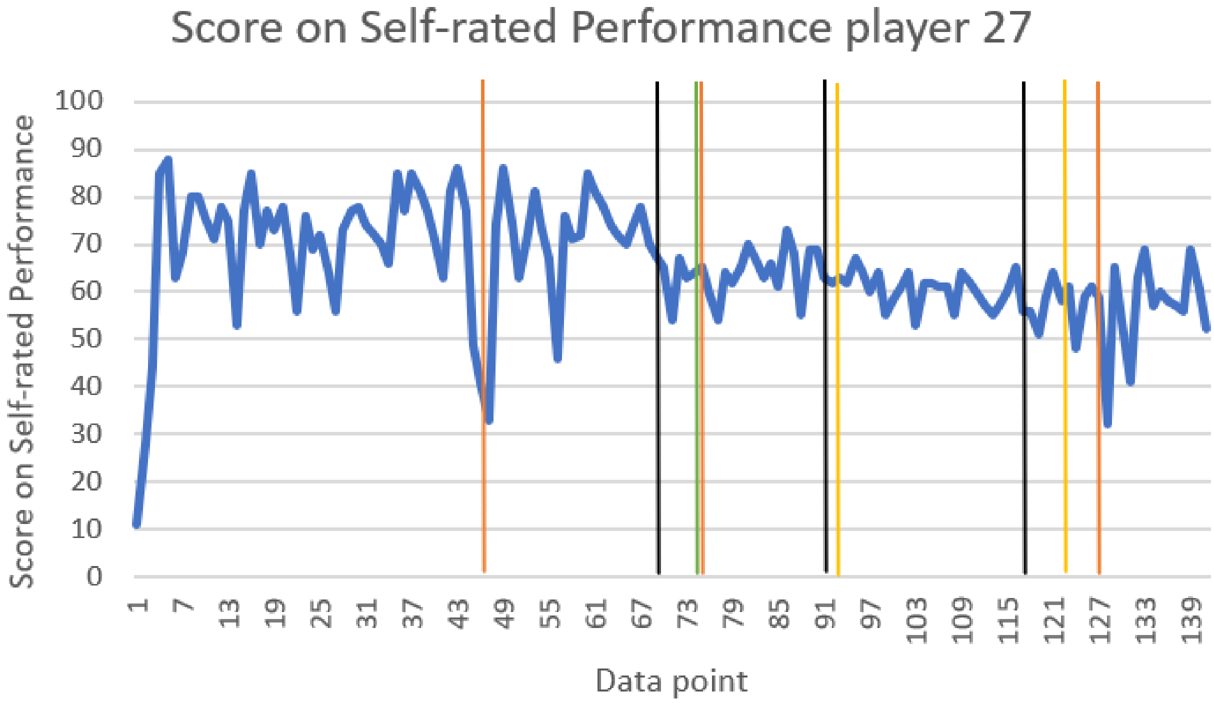


Figure 18

Raw data with changepoints in resilience indicators for self-rated performance of player 29.