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Review article

Relative Performance Index in Triathlon

Domingos R Pandeló[1,4], Kelly Rose Thomas[4], Emilson Colantonio[3] and Christopher Myers*[2,4]

[1] *Head of Centro de Alta Performance, USA*

[2,4] *Department of Human Performance, Radford University, USA*

[3] *Department of Physical Education of Santos, Federal University of São Paulo, USA*

***Corresponding author:** Christopher Myers, Department of Human Performance, Radford University, 801 East Main Street, USA.

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Abstract

The aim of this study is to establish a relative performance measure that can be used to compare the performance of athletes, contemporaries and/or over time, as well as rank current athletes. Twenty-four (n=24) athletes were selected for analysis. The selection criterion was to have figured at least five times in the top 10 in the IRONMAN© World Championship in Hawaii. The proposed model proposal was able to measure the relative performance of athletes, based on the comparison of their performance with the average performance of their competitors, adjusted by the standard deviation of the average performance of the competitors. The overall performance ranking of the 24 selected athletes was calculated, as well as the ranking by modality (swimming, cycling, and running) for each of the competitors. A relative performance measure, based on effect size, and considering the performance of each athlete in relation to the average performance of the other competitors, can be an additional instrument to evaluate the relative performance of the athletes, as well as to assist coaches and athletes in search of better performance.

List of Abbreviations: ARPI: Adjusted Relative Performance Index; ADRPIF: Adjusted Relative Performance Index Family; ARPIg: Adjusted Relative Performance Index–Global; ARPIs: Adjusted Relative Performance Index–Swimming; ARPIn: Adjusted Relative Performance Index n; ARPIcic: Adjusted Relative Performance Index–Cycling; ARPIrun: Adjusted Relative Performance Index–Running; ARPIcor: Adjusted Relative Performance Index–Run Stage; Rcor: Run Correlation; CBScic: Correlations Between Swimming and Cycling; CBCrun: Correlations Between Cycling and Running

Introduction

Measurement of performance in sports practice is critical to performance monitoring, evaluation, and improvement. Performance improvement is the result of a summation of aspects, including technological innovations, specific training, changes in nutritional strategy, in addition to other possible variables Glazier 2017 [1]. In the case of elite athletes, sports performance is particularly complex and multifactorial [2]. Amongst triathlon races, even considering a race performed on the same course, there may be many differences, depending on the current, elevation profile, climate, among other aspects [3]. Thus, although the distances are typically consistent in races of the same type, the elevation profile, conditions of the sea, river or lake, can vary greatly from one race to another. Race terrain diversity also occurs between races, with the swim held in the pool or open water bodies of water in rivers, lakes, or oceans; cycling and running are completed on the smooth road surface or off-road on trails. The elevation profiles of the cycling and running segments in triathlon can vary immensely between races [3].

Proposing a methodology for measuring an athlete's relative performance against his competitive group can be an interesting proposition, with important practical applications. The advantage of measuring the relative performance is the ability to measure the relative performance of athletes over the years, with a more accurate measure of comparison, taking into account not only the final position of the athlete but the general behavior of the same with other competitors. It is worth mentioning that, to date, there are no records of studies in the literature with proposals for similar models of relative performance analysis in sport. Thus, some important issues can be considered in the search for measures or models that allow the comparison of athletes' performance over time and can make the necessary adjustments so that such comparisons may be possible. To elucidate these problems, this paper proposes a model to assess relative performance, able to make the basic settings required for the comparison of athletes at different times in different trials, using this methodology. For this purpose, the IRONMAN© triathlon world championship will be used,although this model can be applied to other sports that have their results measured by time,such as running (cycling, swimming, etc.).A first effort to find a measure of relative performance in triathlon was made by Pandeló Jr & Azevedo in which the authors established a relative performance model in triathlon events, but only based on the time difference between athletes. This study incorporates a measure of performance analysis in terms of effect size, presenting an alternative methodology, and further advancing the concept of relative performance.

Literature Revision

Triathlon and performance

Triathlon characterization

Triathlon is a multisport activity, consisting of three disciplines, held in consecutive order. Triathlons traditionally start with swimming, followed by cycling, and ending with a run; however, there can be variations to the order of events. There are many types of triathlons races of varying distances ranging from the short sprint distance, to longer Olympic, long half IRONMAN©, and ultra-IRONMAN© distance (Table 1). For athletes aiming to push the limits of their endurance even farther than the IRONMAN© distance, the Ultraman race covers 515 km, divided into three stages over three days "IRONMAN© is the trademark name for the long and ultra-distance races, which started at Oahu, Hawaii, in 1978. It's a long-lasting triathlon race. With few exceptions, the race consists of a 3.8 km swim, a 180 km cycling stage, and a run of approximately 42.2 km (length of a marathon). The race must be made within 17 hours "Pandelo Jr & Azevedo, 2016, as the regulation of race (www.ironman.com/triathlon/pages/resources/rules-and-regulations.aspx). However, professional athletes (top 10) currently complete the race with an average time of eight hours. It is worth mentioning that in 1981, such time was close to 10 hours and 30 minutes. This example shows the extent of the reduction of time over the last few decades due to increases in technology and exercise science. The IRONMAN© World Championship is held at Kona, on the Big Island, in the state of Hawaii, in the United States of America. The event takes place in October, and participation, both for amateurs and professionals, takes place by qualification, through ranking in performance of the function in other stages of the circuit of IRONMAN©. Thus, the race in question adds the best professional and amateur athletes' inactivity [4,5].

Table 1: Triathlon event distances.

	Swim (km)	Cycle (km)	Run (km)	Total Distance (km)
Sprint	0.75	20	5	25.75
Olympic	1.5	40	10	51.5
Long (half IRONMAN©)	1.9	90	21.1	113
Ultra (IRONMAN©)	3.8	180	42.2	226

Performance

Some studies have shown the complexity of evaluating performance, especially if considered multifactorial aspects involved [6,7]. Thus, the performance can be thought of as a mathematical function in which the dependent variable (performance), is seen as a function of training, nutrition, recovery, among other factors. [1] Made an interesting attempt to understand performance a little more. Considering the multiple facets involved in the search for a unified model of analysis, the performance is viewed from a multifactorial perspective that impacts physiology, biomechanics, psychology, and nutrition. This model shows the interdependence of these factors. Previously,[7] analyzed physiological stress modulated by several factors, including and environmental conditions. In this study, the multifactorial aspect of triathlon was evident, as well as the importance of nutritional aspects in long-term trials.

Analyzing the performance of triathletes throughout IRONMAN© races, several studies have shown that the time of completion of the races has greatly reduced over the years, probably due to changes in training strategies, nutrition, as well as technological changes [8,9,10,11] Especially in the case of professional athletes, a reduction in race time was found, perhaps due to innovations and advances in various areas, from equipment to nutritional and training strategies [12]. In another interesting study that evaluated results between 2002 and 2015 [13] found that performance improved in all three modalities for professional triathletes, due to several potential factors, including technological changes to changes in training and nutrition strategies. Additionally [14] showed that there is an age at which the best triathlon performance is achieved. The issue is not just age itself, but all the stimuli and adaptations received over years of training, with the potential beneficial effects from this process. It was observed that the age of maximum performance varies according to the distance of the race, being smaller in the Olympic triathlon and higher in long-duration events (like IRONMAN©).

In the study cited above, the authors found an average age of 32.2 ± 1.5 for men and 33, 0 ± 1.6 years for women.In a similar study, they found a mean age of 35.1 ± 3.6 for men and 34 0 ± 4,0 years for women, an IRONMAN©. [15] evaluated the differences in triathlon performance in terms of gender as well as age. This study aimed to analyze the changes in participation and performance trends of older (> 40 years old) triathletes between 1986 and 2010 at the IRONMAN© triathlon in Hawaii, and these authors found a significant difference between the times of athletes, according to gender and age. [16] analyzed, through a mathematical model, the relationship between training and performance, as well as the transfer that can be obtained through training in one modality to another. In this study, the authors found that transfer between modalities (training) was observed between cycling and running (r = 0.56), which may be a strategy to avoid very voluminous running training, with greater muscular impact (in terms of recovery time). However, the correlation of 0.56 is not considered too high, as from 0.70 it could be a considerable value. The authors found that run performance was the key discipline for victories in long-term triathlon trials and occurring transfer between the cycling training for the run, and the relationship between training and performance was significant between run (r = 0.74) and swimming (r = 0.37). Moreover, it was observed that the training of the run seems to have the greatest relationship with the final performance (r = 0.52). A similar analysis was made by Ofoghi 2016 [16], with very similar results in terms of performance, outcome prediction, and key discipline for victory. [17] demonstrated that in shorter duration events, such as the Olympic triathlon (1.5 km swimming; 40 km cycling and 10 km running), the swimming test is of great importance on the result. A good swimming performance will allow the athlete to exit the water with the first group of athletes, thus starting the cycling course as the lead group of competitors, which always for less effort as compared to the second group. The second group must expend excess energy as they attempt to catch the first group of athletes throughout the race. Athletes exiting the water in the first group, cycling within the lead group, will more likely start the run course less physically depleted than the athletes chasing to catch up. This aspect is discussed in the work of Landers 2008 [18], with an interesting approach. The authors concluded that swimming in this kind of evidence is vitally important because of 90% of the winners left in the first block in the male and 70% of the winners left in the first block in the female. One should be careful in interpreting the analyzes of triathlons, concerning nonperception that the triathlon is not simply a test consisting of swimming, cycling, and running, but a composite race of swimming, more cycling, more running. All the steps in the analysis should take these aspects into account, otherwise, the result is undermined. It is not uncommon, an athlete modify your planned pace, adjust your strategy is strategy race, in the middle of the race, depending on various factors, from a better position than expected at an earlier stage to the need for a quick recovery and searching for a rebalancing for subsequent return to a more aggressive pace, in order to avoid premature exhaustion, who could compromise the race Bonacci 2013 [19].

Methods

Ethical procedures

The present study was conducted through a collection of test results from the IRONMAN© World Triathlon Championship, without direct intervention with the athletes. The study was submitted and approved by the Human Research Ethics Committee of the Federal University of São Paulo. (UNIFESP) (3,006,548), under the number 1258/2018.

Sample

The selection criteria for the study were as follows: male, professional triathlete, and finished the race among the top 10 in at least five editions, consecutive or not, of the IRONMAN© World Triathlon Championship, between the years 1981 and 2017. The total number of individuals selected based on these criteria was 24 professional triathletes. The

definition of the sample constitution criterion took into consideration the intended mathematical and statistical treatment, as well as the restrictions, in terms of the sample required by these techniques [20].

Adjusted relative performance index (IPRA)

Theoretical conceptions

This study proposes a model for measuring the relative performance of athletes. Such a model proposal, in its methodological structure, presents a different format from what is normally considered. There is no intervention, no groups to compare, nor hypothesis testing presented. It is a cross-sectional and retrospective study. The final result of this work is the presentation of the proposal of the relative performance model itself, capable of assisting in the ranking of athletes, as well as, especially in the case of multisport activities, assisting in the training strategy, besides the choice of tests. The analysis was made with data from professional triathletes, male participants at IRONMAN© Hawaii, from 1981 to 2017 that was listed among the TOP 10 in addition to other restrictions presented below. However, the proposed model and analysis could be performed with any other test, in any other sport, provided it has its performance measured by time. The database used, Top IRONMAN© Hawaii Finishers Archive, was from the website www.slowtwich.com. The proposed theoretical model starts from some basic premises (P), established as follows: Q1. The performance on the test was given. The data worked on in this study were the athletes' race times; P2. It is assumed that because they are professional athletes and selected from the best in the world, they have access to the best training, nutrition, hydration, and equipment strategies.

Methodological considerations

The calculation of the IPRA is described in stages below, according to the points discussed above regarding the constitution of the sample:

1) Compilation of results for the period 1981-2017.

2) Selection of the top 10 athletes in each of the selected years.

3) Selection of athletes who ranked at least five times in the TOP 10. In the case of athletes who ranked more than five times in the TOP 10, the five best results were chosen.

4) Calculation of the average time of the TOP 10 in each of the years (in seconds).

5) Difference between the performance of the selected athletes in their respective years and the average performance of the professional athletes in the selected period.

6) Based on the difference found in item five, one can verify the relative difference in seconds (and calculate the percentage change, or "overperformance") and, based on a measure of proposed effect size, calculate its relative performance.

It is noteworthy here that, although the race started in 1978, in 1981 alone, the professional category consisted of more than ten athletes. The 1978 year was an amateur competition; the professional category had not yet been established. The choice of at least five times among the TOP 10 categories took into consideration sample size issues, as already discussed, as well as the construction of structure matrices [5x5] for the calculation of some points of the work, such as correlations, for example, as suggested by Johnson & Wichern 1988 [16]. The s results for the season of 2018 did not enter in the calculation of the present study since this project was already underway when the said test. M of, after the results of 2018, an analysis was made and set up for, verifying that they do not influence the constitution of the sample. A first analysis was made with the total test time, calculating the overall performance index. Subsequently, performance indexes were calculated by modality (swimming, cycling, and running). The current model used a measure of effect size as a measure of relative performance among athletes. The use of such a measure can greatly reduce the limitations inherent in comparing athletes' performance results over time, as well as in different events Pandelo 2017 [5,17]. Effect size models can be based on distances between observed points (family d), such as Cohen d, for example, or based on measures of relationships between points (family r), such as Pearson correlation, for example. In the present work, is the theoretical model suggested for calculating a measure of performance based on families d. One possible approach to calculating a relative performance index, based on f superfamily r is available in the link 2 of this work.

Theoretical model - IPRA family

The use of an effect measure from family d is far more common than effect measures from family r. In the present study, the size of e made was calculated by the difference between the athlete's time in the race (or modality considered) and the average time of the TOP 10 considered ("overperformance"), where this difference was divided by the standard deviation of the TOP 10. It is, therefore, an adjustment to the athlete's "overperformance" concerning the average of the TOP 10. The sensitization by the standard deviation is of paramount importance in order to work relatively, to compare the results of one athlete from 1985 with another from 2015. For example, the data show that competition in 1985 was less competitive (higher variability) than in 2015. Thus, an "overperformance" of an athlete of 5%, compared to the average, for example, would have a different reading of the same value in 1985 and 2015. Also, with sensitization by the standard deviation, any performance changes due to variations in the weather conditions are automatically adjusted, even partially. Standard deviation adjustment seeks to resolve these points and allows comparison over time.

$IPRAd = Ra - Rp/\sigma$

Where:

Ra = a athetle performance;

Rp = Top 10 mean performance.

Rp = TOP 10 standard deviation performance.

Results

Number of times in the TOP 10

As previously mentioned, to be part of the sample, there was a need for the athlete to have finished at least five times in the TOP 10. Despite those above, it is worth remembering that, in the case of athletes with more than five figures among the TOP 10, the top five results were chosen (Figure 1).

Changes in race times over the years

Through the analysis of (Figure 2), it is possible to verify the alterations in the race time, of the TOP 10, over the years. A sharp reduction can be seen, especially in the first five years of the race. With increasing competitiveness and the development of new technologies, the reduction has continued to occur over the years. However, the current reductions are less as compared to the early years.

Average time by discipline

Figures 3, 4, and 5 show the average time, in seconds, over the years. One can observe a trend of reduction in general over the years, with occasional fluctuations (for more or less), due to environmental factors such as currents (swimming), wind, heat, and humidity (in cycling and running).

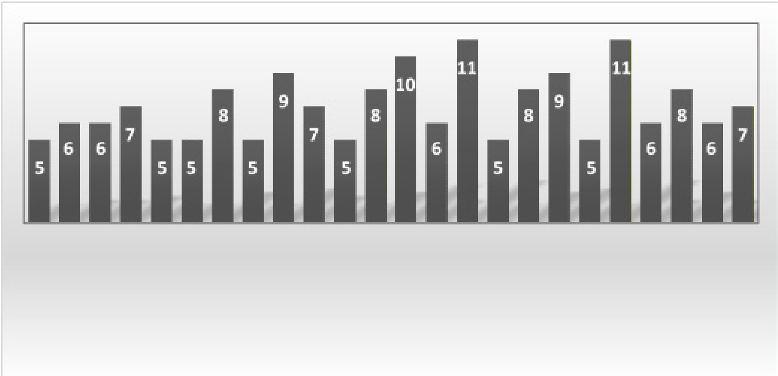

Figure 1: The number of times a triathlete has appeared in the TOP 10.

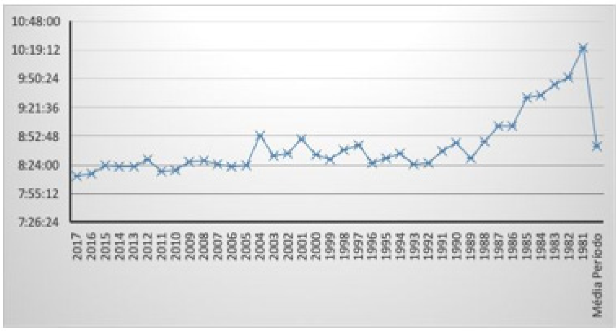

Figure 2: Average time proof of the Top 10 over the years.

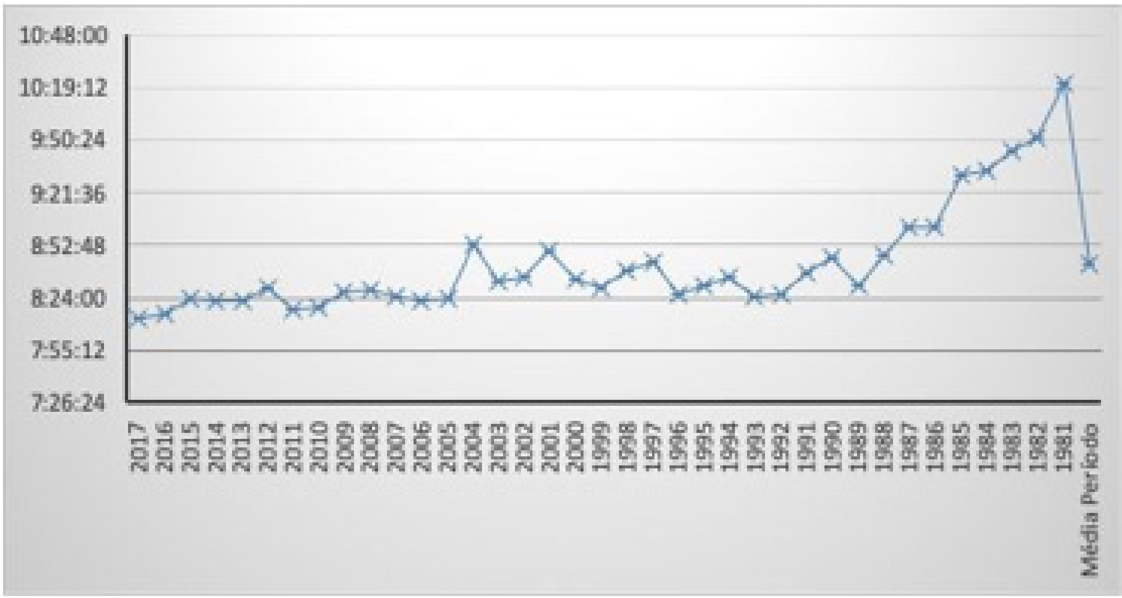

Figure 3: Average time spent swimming by triathletes over the period investigated.

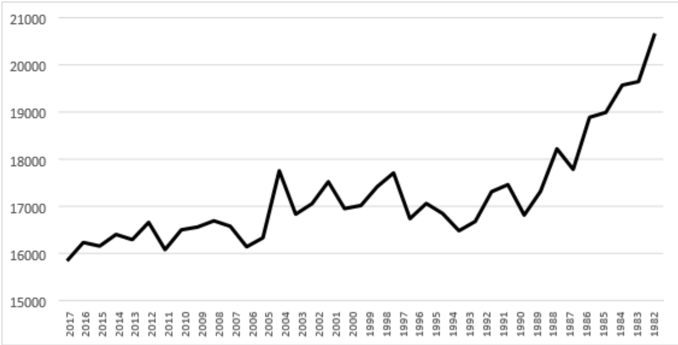

Figure 4: Average time spent cycling by triathletes over the period investigated.

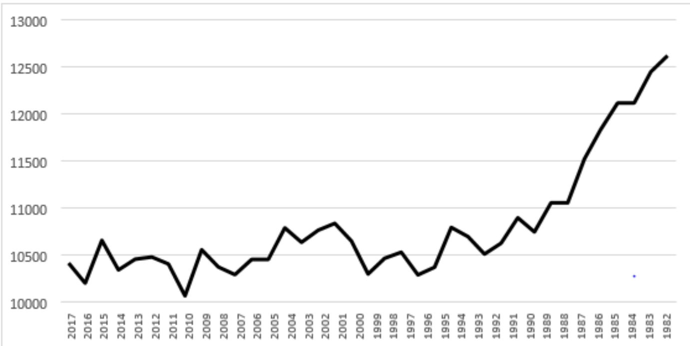

Figure 5: Average time spent on triathletes running over the period investigated.

Annual results - TOP 10 (2017/1981)

The performance of each select athlete was collected and analyzed in the three modalities (swimming, cycling, and running), as well as their time s averages. For space considerations, the annual tables used to calculate the indexes would not be shown; they are available via email.

Proposed model: adjusted relative performance index

IPRA Adjusted relative performance index - global (IPRAg)

The overall performance of athletes was calculated based on an effect size measurement. The IPRAg was calculated by the difference between the athlete's time and the average of the TOP 10 athletes, divided by the standard deviation of their average times. In (Table 2) the time difference is in percentage variation to facilitate the analysis; however, for the performance index calculations, the time difference, measured in seconds, must be used.

Adjusted relative performance index - swimming (IPRAs)

The methodology for calculating IPRAs used the same foundation as the conceptual IPRAg calculation, as shown in (Table 3).

Table 2: Adjusted Relative Performance Index – Global (IPRAg). Where **Δ** % means delta percentage, and SD stands for standard deviation.

	Athlete	IPRAg	Δ%	SD
1	Peter Reid	-32,598	-1,83%	173,39
2	Mark Allen	-30,272	-3,03%	306,42
3	Dave Scoot	-17,804	-6,52%	1246,47
4	Lothar Leder	-17,519	-1,92%	341,46
5	Greg Welch	-16,434	-1,35%	252,16
6	Craig Alexander	-15,807	-1,85%	354,66
7	Andreas Raelert	-12,194	-1,09%	269,15
8	Jeff Devlin	-10,880	-1,65%	468,57
9	Scott Tinlley	-10,880	-4,42%	1387,70
10	Timothy DeBoom	-0,9679	-1,29%	413,70

11	Chris McCormack	-0,8756	-0,89%	308,60
12	Thomas Hellriegel	-0,8466	-1,44%	527,03
13	Pauli Kiuru	-0,7813	-1,19%	468,97
14	Rutger Beke	-0,7278	-0,42%	701,61
15	Sebastian Kienle	-0,6911	-0,82%	355,96
16	Norman Stadler	-0,6210	-1,43%	715,94
17	Faris Al-Sultan	-0,2893	-0,66%	697,46
18	Cameron Brown	-0,2583	-0,43%	512,58
19	Eneko Llanos	-0,2054	-0,21%	309,63
20	Jurgen Zack	-0,0242	-0,03%	412,81
21	Cameron Widoff	0,2730	0,59%	669,48
22	Timo Bracht	0,3195	0,78%	748,14
23	Andy Potts	0,5942	0,30%	153,15
24	Ken Glah	19,646	1,88%	292,79

Table 3: Adjusted Relative Performance Index – Swimming. Where Δ % means delta percentage; SD stands for standard deviation, and Rn means the athlete's classification in the considered index.

	Athlete	IPRAn	D %	DP	Rn
3	Dave Scoot	-49,868	-8,79%	58,87	1
2	Mark Allen	-28,126	-2,32%	25,95	2
23	Andy Potts	-22,979	-3,92%	53,35	3
17	Faris Al-Sultan	-18,713	-3,44%	58,14	4
10	TImothy DeBoom	-18,291	-3,32%	57,41	5
5	Greg Welch	-14,508	-3,66%	80,51	6
24	Ken Glah	-10,898	-2,59%	75,79	7
18	Cameron Brown	-0,8775	-1,70%	61,31	8
6	Craig Alexander	-0,8437	-0,85%	31,29	9
21	Cameron Widoff	-0,6337	-1,26%	63,12	10
19	Eneko Llanos	-0,5752	-0,79%	43,46	11
4	Lothar Leder	-0,5427	-1,37%	80,34	12
1	Peter Reid	-0,4190	-0,51%	37,71	13
12	Thomas Hellriegel	-0,3873	-1,47%	126,00	14
13	Pauli Kiuru	-0,3582	-0,33%	29,03	15
9	Scott Tinlley	0,0101	0,04%	118,52	16
20	Jurgen Zack	0,2150	0,40%	59,54	17
11	Chris McCormack	0,2794	0,52%	57,99	18
7	Andreas Raelert	0,6654	0,72%	33,96	19
16	Norman Stadler	0,8684	2,09%	76,46	20
14	Rutger Beke	15,659	2,88%	58,24	21
22	Timo Bracht	16,615	2,54%	48,03	22
15	Sebastian Kienle	24,607	5,08%	63,72	23
8	Jeff Devlin	27,293	5,64%	65,36	24

Adjusted relative performance index - cycling (IPRAcic)

The methodology for calculating IPRAcic used the same conceptual foundation as calculating IPRAg, as shown in (Table 4.)

Adjusted relative performance index - running (IPRArun)

The methodology for calculating IPRAcic used the same conceptual foundation as calculating IPRAg, as shown in (Table 5.)

Table 4: Adjusted Relative Performance Index - Cycling (IPRAcic).

	Athlete	IPRAcic	D %	SD	Rcic
15	Sebastian Kienle	-32,746	-3,07%	152,69	1
20	Jurgen Zack	-18,355	-2,23%	205,72	2
9	Scott Tinlley	-17,805	-3,16%	335,29	3
12	Thomas Hellriegel	-17,501	-3,48%	342,38	4
16	Norman Stadler	-16,747	-3,50%	356,12	5
3	Dave Scoot	-10,042	-3,58%	671,57	6
24	Ken Glah	-0,6395	-2,19%	587,30	7
2	Mark Allen	-0,5146	-1,12%	369,23	8
13	Pauli Kiuru	-0,3241	-0,57%	296,85	9
10	TImothy DeBoom	-0,1957	-0,24%	207,42	10
17	Faris Al-Sultan	-0,1456	-0,49%	559,09	11
7	Andreas Raelert	-0,0763	-0,09%	199,14	12
14	Rutger Beke	-0,0411	-0,14%	559,06	13
1	Peter Reid	-0,0290	-0,95%	164,41	14
19	Eneko Llanos	-0,0290	-0,03%	185,92	15
11	Chris McCormack	0,0012	0,00%	160,47	16
18	Cameron Brown	0,0391	0,09%	383,66	17
8	Jeff Devlin	0,1170	0,25%	369,33	18
22	Timo Bracht	0,2277	0,75%	549,77	19
21	Cameron Widoff	0,3653	0,73%	343,33	20
6	Craig Alexander	0,5096	0,23%	73,78	21
5	Greg Welch	0,5401	0,57%	178,84	22
4	Lothar Leder	0,7252	1,32%	314,12	23
23	Andy Potts	16,691	2,05%	200,71	24

Table 5: Adjusted Relative Performance Index – Run (IPRAcor).

	Athlete	IPRAcor	D %	SD	Rcor
2	Mark Allen	-54,357	-6,53%	127,56	1
9	Scott Tinlley	-42,549	-7,76%	216,64	2
3	Dave Scott	-40,484	-10,58%	309,70	3
11	Chris McCormack	-36,168	-3,13%	89,80	4
6	Craig Alexander	-28,664	-4,36%	157,20	5
1	Peter Reid	-26,828	-4,02%	158,34	6
4	Lothar Leder	-26,012	-2,76%	112,95	7
10	TImothy DeBoom	-22,396	-3,95%	186,37	8
7	Andreas Raelert	-20,676	-3,34%	168,41	9
13	Pauli Kiuru	-20,442	-2,44%	127,58	10
5	Greg Welch	-19,269	-2,71%	148,73	11
14	Rutger Beke	-18,747	-2,25%	126,42	12
18	Cameron Brown	-18,446	-2,30%	132,17	13
23	Andy Potts	-12,105	-1,27%	109,70	14
22	Timo Bracht	-0,8864	-1,08%	128,39	15
8	Jeff Devlin	-0,6092	-0,71%	125,42	16
17	Faris Al-Sultan	-0,2548	-0,30%	125,59	17
12	Thomas Hellriegel	-0,2310	-0,41%	187,86	18

19	Eneko Llanos	0,4947	0,63%	131,80	19
21	Cameron Widoff	0,9560	0,99%	110,67	20
15	Sebastian Kienle	10,532	1,00%	98,56	21
16	Norman Stadler	12,071	0,91%	80,69	22
24	Ken Glah	15,246	2,20%	155,97	23
20	Jurgen Zack	24,297	3,35%	146,11	24

Discussion

The main objective of the present study was to establish a relative performance model that can be used to compare athletes' performance, regardless of the time they competed, as well as to assist in training strategy and competitions based on these results. Triathlon sports were used as an example, but such a model can be applied to any activity that

has its result measured by time?

Number of times in the TOP 10

This study shows that athletes Mark Allen and Scoot Tinley athletes were figured over the top 10 in the period considered, each with 11 appearances. Then Ken Glah appears with ten appearances in the TOP 10, followed by Faris-Al-Sutan and Peter Reid, with nine appearances each (Figure 1). It can be argued that over the years, as competition has

increased in competition, it has become more difficult to figure so many times in the TOP 10 than it was at the beginning of the IRONMAN© World Championship (Barbosa et al., 2019) [21].

Changes in race times over the years

There was a considerable reduction in the average time to test the TOP 10. This average was to be expected with increasing competitiveness in tests of this kind. It is worth remembering that the World Championship IRONMAN© began, more effectively in 1981, when the location moved to Kona (Big Island, HI).The swimming stage is the shortest, representing approximately 10% of the race, followed by cycling representing 55% of the race, and leaving the run with approximately 35% of the total. Some studies show that the cycling stage is that which has the highest correlation with the final race time [22,23]. From a statistical point of view, this result is found mainly due to the characteristics of swimming, cycling, and running data. Especially in the case of events in which all participants are considered, the cycling stage tends to have the longest duration (average) and a very large variability (standard deviation). One possible explanation of this fact, in light of statistics, may be related to violations of some principles in the use of covariance and correlation techniques, such as linearity, homoscedasticity, normality, and non-multicollinearity, for example Hair 1998 [20]. For the use of correlation, some basic assumptions must be observed. When worked out globally, considering all competitors of a triathlon race, especially IRONMAN© (where the variability of results is greatest), many of the premises are invariably violated (especially homoscedasticity), with direct reflexes on the results found.

Analysis of annual results - Top 10

Overview

The analysis of the top 10, as described in items 5 and 4 (Tables 1 to 37, annex 1), indicates some interesting things. First, as already mentioned, the reduction in the average race time is evident. Several studies give possible explanations for this Bentley 2002, 2008 [2,9,24]. Thus, technological changes, as well as nutritional strategies, training, recovery, among others, may have contributed to this. Regarding technological changes, cycling seems to have been the most influenced modality, with the incorporation of technological innovations such as carbon frames, carbon wheels, as well as power meters [8]. It happens that a better performance in cycling, due to technological innovations tend to lead to a better performance, with reduction of the average time in the run [25, 26], mainly due to the lower level of fatigue in the previous step. Cycling training strategies also had their effect, as they aided in optimizing running results [27,28] [25]. Thus, technological advances, combined with the study of more appropriate training strategies, as well as the study of the effects of fatigue in prolonged activities in cycling [29] , as well as the effects the subsequent cumulative stages of the triathlon in performance [30-33] may have helped to reduce overall race times. Another crucial point, especially in the evidence that was used as an example in the present study, concerns hydration and supplementation issues.

The test is carried out in Hawaii, in a tropical climate with high levels of temperature and humidity. Under these conditions, especially considering the duration of the race as well as the level and efforts made, such nutritional strategy issues are of fundamental importance [11,34] .In a way, all these innovations and strategies are summarized in the works of Lepers [21,35] , in what the authors analyze the changes over time, the performance of elite athletes (professional). Barbosa 2019 [8], to investigate these issues in the period between 1983 and 2018, so similar to the present study. The main findings of this study showed that both men and women (professionals) significantly reduced their testing time over time. The greatest reduction was observed in cycling, then at the run, corroborating with the result is found s in this study.

Pattern search in results

Analysis of the CV over the years showed a gradual reduction in all modalities as well as in the overall result, as observed by Figueiredo, Marques & Lepers 2016 [36] and Malcata & Hopkins 2014 [37]. This result can be considered as indicative of greater competitiveness. In isolation, analyzing the highest coefficients of variation were observed in swimming and running Table 7. Cycling presented a more homogeneous situation over the analyzed period, with a lower coefficient of variation. The analyses of (Figures 3, 4, & 5) indicate a tendency of time reduction in the time races, especially in cycling and running, over the years. Of course, point changes can be observed and are often related to climate factors, as pointed out by Hue 2011 [3] and Kerr 1998 [38]. Also, considering the climatic factors, especially in the editions of this test, where the weather conditions were unfavorable (current, wind, heat, and humidity), the pacing strategy is of fundamental importance [3,38]. Table 7 shows that swimming, despite being the race with the lowest relative participation in the total race time, presented the highest coefficient of variation. This result is interesting and deserves a reflection, as the coefficient of variation is an important measure of variability set to consider the relative importance of the steps. The second highest coefficient of variation was the running and cycling; in turn, despite more than 50% of the time to such race, it presented a lower coefficient of variation. This fact can be an indication that further efforts are undertaken in the cycling stage, causing an impact on athletes, as was observed by the coefficient of variation in the run stage. On average, analyzing the whole period considered, it was observed that swimming represented 10.23%, cycling 54.91%, and running 34.47% of the total race time, respectively (Table 6). The average coefficient of variation over the period considered (1981 to 2017) was 2.63% in swimming, 1.28% in cycling, and 1.57% in running. In the search for patterns, the most interesting point is the analysis of correlations. The analysis of correlations between swimming and cycling (naticid) and between cycling and running (cic_cor) can come up with some interesting reflections. Note that the correlation naticid, the last ten years, had seven negative results and only three positives.

Table 6: Correlation Between Stages.

Stages	Correlation
IPRAg x IPRAs	0,174
IPRAg x IPRAcic	0,007
IPRAg x IPRAcor	0,690
IPRAs x IPRAcic	- 0,253
IPRAcic x IPRAcor	- 0,279
IPRAn x IPRAcor	0,403

Table 7: Coefficient of Variation (CV) Between Stages.

	Swimming	Cycling	Running
Mean	10.23%	54.91%	34.47%
SD	0.27%	0.70%	0.54%
CV	2.63%	1.28%	1.57%

It cannot be said to be a trend. However, looking at the athletes' performance, in some cases, one can imagine a situation in which an athlete with above-average swimming, who comes out with a few minutes of water advantage, can print a more conservative cycling, saving energy for the decisive stage, namely the run. Some studies were supporting this view [18,39] beyond the working [40] commenting on the relevance of the run in terms of the final result. The analysis of the correlation between cycling and running in the present study seems to make this very clear, in terms of the average pattern, since as a rule, in only six years, there was a positive correlation between thus, in general, the athlete who rides faster than average should run at a rate below average. The question is how much more effort is worth at the cycling stage; and what will be the impact of this strategy on the run stage. The analysis of the overall performance during the IRONMAN© race, among elite athletes, over time, appears to support this assumption, as has been observed by some authors [12,21,35].

Proposed model: adjusted relative performance index family d- IPRAd

General IPRAd

The overall performance of athletes was calculated based on an effect size measurement. The IPRAd was calculated by the difference between the athlete's time and the mean, divided by the standard deviation of the athletes' average times. That is, it is a measure of relative adjusted performance. This result makes it possible to compare results over time. An athlete who competed at a less competitive time, such as Dave Scoot, would have his "overperformance" (D) sensitized (divided) by greater variability due to the greater dispersion of results among the TOP 10, probably due to lower competitiveness. A negative IPRA value indicates above-average performance, and a positive index indicates below-average performance. Although it allows the comparison of athletes who competed in different periods, the present model works better with athletes who competed simultaneously, because in this case, the assumptions to be imposed on the model are smaller. Based on this model, Peter Reid, Mark Allen, and Dave Scott are among the three biggest names of all time, according to (Table 2). We can note that the "over-performance" D (athlete's time - time average of the TOP 10) was divided by the standard deviation (SD) of the TOP 10 times to make the relative adjustments. Thus, who competed one "less competitive" period, you have a higher DP, and you ve an impact directs it in its index. This method made it possible to compare results from different timeframes. This metric explains why Peter Reid ranked first, and Dave Scott, who had the biggest "overperformance" came third. The same reasoning explains how Mark Allen's runner-up even though he has a higher "overperformance" than runner-up Peter Reid. This model can be applied to any athlete level. If the objective is only the calculation of relative performance indices, the heterogeneity of competitors will not be an obstacle, as the DP will adjust this fact. It is of interest to observe the correlations between the steps or to run some regression to verify the relative weight of each step. We recommend working with sub models, dividing the sample into more homogeneous competitive groups, because in this case, the risk of violation assumptions required for the use of correlation or regression analysis would be better observed.

IPRAd Swimming (IPRAn)

The methodology for calculating IPRAn used the same conceptual foundation as calculating global IPRA. Dave Scott presented the best index on the swim step, followed by Mark Allen and Andy Potts, as we can see in (Table 3).

IPRAd Cycling (IPRAcic)

The methodology for calculating IPRAcic used the same conceptual foundation as calculating global IPRA. Sebastian Kienle recorded the best index in cycling, followed by Jurgen Zack and Scott Tinley (Table 4).

IPRAd Running (IPRAcor)

The methodology for calculating IPRAcor used the same conceptual foundation as calculating global IPRA. Mark Allen showed the best performance, followed by Scott Tinley and Dave Scott (Table 5).

Multivariate analysis with relative performance indexes

IPRAg, IPRAn, IPRAcic, and IPRAcor can be analyzed together, seeking to infer the relationships between them. Based on the data available at (Tables 2, 3, 4 and 5) calculated the correlation the data, and applied to a regression to estimate the coefficients in an attempt to verify, the weight on of each test step in the overall result, based on the results of the proposed model. There is a negative correlation between swimming and cycling and between cycling and running. This correlation seems to corroborate the thesis that in triathlon events, being a good swimmer can be important, although the swimming stage distance is unrepresented in the overall race. The analysis of the correlations present in Table 6 brings some interesting points for reflection. Firstly, it appears the run is the stage that correlates most with the overall result, which may indicate that this is a decisive stage. Noteworthy is the correlation between the swimming and running stages, as it seems to indicate that good swimming can be important for good running. By analyzing the correlations between swimming and cycling and between cycling and running, an interesting analysis model could be elaborated, since it can be inferred. In general, that good swimming could lead to more conservative cycling (less intense), which on average could lead to a better run. This aspect is an interesting finding that can be further explored in other studies, as this fact may be vitally important for testing strategies. Overall, the importance of swimming was already raised in the works of Landers 2008 [18] and Peeling, Bishop & Landers 2005 [39]. The importance of run performance to the result of a triathlon event also has been supported by Frohlich 2008 [40]. The authors showed that running was the most important part of the triathlon test based on the correlation analysis between the three disciplines (swimming, cycling, and running). Undoubtedly the race is decisive, but such an analysis is complex, as the stages are not independent, as the effort undertaken in one stage tends to impact performance in the subsequent stage. Thus, correlation analysis has to be relativized, especially in studies that consider all athletes, all age groups, all genders, as this tends to increase data variability (and inflate correlations), as previously discussed. The present study showed that it is possible to use a relative performance measure to evaluate athletes. Throughout the work, it was demonstrated not only the possibility of creating a global index, [41-55] as well as the subdivision, in derived indexes, in the case of multisport activities. As the model works with the standardization of results, results could be compared over time. The main objective of the model was its use among contemporary athletes for its ranking, for the adoption of strategies or in optimizing performance.

Practical applications

The IPRAd allowed the comparison between the performance of athletes who competed in different seasons in different events because it did consider the times obtained in their analysis and the relative times (relating to the average time of the competitors). Therefore, it can be considered a more effective measure of performance analysis. At the limit, an athlete may win fewer races, but if he is more consistent in his results compared to the average of the competitors, he may have a good performance index. Likewise, an athlete who has won one or more events for a small difference but sees a fickle performance (greater variability of his times compared to the average) over time when compared to his competitors may have the lowest relative performance index. Thus, such a performance measure can represent a major change in the way athletes rank.

This aspect has important practical [56-65] applications from a training structuring standpoint. For a consistent athlete, this measure may imply a relative performance increase with positive effects in the pursuit of such benefits. Another point to considerer is that IPRAd can be calculated by modalities, not based on the overall result. Even transitions performance (time spent between modalities changes, such as swimming for cycling and cycling for running) can be considered, provided that such data are available for calculating the IPRAd of transitions. However, the main aspect of being considered in IPRAd is the possibility of making comparisons of athletes' performance in different events and different periods. This kind of analysis is not possible by simply comparing the times. Because of this, the IPRAd can be used, even as a selective instrument, to determine athletes who will represent a country, or a team, in a given competition. If the IPRAd is calculated in a fragmented manner, as in the case of triathlon, with specific indexes for the swimming, cycling and running stages, this information can be used for coaches and athletes to redirect the training strategy in order to improve relative performances in the required subjects.

Model Limitations

Like all models, some simplifications are made, and this entails some degree of weakness. One of the limitations of this model is the assumption that all athletes analyzed have and/or had access to the same technologies (equipment, training strategy, nutrition, among others). Another possible limitation concerns the fact that the model, especially in comparisons of athletes competing at different times, supposing that [66-78] they were all affected by 613 weather conditions in the same way. This result is an assumption that can be made. However, 614 it cannot be said that a higher current at sea, or a stronger wind on the day of the race, or even 615 a higher temperature and/or relative humidity would similarly affect the conditions of the competitors Hue, 2011 [39].

Conclusions

According to the establishment of the relative performance model for comparing the performance of three athletes, regardless of the time in which they competed, the main findings of this study were:

I. The possibility of constructing a model for assessing the relative performance in triathlon events by constructing a global model as well as specific models by modalities of each of the test components.

II. The suggestion that swimming can be a decisive step even in long-term triathlon races such as IRONMAN©.

III. The importance of the adjustment made by the standard deviation, so that the analysis can 627 be done to try to extract eventual changes in the conditions of the test (current, wind, 628 heat, humidity).

IV. The importance of calculating the performance index by sport so that it can be used as a 630 support for the coach. in the preparation of his athletes and the choice of events, considering the strengths and weaknesses of the athletes and the characteristics of the events.

V. The importance of the consistency of performance, overall, to obtain a good index.

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Conflicts of Interest

None.

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