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Variability of competition results during one season in swimming

Introduction

In many sports, it is very difficult to measure and compare the individual performance of an athlete objectively. An athlete in team sports is dependent on the performance of the team mates and in most individual sports external factors limit optimal performance such as weather conditions in track and field or the opponent in contact and racket sports. By contrast in swimming, we are able to measure competition performances in a highly objective manner. All international events are measured by automatic timekeeping systems. In official FINA (Federation Internationale de Natation Amateur) rules, competition pools for long course events are normed by exact 50.00 meters with a tolerance of 0.01 meters from touch pad to touch pad. Other conditions, like the temperature of the water and the depth of the pool are also standardized. This makes swimming an optimal sport for reliably and comparably measuring racing times. Taken together, due to the combination of a task that is straight forward to both execute and measure and a high level of standardization, swimming enables researchers to attribute results and athlete progression mostly to the performance of the athletes themselves and thus to easily compare athletes to one another.

Another feature that makes swimming an interesting research objective is that the gap between athletes to each other and to the world record times is small. Every international championship leads to new world records. Costa et al. (2010) observed that there is permanent development in swimming performance. During the Rio 2016 Olympics, there were

six world records in swimming compared to two world records in the running competitions in track and field. Both these sports have comparable numbers of events. Even some single events in swimming may be very close. For instance, in the 2016 Olympics men's two-hundred-meter breaststroke final, all eight athletes were within 0.88 s. This is 0.7% of the winning-time, or less than 1.4 m converted to distance.

With increasing professionalism in sports, practitioners have tried to optimize training and competitions schedules. Nevertheless the Summer Olympic Games is the most important competition in swimming.

Research interest in performance progression has increased markedly since the beginning of the 21st century. The variability of swim performances offers practitioners useful insights into how champions are made because “the variation in performance from race to race is an important determinant of an athlete's chances of winning the race” (Pyne, Trewin, & Hopkins, 2004, p. 613). This “random variability of a single individual's values on repeated testing is the standard deviation of the individual's values” (Hopkins, 2000) and is measured as coefficient of variation (CV). Although performance variability is a crucial parameter in swimming, research on this topic is still in its infancy.

Of the few studies published to date Pyne et al. (2004) analysed performance variability in swimming over a 12-month period of time, measured at three major events. They found an improvement rate of 0.9% averaged over all athletes. Trewin, Hopkins, and Pyne (2004) compared FINA world ranking results with

the results at the 2000 Olympics and found a within-athlete variability of 0.8%.

Third Stewart, and Hopkins (2000) investigated junior and professional athletes and found that faster swimmers were more consistent in their performance than slower ones. They proposed two explanations: “First, the faster swimmers may prepare for competitions more consistently and therefore compete more consistently. Second, the faster swimmers may have more competitive experience and may therefore select a pace closer to their optimum for a given stroke and distance” (p. 1001).

Finally, Costa et al. (2010) tracked the season's best performance of top ranked freestyle swimmers over a five-year interval to analyse their stability. They found a 0.6–1% improvement per season.

These four studies are limited in that they do not investigate performance variability over a continuous period of time but rather compare just a few fixed dates. Hence, it is difficult to draw conclusions as a coach or athlete for planning and peaking the season. An example for a study with a continuous measurement scheme is provided by Noordhof, Mulder, de Koning, and Hopkins (2016) who investigated performances of speed skaters. The authors looked at a continuous period of time and clustered results which are close (less than 14 days in between two competitions). They found that the race-to-race variability of an athlete ranged from 0.32 to 1.3% and that speed skaters were faster in competitions that are more important.

The purpose of the present study is to investigate how performances of elite swimmers develop during an eight-month period of time within one compe-

Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
Athlete 1				x	x			x	x	x			x				x	x		x		x	x			x						OG
Athlete 2				x				x	x									x	x			x	x		x							OG
Athlete 3				x					x						x							x	x				x					OG
Athlete 4								x						x							x	x	x					x				OG
Athlete 5				x					x						x							x	x					x				OG
Athlete 6				x				x	x													x	x									OG
Athlete 7				x					x		x										x		x									OG
Athlete 8								x	x													x	x					x				OG
Athlete 9				x						x						x							x					x				OG
Athlete 10		x	x	x	x				x							x					x	x	x	x					x			OG
Athlete 11		x		x	x				x												x		x						x			OG
Athlete 12			x													x					x		x					x				OG
Athlete 13			x							x						x							x					x				OG
Athlete 14			x						x												x		x	x								OG
Athlete 15				x	x					x																			x			OG
Athlete 16				x		x			x	x																				x		OG
Athlete 17										x													x	x						x		OG
Athlete 18								x	x												x	x								x		OG
Athlete 19								x	x														x							x		OG

Fig. 1 ▲ Competition schedule for all athletes in the study. The header row indicates the week number. The first 30 weeks are divided into three sections, indicated by *solid lines*. Each athlete is represented by a row, in which *crosses* indicate weeks with competitions. Weeks connected into a common *grey highlighted area* form a cluster, i.e., competition streaks with less than 14 days of a break in between. Competitions separated by more than two weeks were treated as independent events as indicated by the *arrow* in row 1. OG Olympic games

tion season. The period of eight month equals the long course season in swimming. In general, it starts in January, after a short transition period past the major competition on short course (European or World Championships) in December. By analysing continuous periods of performances assessed in clusters, this study provides a more complete picture of athlete performance during the entire season. This will enable practitioners to design an optimized training and competition schedule around the major competitions in a season.

Methods

Data

We selected all German swimmers who finished an individual event at the Rio 2016 Olympics and all individual athletes from other European countries who either won a medal at the Rio 2016 Olympics or won the FINA World Championships in Kazan 2015. If an athlete won more than one medal, we used data from his or her best event defined as the one at which the athlete won gold medals at the Olympics 2016 and World Championships 2015. We filtered this set of athletes to only include those who competed in seven or more events during the long course season (January

through August) 2016. A minimum of six competitions per athlete, in addition to the Olympics, was necessary to include every athlete in every cluster (see below). The final dataset includes 19 athletes, all stroke types, and Olympic distances from 50 to 400 m on long course in 155 single performances from all over the world. Those 19 athletes are divided in different subgroups. We merged in total six female and thirteen male athletes. For another subgroup, we merged all 50 m and 100 m athletes together (short distances) as well all 200 m and 400 m athletes (middle-distance). In total this investigation included eight short distance athletes and eleven middle distance athletes. The distances included compare well to other individual endurance

sports. Swimming competition times are publicly available so that no consent was obtained from individual athletes. The ethics committee of the Institute of Sport Science at the University of Kiel accepted and has approved this investigation. We downloaded all data from www.swimrankings.net.

Experimental design

We analysed past competition results of the study participants. For measuring the coefficient of variation (CV), we followed Trewin et al. (2004). They described the within-athlete CV as “the random variation in performance between competitions for a group of swimmers” (p. 340).

In a first step, the within-athlete CVs of all results during this period of time were analysed, followed by analysis of different subgroups including nationality, distance, and sex. We focussed our investigation during the eight-month period of time on similarities, differences and individual specifics. We wanted to see if competitions were planned similarly in different nations and different athletes.

In a second step, we wanted to see if the final weeks of the eight-month training cycles we investigated in the first step, were the most important. Therefore, we split those eight months into three sections of ten weeks each and clustered competitions. A fourth sections with weeks 31 and 32 include only one competition, the Olympics. Because there were no competitions close to the Olympics and the special value of the Olympics, we made this classification. **Fig. 1** shows all competitions of all nineteen athletes. The eight-month period of time this research includes comprises 32 weeks (**Fig. 1**).

To cluster competitions results, we put all those races into one cluster, where the time interval between consecutive races was less than 14 days (grey in **Fig. 1**; Noordhof et al., 2016). Competitions with more than two weeks in between were treated as single events or groups of events. An example of competitions with two or more weeks in between is shown at “Athlete 1” with an arrow (**Fig. 1**). Some athletes had no clustered competitions at all, like “Athlete 9”.

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Variability of competition results during one season in swimming

Abstract

Aims. The purpose of this study was to investigate how performance of elite swimmers develop during one season from competition to competition. A small variability of performance has been suggested to correlate with superior competition results, which is why understanding the connection between performance and its variability is interesting for sports science researchers, coaches, and athletes alike.

Methods. We analysed all competitions of ten European Olympic medallists and nine German Olympic swimmers in an eight-month competition period culminating in the Rio Olympics in 2016. We analysed the variability in performance using the coefficient of variation (CV).

Results. We estimated CVs for German (0.68%) and European (0.52%) athletes, as well as for certain subgroups (sprinters [0.60%], middle distance athletes [0.45%], males [0.57%], females [0.40%]). The variability decreased from the first section of the measurement to its end period by 71%.

Conclusion. We conclude that a small performance variability is an important indicator for peaking performance at the season’s major event.

Keywords

Coefficient of variation · High performance sport · Season planning · Variation in performance · Elite athlete

Variabilität der Wettkampfergebnisse im Verlauf einer Schwimmsaison

Zusammenfassung

Zielsetzungen. In der vorliegenden Studie wurde untersucht, wie sich die Leistung von Spitzenschwimmern im Verlauf einer Saison von Wettkampf zu Wettkampf entwickelt. Es wird postuliert, dass eine geringe Leistungsvariabilität mit besseren Wettkampfergebnissen korreliert. Aus diesem Grund ist es für Sportwissenschaftler, Trainer und Athleten gleichermaßen bedeutsam, die Beziehung zwischen der Leistung und ihrer Variabilität zu verstehen.

Methoden. Untersucht wurden alle Wettkämpfe von 10 europäischen Olympiamedaillengewinnern und 9 deutschen Olympiateilnehmern in einer 8-monatigen Wettkampfphase, die ihren Höhepunkt mit den Olympischen Spielen 2016 in Rio fand. Die Leistungsvariabilität wurde anhand des Variationskoeffizienten (VK) analysiert.

Ergebnisse. Es wurden die VK für deutsche (0,68%) und europäische Sportler (0,52%) sowie für bestimmte Untergruppen geschätzt (Sprinter 0,60%, Mittelstreckenschwimmer 0,45%, Männer 0,57%, Frauen 0,40%). Die Variabilität sank vom ersten Abschnitt der Messung bis zur Endphase um 71%.

Schlussfolgerung. Aus den Ergebnissen lässt sich schließen, dass eine geringe Leistungsvariabilität ein wichtiger Indikator für eine Höchstleistung beim Hauptereignis einer Saison ist.

Schlüsselwörter

Variationskoeffizient · Hochleistungssport · Saisonplanung · Leistungsvariabilität · Leistungssportler

We then analysed if the within-athlete cluster CV was different over the three sections and compared to the overall within-athlete CV. We also investigated if the within-athlete CV in clusters was different going closer to the Olympics. This should help us to investigate how meaningful the results of each cluster are.

To compare clustered results of different sections, we assigned clusters to three sections (1–3, **Fig. 1**). In the case

of a cluster overlapping two sections, clusters were assigned by their midpoint. In the case when there was more than one cluster in one section, clusters were assigned to neighbouring clusters (cluster 2 of Athlete 1 and cluster 2 of Athlete 16).

Statistical analysis

Before we examined the CVs, we checked if using a linear mixed model (LMM)

Table 1 Within-athlete coefficient of variation (CV) of different subgroups

Athlete group	n	Within-athlete CV (%)
German athletes	9	0.68
European athletes	10	0.52
Sprinters	8	0.60
Middle distance athletes	11	0.45
Male athletes	13	0.57
Female athletes	6	0.40

with the full information maximum likelihood estimator was more appropriate for our data than general linear models by calculating intraclass correlations. We tested three different mixed models against each other and decided to use the random intercept constant slope model (RICS).

We used mixed models because those are often used to measure inter- and intra-subject variability. Here, we followed the recommendations of Tabachnick and Fidell (2013) and first examined null models for each task with no predictors. According to Hox, Moerbeek, and van de Schoot (2010) the intraclass correlation should be interpreted as large for each task (ICC=0.99) indicating that a high percentage of the total variance was explained by the difference between our participants and warranting LMMs with random effects to be more appropriate for our data than general linear models.

To examine the variability of competition results during the eight-month period of time with LMMs, we followed the statistical design by Noordhof et al. (2016). Estimating the practical significance of observed effects addresses a potential limitation of statistical significance testing, where an outcome is declared as nonsignificant but is of sufficient magnitude to be practically or clinically important. In a first step, we calculated several LMMs for the variation of performance to examine the within-athlete CV with the week of the competition as independent variable. Following Trewin et al. (2004) we calculated the dependent variable as 100 times the natural logarithm of race time, which produces results approximately

Table 2 Within-athlete cluster coefficient of variation (CV) of different sections

	N of clusters	Within-athlete CV
Cluster Section 1	11	0.55
Cluster Section 2	6	0.31
Cluster Section 3	13	0.21

in percent. First, we separately analysed the variability of different sexes, distances and nationalities. Second, we measured the variability of clusters. Our results showed that models with random intercept constant slope were the most appropriate for all measurements. For this analysis, it is irrelevant whether an athlete performed better or worse. The interesting information is the value of the deviation.

When comparing, and estimating the trend of the athletes during this time period towards the Olympics, we set the fastest time of the seven week cycles to one-hundred percent and estimated deviations from there.

All statistical analysis and figures were done using R Studio (Version 1.0.153) and Microsoft Excel.

Results

Variability of Performances

We first compared different groups of athletes for their within-athlete CV (Table 1). The overall variability of all German athletes was 0.68% ($n=9$) while the variability of the other European athletes was estimated to be 0.52% ($n=10$). The within-athlete CV of sprinters (50 and 100 m swimmers) was larger (0.60%, $n=8$) than the within-athlete CV of the 200 and 400 m middle distance swimmers (0.45%, $n=11$). We estimated a larger within-athlete CV of 0.57% for male swimmers ($n=13$) than for females (0.40%, $n=6$).

Looking specifically at the subgroups, it appears that German athletes, sprinters and male athletes all have a higher variability than their comparables (other European athletes, middle distance athletes and females). Surprisingly the gap between the opponents in each subgroup was very close (0.15% in sprinters vs.

middle distance athletes to 0.17% males vs. females).

Looking more specifically into the competition schedule in Fig. 1, there are various differences between athletes in the different sections. Section 1 and section 3 had a similar amount of competitions (49 competitions in section 1 and 47 in section 3) and both more than section 2 (40 competitions). The amount of competitions also affected the number of clusters in all sections, although the number of clusters deviates much more. While sections 1 and 3 again had similar numbers of clusters, section two had only the half number of clusters (Table 2).

Nine out of ten athletes of the other European countries competed at the European Championships. Three of them made their best pre-Olympics results there. All other European athletes made their best competitions at the national championships which serve as trials for the Olympics. Every nation made their trials in a different week between week 13 and 22. German trials were split into two competitions. The first one was in week 18, in the middle of the other European trials and the second one was in week 27, five weeks before the Olympics. Eight of nine German athletes performed best at one of those two qualification events, but only two athletes were able to increase their performance at the Olympics. In contrast, eight out of the ten European athletes were able to increase their performance at the Olympics. There were also weeks, where a few athletes competed at the same day or event like in weeks 4, 9, 20 and 23. In contrast there were also weeks without any competition like weeks 12 or 29 to 31.

Only two athletes competed very frequently over the entire eight months. The data of those two athletes are very interesting because they had also the highest volume of competitions during the eight month time period. We are therefore able to get a good understanding of their performance. Those two athletes competed 14 times each in 32 weeks respectively. Over all competitions, their performances changed in less than 1.8% (Fig. 2). The two distributions have dif-

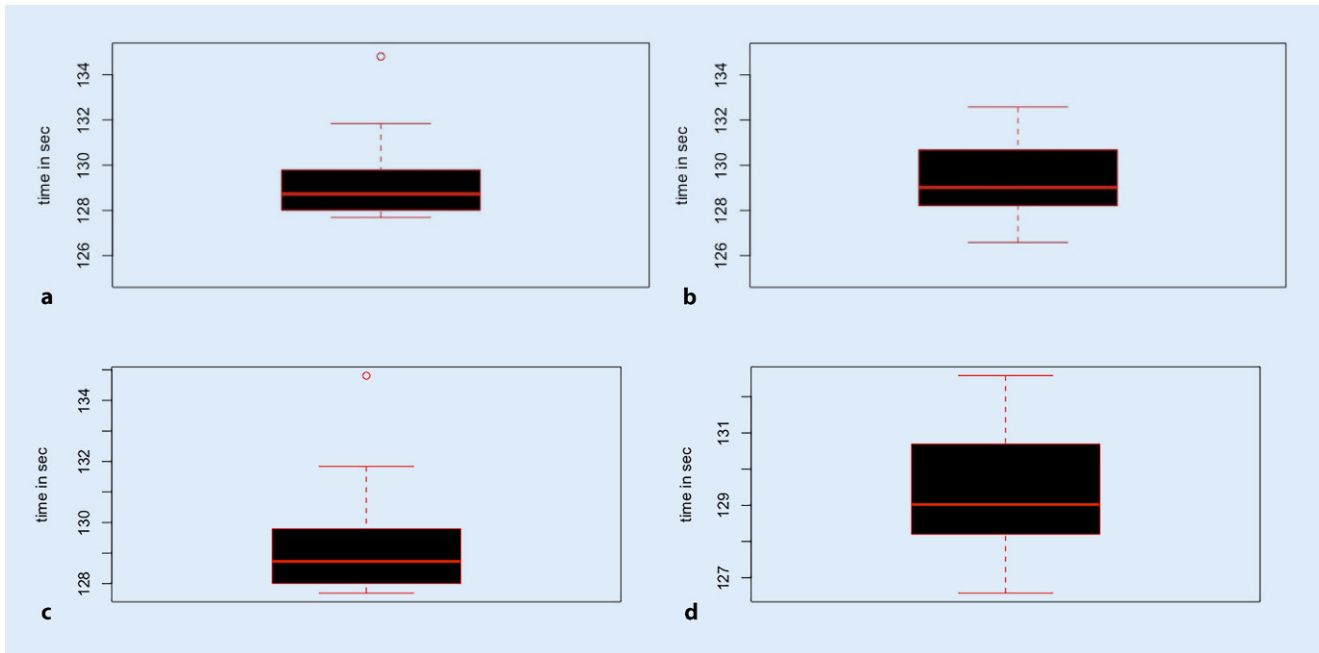


Fig. 2 ▲ Comparison of the distribution of race times of two frequent competitors: athlete 1 (a, c) and athlete 2 (b, d). Boxes show the interquartile range with the median shown in red. Error bars (values in seconds) show 1.5 times the interquartile range or the maximum of the distributions, whichever is smallest. Measures outside the interquartile range are shown as outliers

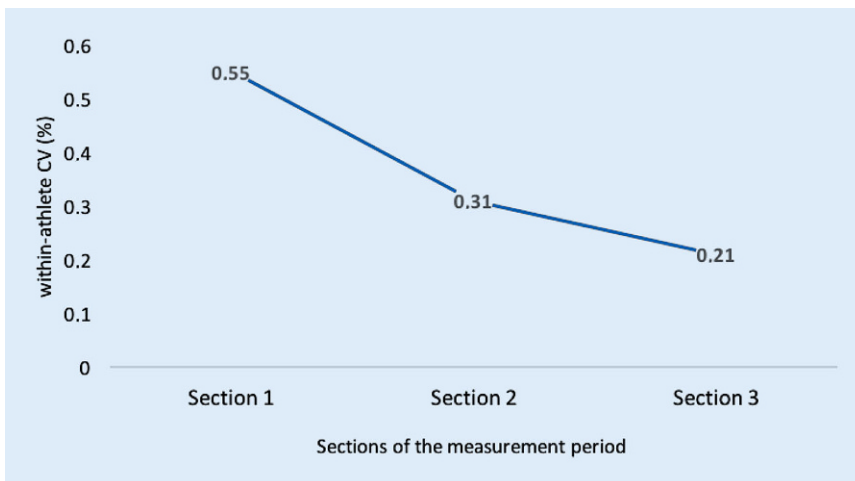


Fig. 3 ▲ The within-athlete cluster coefficient of variation (CV) over all athletes decreases over three sections

ferent shapes. The results of Athlete 2 are quite evenly spread around the median. Athlete 1 had a number of slower results, generating a tail to the distribution, while many of his fastest results cluster closely together with the median.

Both athletes ranked top three in the FINA world ranking in all disciplines in which they started at the Olympics. Although their performances during the season were comparable, their results at the Olympics were strikingly different.

One athlete won three gold medals and one silver medal (Athlete 2) whereas the other athlete (Athlete 1) finished seventh in his only competition. The main difference between those two athletes was in the progression. The Olympic champion swam faster during the Olympics than at any other time during the eight-month measurement period. The second athlete was not able to improve the performance. Compared to the fastest time before, the Olympic champion im-

proved by 0.56%, while the other athlete decreased by 0.24%.

Variability of clusters in different sections

The within-athlete cluster CVs over all athletes of the sections are shown in **Fig. 3**. The variability of section 1 is very similar to the measured variabilities in the analyses above. Section 1 includes the results all athletes during the first third of the eight-month period.

Interestingly the variability of section 2 is nearly half of the variability of section 1 (0.31% to 0.55%). The variability of section 3 is again smaller than the variability of section 2 (0.31% to 0.21%). The performances in section 3 are more than twice as constant as in section 1 (**Table 2**). Overall, performance variability decreased steadily throughout the season.

Discussion

In this study, we tracked performance variability of swimming athletes over the course of one competition season. We focussed only on the Olympic season because results become more consistent

as the time to the Olympics decreases (Costa et al., 2010). The main finding of our study lends further support to that finding within one season as well. We found that the within-athlete CV decreases over time towards the peak of the season. Importantly, those athletes that stabilize their CV most, end up being more successful than those athletes with higher variance at the season's end. In addition, we have estimated a within-athlete CV of 0.52% for European medallist athletes and 0.68% for German athletes. Although the variability between the German athletes and the European medallists is not that large, it may indicate a difference in success. Olympic medallists from many European countries excluding Germany had a smaller variability than the German athletes. This finding again indicates that the variability is one predictor for this success and that a larger variability could be one reason why no German athlete was able to win a medal. This conclusion is supported by the results of Stewart and Hopkins (2000), showing that more successful swimmers had more constant results than their competitors.

Similarly, to the variability we measured, Pyne et al. (2004) found that the variation of performance between competitions was 0.8%. It indicates that athletes are within one season are more stable than from one major event to another. Because a small variability is a determinant for success, this finding underlines the importance of a small variability from competition to competition within one season. In addition, Macata and Hopkins (2014) showed in a systematic review that in many sports, variability has a huge impact. In total, they included 16 investigations in their study and found that some investigations on variability also measured predictability. Indeed, we found that more successful athletes had a smaller within-athlete CV and that the within-athlete CV overall athletes became smaller towards the final section close to the major competition. Further investigation could be focus on predicting results via the variability.

As illustrated in [Fig. 3](#), the within-athlete CVs decrease from section to section as would be expected for athletes preparing to peak at the main event at

the end of the season. The mean CV over those three sections was 0.36% which is similar to the results from Noordhof et al. (0.47%; 2016). Successful season planning and preparation should lead to an increase in performance which we see reflected in lower CVs as time progresses through the season. The regression of the within-athletes over the clusters might underline the assumption that the last (here, third) period is the most important in stabilizing and peaking an athlete's performance. The overview of [Fig. 1](#) led to hypotheses how high performance athletes plan their training. In section two we found the smallest number of competitions, but most athletes made their fastest time before the Olympics in section 2. This finding suggests that athletes need to be prepared for best performances. Because we had no additional training data, we can only assume that the small number of competitions in contrast to the highest number of seasonal best ahead the Olympics is based on a training strategy in high performance athlete. In addition to that we found in weeks 4, 9, 20 and 23 ten or more athletes competed at the same time. There seemed to be interesting events in those weeks for coaches to peak the performance of their athletes. In week 4, most athletes competed at the same event at an international competition where most European athletes start into the long course season. The European championships took place in week 20. It was the first major event for European athletes in 2016. In weeks 9 and 23, there were also high level competitions. Therefore, they may represent a good opportunity to simulate a major event for coaches and swimmers. In contrast, during the final weeks before the Olympics (week 29 to 31) no athletes competed anywhere at all. This fact suggests that those weeks were important for final preparations. Usual training strategies in swimming are still based on 8–16 week cycles (Hellard, Scordia, Avalos, Mujika, & Pyne, 2017). This is in line with the fact that we found the fastest time before the Olympics was measured in the second section.

Another interesting finding in this investigation was that two athletes out of the participants showed a very individual

approach of planning their competition. They competed in more than ten competitions during the season and their results are in a small range of less than 1.8%. Compared to all other athletes this number of competitions was an outstanding performance. This high number of competitions indicates that the competitions are integrated into the peaking process like Tønnessen et al. (2014) showed, but this strategy led to very different results in both athletes. One athlete became Olympic Champion and the other athlete was not able to reach the personal best at the Olympic final. In research, there are few investigations on the development of performances during one season. For example a retrospective study by Suslov (2001) found a few stable performances in track and field during the 1990s. Sergey Bubka, long time world record holder in pole vault is one of those athletes. In a nine-month period of time Bubka “took part in a number of competitions and his results ranged from 92 to 100% of personal best” (Issurin, 2010). Issurin (2008) asserts that such performances requested a different training approach because such a performance would not be possible with a traditional periodization design. Already Kalinin and Osolin (1974) defined performances in a 2% range of the best time as a criterion of the so-called “sporting form”, when they investigated ten competition periods of the world's best middle distance runners all over the world. They reached this conclusion because nearly half of all performances were in this 2% area. Compared to our results all competition results are in this 2% range, but not all results have been performed in the best shape. In contrast, our results show that it is possible to reach a lot of results with a variability of less than 1% during an eight-month period of time. This again leads to the conclusion that variability is an important performance indicator and performance predictor.

Conclusion

This paper points out the importance of a small variability in swimming. For peaking the performance, our data suggest that it is necessary to decrease the

variability to a minimum. For winning a medal at a major event, we can conclude that it is important to show stable performances before. A small performance variability is an important indicator for peaking performance to the major event of a season.

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Compliance with ethical guidelines

Conflict of interest. C. Clephas and A. Wilhelm declare that they have no competing interests.

The ethics committee of the Institute of Sport Science at the University of Kiel accepted and has approved this investigation. Swimming competition times are publicly available so that no consent was obtained from individual athletes. We downloaded all data from www.swimrankings.net.

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