



# Heart Rate Variability: Validity of Autonomic Balance Indicators in Ultra-Short Recordings

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**Abstract.** This work aims to find the minimum recording times of ultra-short heart rate variability (HRV) that enable the analysis of autonomic activity indexes. Samples covering 5 min are employed to extract SS and S/PS from the Poincaré diagram from a group of 23 subjects. The RR series, extracted from the electrocardiogram signal, were recorded for 300 s at rest – used as the gold standard – and at intervals of 60, 90, 120, 180 and 240 s to perform the concordance analysis with the gold standard derived indexes. We used four different techniques of concordance: Spearman, Bland, and Altman correlation, and Cliff’s Delta.

The SS times within records of 120 s were equivalent to those of short-term HRV and S/PS of 90 s. Also, ultra-short HRV indexes were similar to those obtained for the short-term HRV analysis. Such a reduction in measurement times will allow expanding the use of HRV to monitor the state of health and well-being and help physical trainers achieve better performance in the registration and processing of the information obtained.

The results motivate the conduct of new studies to analyze the behavior of these indicators in different populations, using different pre-processing methods than the RR series.

**Keywords:** HRV · ultra-short HRV · Poincaré · SS · S/SP

## 1 Introduction

Heart rate variability (HRV) is a physiological phenomenon, where the regulatory action of the autonomic nervous system (ANS) on the sinus node produces beat-to-beat changes. HRV is analyzed non-invasively by recording the electrocardiogram (ECG), in whose tracing R waves are identified. The time distance

between two consecutive R waves (cardiac period) is defined as the duration of the RR interval [1]. Another proposed method for HRV, is the measurement of the photoplethysmographic arterial pulse wave (PPG), in this non-invasive method, changes in blood volume in peripheral tissue, which are caused by heart rate, are recorded [2,3].

HRV is used as an indicator parameter of the level of cardiovascular health, since it is possible to study the changes in the sympathetic-vagal balance of the cardiac response, resulting in a very useful tool in the study and analysis of the evaluation of individuals who perform sports activities [4,5]. Depending on the duration of the records, HRV studies are classified into long-term studies (24-hour records) [6] and short-term studies (5 min records) [1,7,8].

Recently, short-term HRV analyzes for monitoring the health and well-being of people increased due to the use of portable devices (smart watches and bracelets) and applications for smartphones, a record of 5 min is very long in comparison with those required for measurements of blood glucose, blood pressure, body temperature, heart rate, oxygen saturation and body weight. Therefore, there is a trend towards the use of ultra-short-term records for HRV, with times less than 5 min. [9], This would allow, on the one hand, practically real-time monitoring and, on the other hand, increase the use of HRV in the daily clinic [10]. Although there are still no clear guidelines or a standard method to analyze ultra-short-term HRV, the methods currently used in short-term HRV are; time domain analysis using a statistical approach, frequency domain analysis, by power spectral estimation, geometric and nonlinear analysis [1].

Poincaré analysis is a geometric method that allows to analyze, visually or through calculations of the plot parameters, beat-by-beat information on the behavior of the heart and can be a better way to monitor dynamic change in function. autonomic [11], Fig. 1. Cross axis ( $SD1$ ) reflects short-term changes in RR and is directly related to parasympathetic activity. However, the longitudinal axis ( $SD2$ ) not as well defined, but appears to be inversely proportional to sympathetic activity [12]. The relationship  $SD2/SD1$ , is typically used to assess the interaction between sympathetic-parasympathetic activity ( $SD2/SD1$ ) [13]. However, its interpretation is still unclear, when both terms of the relationship increase or decrease simultaneously, so [12] proposed new indices of stress level (SS) (stress score) and the sympathetic-parasympathetic balance (S/PS) (sympathetic-parasympathetic ratio). The use of SS as a direct index for the evaluation of sympathetic activity and of S/PS (SPS) as an indicator of autonomous balance used in athletes, improve the physiological interpretation of HRV [12].

Ultra-short HRV is a new methodology for HRV analysis because of this, recent studies suggest minimum lengths of the RR series depending on the index to be calculated. [9], but we still have not found studies where SS and SPS are analyzed. Therefore, the objective of this work is to find the minimum recording times for ultra-short HRV, required for the SS and SPS indices to be equivalent to those obtained using HRV of 5 min.

The reduction of the recording times of the SS and SPS indicators, on the one hand, will increase their application in the evaluation of sports performance in athletes and, on the other, improves the knowledge of the physiological meaning of HRV.

## 2 Materials and Methods

### 2.1 Subjects

Twenty-three subjects, twelve women, between the ages of 21 and 25 voluntarily participated in the experiment. Subjects were healthy and medication free. Each subject provided their written consent before starting the experiment and all subjects were free to terminate the experiment at any time. This study was approved by the Ethics and Research Committee of the University of Quilmes, Buenos Aires, Argentina (04/07/2016/No.3).

### 2.2 HRV Analysis

The ECG signal of each subject was obtained in the supine resting position, for 5 min (300 s) and 2 min of stabilization time, with a Holter, by means of the DI lead, at a sampling frequency 225 Hz. ECG signal was processed, 50 Hz notch filter was applied to remove interferences from the electrical power supply network, the non-linear trend of the ECG was eliminated by means of its difference with a polynomial of order 6 previously adjusted to the signal and then oversampled at 1 KHz, to improve the determination of the maximum point of the R wave. The modified Pan-Tompkins algorithm was used [14] to detect R peaks, in the QRS complex of the ECG, followed by visual inspection, then the RR time interval series was calculated. In this series, the linear trend and the continuous component were eliminated, in addition to being able to detect atypical beats, an impulse rejection filter was used [15, 16]. Atypical beats were replaced by interpolation by another interval whose value was the average of the six RR intervals neighboring the one considered artifact. [17, 18]. Subsequently, for the analysis of ultra-short HRV, to each series of 300 s (the “Gold Standard” (GS) series) windows of different time lengths (60, 90, 120, 180 and 240 s) were extracted, starting from the beginning, considering the natural way of making the measurements.

### 2.3 Poincaré Geometric Domain

The Poincaré plot, Fig. 1, describes the nature of the fluctuations of the RR interval when plotting a certain interval  $RR_n$  versus the next  $RR_{n+1}$ . To extract HRV parameters, fit the graph to an ellipse where the width relative to the axis  $y = x$ ,  $SD1$  (Standard deviation short-term RR intervals) can be considered as an indicator of parasympathetic activity. The length of the ellipse on the axis is  $SD2$  (Standard Deviation RR intervals in the long term) is an inverse function of sympathetic activity, (1), (2):

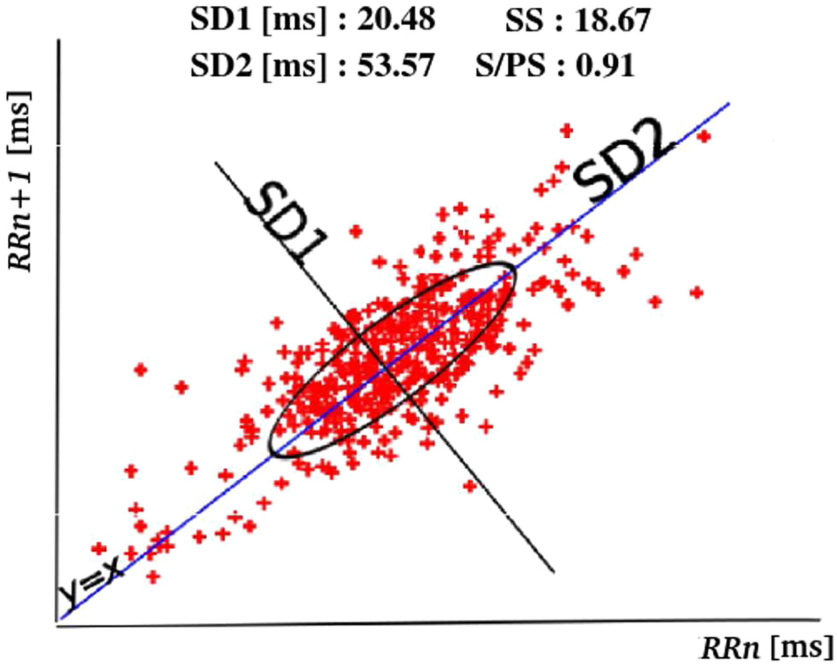
$$SD1 = \sqrt{\text{Var}\left(\frac{RR_n - RR_{n+1}}{\sqrt{2}}\right)} \quad (1)$$

$$SD2 = \sqrt{\text{Var}\left(\frac{RR_n + RR_{n+1}}{\sqrt{2}}\right)} \quad (2)$$

where  $RR_n$  is the  $n$ th interval,  $RR_{n+1}$  is the interval following the  $n$ th interval and  $Var$  represents the variance.

It was calculated from the indexes extracted from the Poincaré diagram [12];  $SS = 1000 * 1/SD2$  and  $SPS = SS/SD1$ . For the series of 300 s, GS, of short-term HRV and the ultra-short-term, of 60, 90, 120, 180 and 240 s.

All signal processing and HRV calculations were performed by the GNU/Linux environment, using algorithms developed in GNU Octave, version 4.2.2, Copyright (C) 2018, John W. Eaton and others.



**Fig. 1.** Poincaré graph, used to determine HRV parameters. The abscissa represents the time interval  $RR_n$ , the ordinate the next interval  $RR_{n+1}$ . The fit to an ellipse is represented, the identity line  $y = x$ ,  $SD1$  width of the ellipse (perpendicular dispersion of RR intervals),  $SD2$  length of the ellipse (longitudinal dispersion of RR intervals) with respect to the identity line  $y = x$ .

### 2.4 Statistical Analysis

To analyze the equivalence between the GS series and each of the ultra-short series, the algorithm proposed by [19] for the rest condition and also the concurrent validity criterion similar to that used in the work of [9], because it is an analysis between series of the same sample.

In addition, non-parametric statistics were applied, given the lack of normality in some series [19]. The Spearman correlation coefficients ( $\rho$ ) [20] of the

SS series of the GS and each of the SS indicators corresponding to the HRV-US series of 60, 90, 120, 180 were calculated and 240 s, in the same way we proceeded with the SPS indicator.

To establish the degree of agreement, the Bland-Altman (BA) [21] method was used between the GS series and each of the ultra-short series for each index. The bias was calculated for each index as the median of the difference between the HRV measurements of the GS and that of each ultra-short series. The test of Wilcoxon was used to analyze bias.

In addition, the Cliff Delta, ( $d$ ) [22], was calculated to quantify the effect size, a quantitative measure of the magnitude of a phenomenon, in this case, the bias of the parameter measurements of HRV of the different series time lengths and the GS. The value of  $d$  can be between 1 and  $-1$ , being the threshold proposed by CLiff for  $|d| < 0.15$  a “negligible” effect size,  $|d| < 0.33$  “small”,  $|d| < 0.47$  “medium” and “large”, for another situation.

In all the tests, values of  $p < 0.05$  were considered statistically significant.

The relative error percentage ( $e$ ) between the GS series and each of the ultra-short RR series was also calculated for each SS and SPS index, using (3) and (4) [23]:

$$e(\%) = \frac{\text{median}(GS_{SS}) - \text{median}(\text{serie}X_{SS})}{\text{median}(GS_{SS})} * 100 \quad (3)$$

$$e(\%) = \frac{\text{median}(GS_{SPS}) - \text{median}(\text{serie}X_{SPS})}{\text{median}(GS_{SPS})} * 100 \quad (4)$$

with  $X = 60, 90, 120, 180$  and  $240$ . All algorithms for statistical calculations were developed with free software R version 3.6.3, Copyright (C) 2020. The R Foundation for Statistical Computing. Platform: x86\_64-pc-linux-gnu (64-bit).

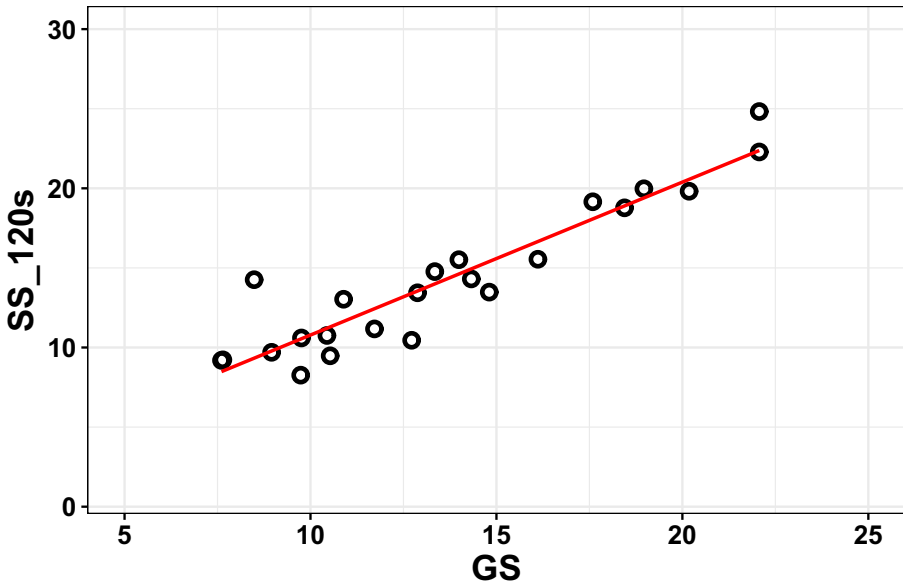
## 2.5 Results

The ECG signals of the 23 subjects in a resting situation were processed and as a result the series of RR time intervals were obtained, which prior to the HRV analysis using the Poincaré plot, editing and artifact correction methods were applied.

Table 1 shows the values of the medians and quartiles (1st; 3rd) of the SS and SPS indicators for the different lengths of the series of time intervals RR, 60, 90, 120, 180, 240 and 300 s for both indices the values are practically constant.

**Table 1.** HRV indexes calculated after pre-processing RR series. Values for each index expressed in median and [1st; 3rd] quartile.

RR series	SS	SPS
60	13.61 (10.63 21.12)	0.39 (0.21 1.26)
90	14.10 (11.48 17.36)	0.48 (0.23 1.07)
120	13.48 (10.53 17.16)	0.47 (0.24 1.05)
180	13.18 (9.92 17.62)	0.47 (0.23 1.09)
240	13.47 (10.07 17.88)	0.45 (0.24 1.01)
300	12.87 (10.10 16.85)	0.43 (0.25 0.96)



**Fig. 2.** Spearman correlation GS vs SS 120 s of the SS index,  $\rho = 0.90$ ,  $p = 3.28e-06$ .

Figure 2 is the plot corresponding to the analysis of the Spearman correlation of the SS index, between the GS series and the 120 s series.

Figure 3 shows the Bland-Altman plot corresponding to the concordance analysis between the 120 s series and the GS of the SPS index, showing the lines corresponding to the Bias, the median of the difference between the series, and the LoA 95%, estimated using the 2.5 and 97.5 percentiles. Note that GS is represented on the abscissa axis instead of the average of the measurements [24].

In Table 2, the results of the different methods used in the comparison between the GS series and each of the RR series for the SS indicator are presented.

In this table, a positive relationship is observed between the variables that as the length of the series increases, the values of ( $\rho$ ) the correlation coefficient of Spearman increase with a  $\rho = 0.90$ ,  $p = 3.28e-06$ , from the series of 120 s and the values corresponding to  $d$  the Delta of Cliff decrease, being negligible for the 60 s series and small for the 90 s series and negligible for the 120, 180 and 240 s series, while the % error ( $e$ ) is less than 10 % in each series.

The results of the Wilcoxon test, and the Bias values show that it is equal to 0, only, for the series of 120 s. The negative values obtained from the Bias show an overestimation of the GS series. The LoA of 95 % decreased with the temporary increase in the series, evidencing the decrease in LoA.

Figure 4 shows the graph of the Spearman correlation between GS and the series of 90 s corresponding to the SPS index. An accumulation of values below 0.5 can be seen in the graph.

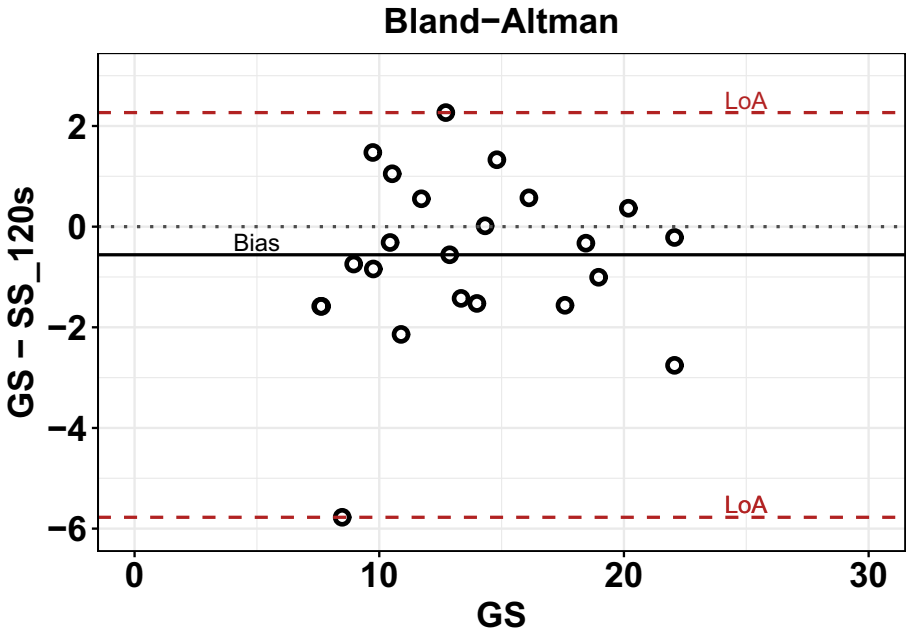


Fig. 3. Bland-Altman concordance analysis of GS vs SS 120 s series, of the SS index.

Table 2. Table SS.

SS RR series (s)	Correlation( $\rho$ ) (p)	Cliff ( $d$ ) (c.i. 95%)	% error ( $e$ )	Wilcoxon (p)	Bias (1st; 3rd)	LoA 95%
300 vs 60	0.71 (1.98e-04)	0.14 (-0.20 0.45)	5.74	0.04	-1.51 (-3.90 0.57)	-14.65 5.10
300 vs 90	0.84 (1.71e-06)	0.16 (-0.18 0.48)	9.48	0.02	-1.04 (-2.56 0.35)	-6.67 1.89
300 vs 120	0.90 (3.28e-06)	0.09 (-0.25 0.41)	4.66	0.09	-0.56 (-1.54 0.46)	-5.78 2.27
300 vs 180	0.96 (2.45e-06)	0.06 (-0.28 0.38)	2.37	0.03	-0.58 (-1.36 0.35)	-3.90 1.61
300 vs 240	0.98 (1.99e-06)	0.06 (-0.28 0.38)	4.61	0.01	-0.48 (-0.95 -0.07)	-3.23 1.40

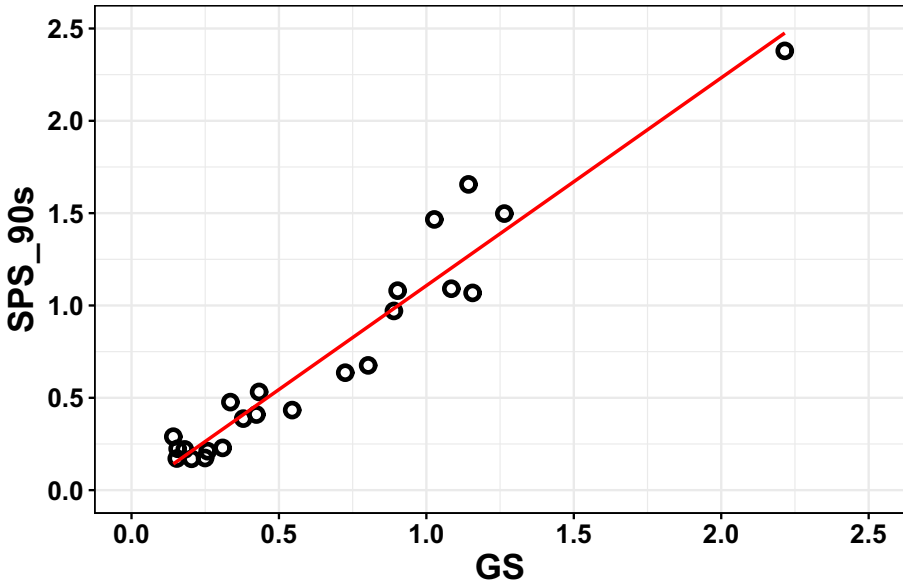


Fig. 4. Spearman correlation GS vs SPS 90s of the SPS index,  $\rho = 0.93$ ,  $p = 3.15 \times 10^{-6}$ .

In Fig. 5 the Bland-Altman graph is presented, for the concordance analysis between the GS series and the SPS 90s of the SPS index, an overestimation of the GS is observed, given by the negative value in the Bias and an accumulation of values between 0 and 0.5, in addition to a marked asymmetry between the LoA.

In Table 3, the results of the methods used for the concordance analysis between the GS series and each of the series of different time lengths of the SPS indicator are presented.

A positive relationship between the variables is observed, the values of the correlation coefficients ( $\rho$ ) increase with the temporal increase of the series with a value of  $\rho = 0.90$  from the series of 120 s. The values corresponding to  $d$  Delta of Cliff are negligible for all series, while the % error ( $e$ ) does not exceed 10% in all series.

The results of the test of Wilcoxon and those of the Bias show for this indicator that it is possible that the Bias is 0 for the different series and the negative values show an overestimation of the GS series. The values corresponding to LoA 95 % decrease with the temporal increase of the series and improve symmetry from the 90 s series.

Table 3 shows the results of the comparison between the series corresponding to the SSP indicator, a high correlation value is observed between the GS series and the 60 s series with a value of  $\rho = 0.95$ ,  $p = 2.79 \times 10^{-6}$ , in coefficient of then correlation of Spearman ( $\rho$ ) that is incremented until arriving at  $\rho = 0.99$ ,  $p = 1.71 \times 10^{-6}$ , for the series of 240 s. The values corresponding to the Cliff Delta



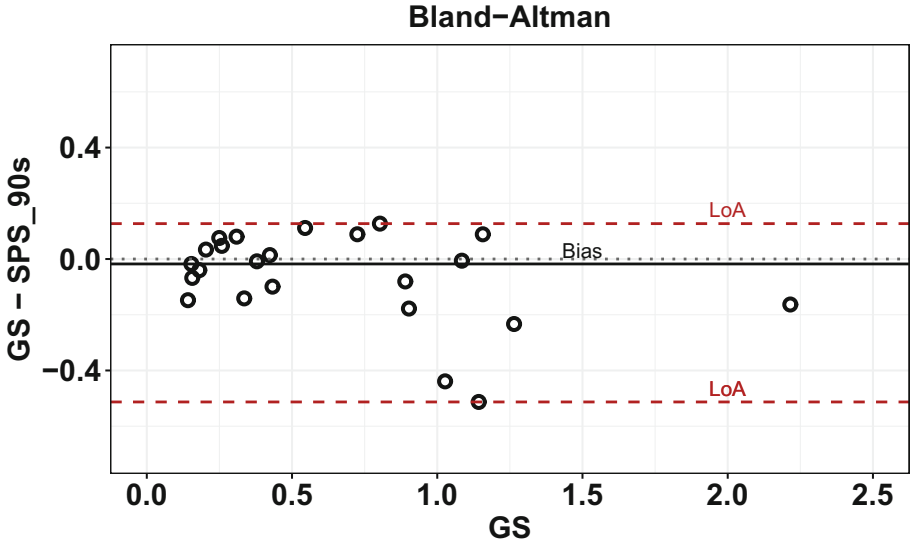


Fig. 5. Bland-Altman concordance analysis of GS vs SPS 90 s series, of the SPS index.

(*d*) denote negligible differences between the GS series and each of the 90, 120, 180 and 240 s series. The % error (*e*) is less than 10% in all comparison cases, and their absolute values are similar for all comparisons between series. The values corresponding to bias are also negative, showing an overestimation of the GS series in each comparison, although the Bias values are lower than in the case of SS and in the Student test it is observed that the bias could take the value null in any of the comparisons, the values extracted from the Bland-Altman LoA 95% graphs show a decrease with the temporal increase of the series, evidencing a better level of agreement between each time series and the GS.

## 2.6 Discussion

The signal from the ECG was used to perform the HRV analysis, this is because although both signals, ECG and PPG, have been used, in different methods, to evaluate autonomic activity and their results are considered equivalent in subjects healthy [25]. But, on the one hand, differences in their results have been observed under various physiological conditions and the reasons for their

Table 3. Table SPS.

SPS RR series (s)	Correlation( <i>rho</i> ) ( <i>p</i> )	Cliff ( <i>d</i> ) (c.i. 95%)	% error ( <i>e</i> )	Wilcoxon ( <i>p</i> )	Bias (1st; 3rd)	LoA 95%
300 vs 60	0.80 (7.02e-06)	0.01 (-0.33 0.34)	9.63	0.52	-0.02 (-0.15 0.08)	-1.04 0.74
300 vs 90	0.93 (3.15e-06)	0.05 (-0.28 0.38)	10.15	0.15	-0.02 (-0.14 0.06)	-0.51 0.13
300 vs 120	0.95 (2.79e-06)	0.03 (-0.30 0.35)	9.48	0.71	0.00 (-0.09 0.06)	-0.22 0.18
300 vs 180	0.98 (2.05e-06)	0.05 (-0.29 0.372)	8.85	0.29	-0.02 (-0.08 0.03)	-0.32 0.22
300 vs 240	0.99 (1.71e-06)	0.06 (-0.28 0.38)	4.91	0.20	-0.03 (-0.06 0.01)	-0.26 0.23

disparities in the evaluation of autonomous activity are unknown [26]. And on the other hand, the SS and SPS indicators found by [12] are the result of a short-term HRV analysis from the ECG signals.

This indicators propose a clearer interpretation for understanding the physiological meaning of the autonomic equilibrium resulting from the analysis of the Poincaré diagram, and also provide reference values for the short-term HRV analysis in elite soccer players.

Currently, short-term HRV analyzes have increased in sport, but physical trainers require HRV registration processes of shorter duration and with results of simple interpretation, for which there is great interest in ultra-short HRV. Although there are still no clear guidelines for carrying out these studies or for the times required to measure the different indices (Forner-Llácer FJ. Heart Rate Variability as an Indicator of Fatigue in Professional Soccer. Doctoral Thesis. Univ Catholic of Valencia, 2021). On the other hand, we have not found ultra-short record analysis studies for SS and SPS.

In this work, a rigorous method was used to reliably evaluate that the characteristics of the ultra-short-term HRV, of the SS and SPS indicators, could be a substitute for the short-term HRV. Therefore, a value of  $\rho = 0.90$ , as a minimum, was adopted as the cutoff criterion. As stated by [9], this threshold ensures that an acceptable measurement of HRV-US represents at least 81 % of the variability ( $\rho^2 = 0.81$ ) in the value corresponding to 5 min and a extremely low risk of making a Type 1 error.

The analysis of the results shows a similarity in the values of the medians in most of the series of each index with differences in the series of 60s, this is probably due to the fact that a time window of 60s is small for the measurement of these indices [27], in addition an increase in general is observed in all the indicators of the levels of agreement calculated as the length of the series increases, both for SS and SPS.

The ultra-short series of the SS indicator, whose correlation value meets the cut-off criterion is given from the 120s series, in addition a negligible difference value is observed for the Delta of Cliff, very low values of the error ( $e$ ) and this behavior is similar in the series of 180 and 240s. The values extracted from the Bland-Altman graphs reflect a high level of agreement between the GS series and the 120s series, similar to GS with 180s and GS with the 240s time length, showing the similarity between the series. This allows the exchange of one series for another, that is, the 120s series of the SS indicator is equivalent to the GS series, of 5 min, of the same indicator.

A similar analysis for the SPS indicator allows us to establish that the 90s series meets the established cut-off condition given that  $\rho = 0.93$ ,  $p = 3.15\text{e-}06$ , the values of the Delta of Cliff show negligible differences with the GS, so it is concluded that the series are similar to the GS from the time-length series of 90s, that is, the series of 90s is equivalent to the GS series of the SPS indicator.

This study is preliminary and has limitations, on the one hand, the sample size of 23 subjects, which should be larger to investigate the effect of the variables associated with HRV, such as age, sex, physical activity, etc. On the other

hand, different stabilization times prior to the records were not analyzed. In addition, for this analysis, no other position than the supine was used, nor was another segment of the signal different at the beginning, although we consider it possible to keep the ECG signal stable, avoiding artifacts and using robust methods for pre-processing and edition of the series RR, GS, the results of the comparison between the series present similar levels of agreement. However, all these limitations require further studies.

## 2.7 Conclusions

Ultra-short recordings of 120 s were obtained for SS, an index for the evaluation of sympathetic activity and 90 s for SPS, an indicator of autonomic balance, equivalent to those obtained for short-term HRV analysis (5 min). This reduction in measurement times will allow an increase in the use of HRV to monitor people's health and well-being. Enabling physical trainers to obtain better performance in the registration and processing of the information obtained.

The results found motivate the carrying out of new studies to analyze the behavior of these indicators in different populations and with the use of different methods of pre-processing and editing of the RR series.

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