

Smartwatches as tools for measuring biomechanical parameters in swimmers of different expertise levels

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Abstract:

Smartwatches offer promising potential for swimming biomechanics research due to their ease of use and ability to collect data in real time. However, data accuracy may depend on the swimmer's expertise levels, highlighting the need for comparative studies. Thus, this study compares biomechanical parameters measured at different swimming speeds and distances, using two smartwatches and video analysis in both experienced and novice swimmers. Garmin Fenix 6 Pro and Polar Advantage M2 smartwatches were used to monitor inexperienced and experienced swimmers during 50 m and 200 m freestyle at low and maximal effort, and were compared with a gold standard measure (video analysis). The analyzed variables were total distance, average time, average pace, total strokes, and average strokes per 25 m at low and maximal efforts. Data were compared among smartwatches and video analysis using repeated measures ANOVA, and the partial eta squared was used to quantify the effect size. Our results demonstrated considerable variations among smartwatches and video analysis in both groups. Interestingly, the inexperienced swimmers' measurements demonstrated inconsistencies in most variables assessed, regardless of the smartwatch used. Conversely, less variations were found in experienced swimmers, especially when parameters such as stroke rate and total distance were evaluated. In conclusion, the smartwatches Polar Advantage M2 and Garmin Fenix 6 Pro can be useful tools, especially for experienced swimmers. However, due to the potential variability in technical patterns among swimmers with different levels of expertise, the use of smartwatches should be approached with caution, as highly experienced swimmers require accurate and reliable data to optimize their performance.

Key Words: Wearable devices; Technology; Swim expertise.

Introduction

In the last decades, the rise of sports coupled with technology has made it possible to identify a variety of biomechanical parameters, especially in swimming (e.g stroke length, stroke rate and average swimming speed) (Engel et al., 2021). The access to these data allow coaches to prescribe refined training cycles, evaluate athletes at real time, thus optimizing training program and athletes performance throughout the competitive calendar (Barbosa et al., n.d.). Unfortunately, most of the technological devices are expensive, require expertise for application and data interpretation, and do not provide the data in real time. Another barrier is the challenge of accessing necessary monitoring technologies adaptable to aquatic environments (Zacca et al., 2020), and the particularities related to water, such as distortions. In swimming, it becomes even more critical, considering the need for technologies that are adaptable to aquatic environments, accessible, cost-effective and suitable for different levels of swimming expertise (Brunner et al., 2019).

The usage of wearable devices has increased in the last decades, wherein several application forms have been described, especially in the health field (Shell et al., 2021). Among the devices, those characterized as wearable can provide easier and faster data access, lower cost, and simpler interface, popularizing their usage. In this context, the smartwatch emerges as a useful tool capable of meeting all of these previous requirements. The most commercially available equipment provides kinematic information such as distance swum and number of strokes per distance. It can also identify which swim stroke was performed and an efficiency metric called "SWOLF", which represents the sum of the time and the number of strokes needed to complete the pool length. The lower the value, the more efficient the swim. Therefore, questions about accuracy and precision may arise regarding the use of smartwatches for swim monitoring. One important point to highlight is that, for many brands, the way the variables are calculated or measured is not disclosed in the user manual.

Morais et al. (2022) conducted a systematic review examining the accuracy of wearable devices that provide real-time data. The review included 18 studies, all of which used wearable devices specifically

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developed by the authors and positioned either on the lower back or on the head of the swimmers. Among the selected studies, eight focused exclusively on front crawl, six analyzed all four competitive strokes, two investigated front crawl turns, one evaluated breaststroke, and one assessed butterfly. Across the results, device accuracy, measurement error, and/or consistency into different strokes, the authors indicated that most studies reported satisfactory accuracy and reliability among the wearable devices.

Thus, smartwatch emerges as a tool capable of meeting the aforementioned characteristics while also being intuitive, widely accessible, and relatively low-cost compared to traditional assessment instruments. Using a smartwatch, you can obtain general biomechanical parameters such as average swimming speed, total distance covered, average pace, and total training session time (Brunner et al., 2019; Mooney et al., 2017). Also, sport-specific metrics can be extracted. In swimming, for instance, smartwatches can provide stroke count, pool length detection, and even identification of stroke variations across the four competitive styles (freestyle, backstroke, breaststroke, and butterfly). Ultimately, smartwatches enable real-time feedback during training sessions or competitions, overcoming the delays and lack of practicality associated with traditional assessment methods (Hagem et al., 2013; Morais et al., 2022).

Cosoli et al. (2022) compared the accuracy and precision of heart rate measurements obtained from two smartwatches (Garmin Venus Sq and Polar Vantage V2) in both dry-land and aquatic environments, using the Polar H10 chest strap as gold standard. The tests protocol included treadmill running and swimming at different intensities. The results showed that water and arm movements worsen signal quality, but both devices still demonstrated acceptable precision. Variability was lower on dry-land (Garmin: 95% CI 14-12 bpm; Polar: 27-18 bpm) compared to water (Garmin: 95% CI 117-30 bpm; Polar: 74-46 bpm). Accuracy also declined in water (Garmin: SD = -44 bpm; Polar: -14 bpm) compared to land (Garmin: SD = -1 bpm; Polar: -5 bpm). Mooney et al. (2017) tested the accuracy in parameters of swimming performance using the Garmin Swim and Finis Swimsense smartwatches along with video analysis. They found high accuracy in sensitivity in detecting changes in formal strokes and distance swim.

Noteworthy, swimmers of different skill levels may exhibit distinct technical patterns (Ruiz-Navarro et al., 2023). Experienced swimmers tend to maintain more consistent technique even under fatigue, while less experienced swimmers show greater variability in their technique and are more susceptible to the effects of fatigue (Mooney et al., 2017). This can affect the precision and quality of the measurements. Therefore, this study goal was to compare biomechanical parameters of experienced and novice swimmers at different speeds and distances on two smartwatches and a video analysis.

Material & methods

Participants

The test population of this study consisted of 40 swimmers (23 men and 17 women) with an average $\pm$ standard deviation age of 30.85 ± 8.71 years and 12.70 ± 11.08 years of swimming practice, divided into experienced and non-experienced swimmers. To classify swimmers as experienced or inexperienced, a 50-meter freestyle test was conducted, with the participants prohibited from performing a flip turn. The median time of all participants was calculated. Individuals who completed the test in less than 39.1 seconds were classified as experienced swimmers, while those with times exceeding this threshold were categorized as non-experience swimmers (Bachlin; Troster, 2012). The following inclusion criteria were adopted: (1) being over 18 years of age; (2) have been swimming for at least six months; (3) not have any musculoskeletal and/or intellectual diseases or any illnesses that make it impossible to perform the tests. The established exclusion criteria were: (1) the individual was unable to perform a 50 m crawl; (2) acquiring an illness that would make it impossible to perform the tests; (3) giving up at the time of testing. This study was accepted by the local ethical committee under the number CAAE: 63038022.3.0000.8267.

Procedure

For the tests, the individuals performed four experimental conditions:

- 50m at low intensity
- 50m at maximum intensity
- 200m at low intensity
- 200m at maximum intensity

The low intensity (“warm-up”) was defined as the speed at which the participant was able to move through the water in the prone position with minimal effort. Maximum intensity was defined as the highest physical effort that the participant could perform throughout the tests. The intensities of the experimental condition were self-selected by the swimmers. For low intensity, participants were instructed to swim at a warm-up pace, while for maximum intensity, they were instructed to swim at their maximum speed and exertion. Among each experimental condition, a five-minute passive recovery interval was adopted (Pratama & Yimlamai, 2020) to minimize the effects of fatigue.

The experimental conditions were individually randomized. To do this, papers corresponding to all possible experimental conditions were added to an urn, then the individual removed one paper at a time to define the order in which he/she would carry out the experimental conditions. Before entering the water, the researchers

positioned the two smartwatches (Polar Advantage M2 and Garmim Fenix 6 Pro), one on each wrist, one centimeter from the styloid process of the Ulna. For all participants, the smartwatches were positioned at the same upper limb (right or left). Once the equipment was positioned, the individuals were instructed to enter the pool and carry out a preestablished preparatory activity and, at the end, the tests began. All experimental conditions of the individuals were recorded, in the sagittal plane, wherein the camera was positioned in the middle of the pool (12.5 m from both edges) on a fixed tripod with a 360° rotation axis. As the swimmer swam, the author rotated the tripod.

Instruments and Variables

For the present study, two models of Smartwatches were used, Polar Advantage M2 (Polar®, UK) and Garmim Fenix 6 Pro (Garmin®, USA), in addition to a GoPro Hero 10 Black action camera (GoPro®, USA).

- Polar Advantage M2: is a device that features pairing via Bluetooth®, Global Positioning System (GPS), water resistance of 30 meters, in addition to being able to obtain metrics from different sports. In the case of swimming in a pool, it is possible to configure the distance from the pool where the training session will take place. In the present study, the smartwatch was configured for 25 m.
- Garmim Fenix 6 Pro: provides the swimmer with Bluetooth® pairing, GPS, and 5 ATM water resistance. It is possible to use the smartwatch for various sports, such as swimming in the pool and in open water. In the case of swimming in a pool, it is possible to configure the distance from the pool where the training session will take place. In the present study, the smartwatch was configured for 25 m.
- GoPro Hero 10 Black: action camera that has video resolution of up to 5.3 K and 60 frames per second. The camera has a 23.6-megapixel sensor, its own video stabilization technology (HyperSmooth 4.0) and night shooting mode.

The authors accessed the smartwatches data through links generated by the devices themselves. The Tracker 6.1.1 program was used for video analyses. Only one evaluator analyzed all the videos.

The variables analyzed were total distance, average time, average pace every 100 meters, total strokes, and average strokes in 25 meters in conditions maximum intensity (considered as the fastest speed) (TDF, ATF, APF, TSF and ASF, respectively) and low intensity (considered the slowest speed) (TDS, ATS, APS, TSS AND ASS, respectively).

In the video analysis (Table 1), TDF and TDS were considered constant variables, as the test distances were always 50m or 200m. For the ATF and ATS, the exact frames/video time in which the participant completely immersed their head in the water until their hand touched the wall were marked. APF and APS were characterized as average pace swum in seconds per 100m. For this, a simple rule of three was made with the average time obtained previously, the distance of the test performed and the distance of 100m. TSF and TSS were counted by the study authors. ATSF and ATSS were the quotient between Total Strokes and 25m. The smartwatches' variables were obtained directly from their analysis software, without the need to perform any additional calculations.

Statistical analysis

A descriptive analysis was carried out with the mean, standard deviation and 95% confidence interval for the study's dependent variables. The Shapiro-Wilk test identified normality data. For statistical analysis comparing the variables collected between the two smartwatches and the video analysis, the analysis of variance (ANOVA) test with repeated measures and Bonferroni Post-Hoc were used separately for each group. The partial eta squared effect size (η^2_{partial}) was used to compare the results between the two groups. Consider $\eta^2_{\text{partial}} < 0.01$ as small effects; η^2_{partial} between 0.02 and 0.06 as medium effects and $\eta^2_{\text{partial}} > 0.14$ as large effects. To compare means between equipment, Cohen's d effect size was used, with Cohen's d being considered between 0.2 and 0.5 as small effects; Cohen's d between 0.5 and 0.8 as medium effects and Cohen's d > 0.8 as large effects (Cohen, 1988).

Results

Distance of 50 Meters

For the 50 m distance of non-experienced swimmers, there were significant differences between the equipment in the variables ATF ($F(2, 64) = 18.41, p < 0.05; \eta^2_{\text{partial}} = 0.36$), ATS ($F(2, 64) = 6.08, p < 0.05; \eta^2_{\text{partial}} = 0.36$), APS ($F(2, 64) = 8.13, p < 0.05; \eta^2_{\text{partial}} = 0.20$), APF ($F(2, 64) = 5.68, p < 0.05; \eta^2_{\text{partial}} = 0.15$), TSF ($F(2, 64) = 53.12, p < 0.05; \eta^2_{\text{partial}} = 0.62$) and ASF ($F(2, 64) = 24.56, p < 0.05; \eta^2_{\text{partial}} = 0.43$), with a large effect size for all differences (Table 1). In the pairwise comparison, there were differences between Polar and Garmim for ATF (Cohen's d = -0.68), ATS (Cohen's d = -0.61), APF (Cohen's d = -0.72), TSF (Cohen's d = -1.10) and ATSF (Cohen's d = -1.32), with medium to large effect sizes. Between the Polar and Video, the differences were in TSF (Cohen's d = -1.55) and ASF (Cohen's d = -1.40), with large effect size. Finally, between the Garmim and Video the differences were ATS (Cohen's d = 0.55), APF (Cohen's d = 0.70), APS (Cohen's d = 0.48), with small to medium effect size (Table 1).

Table 1. – Mean ($\pm$ standard deviation) and 95% confidence interval of the biomechanical variables of the non-experienced swimmers at 50 m

Variable	Polar		Garmim		Video	
	Mean ($\pm$ SD)	CI (95%)	Mean ($\pm$ SD)	CI (95%)	Mean ($\pm$ SD)	CI (95%)
TDF (m)	43.75 (11.10)	38.55 - 48.94	48.75 (5.59)	46.13 - 51.36	50.00	-
TDS (m)	51.25 (5.59)	48.63 - 53.86	50.00 (0.00)	50.00	50.00	-
ATF (s)	40.36 (9.87)	35.74 - 44.98	46.81 (8.91)*	42.63 - 50.98	43.14 (6.90)	40.08 - 46.26
ATS (s)	59.00 (7.66)	55.41 - 62.58	64.22 (9.22)*	59.90 - 68.53	59.41 (8.21)#	55.76 - 63.05
APF (s/100m)	87.25 (13.58)	80.89 - 93.60	100.45 (21.82)*	90.23 - 110.66	87.92 (12.75)#	82.27 - 93.58
APS (s/100m)	116.45 (14.50)	109.66 - 123.23	127.15 (20.36)	117.62 - 136.67	117.46 (19.80)#	108.68 - 126.24
TSF	32.35 (17.62)	24.10 - 40.59	48.50 (10.71)*	43.48 - 53.51	54.86 (10.43)*	50.23 - 59.49
TSS	47.20 (8.16)	43.37 - 51.02	48.4 (10.65)	43.41 - 53.38	48.22 (7.38)	36.62 - 44.37
ASF	16.77 (8.10)	12.98 - 20.56	25.40 (4.40)*	23.33 - 27.46	28.86 (9.04)*	24.85 - 32.87
ASS	24.75 (9.07)	20.50 - 28.99	26.20 (4.29)	24.18 - 28.21	24.02 (3.84)	22.31 - 25.72

TDF = Average distance of fast condition in meters; TDS = Average distance of slow condition in meters; ATF = Average time of fast condition in seconds; ATS = Average slow condition time in seconds; APF = Average pace of fast condition (s/100m); APS = Average pace of slow condition (s/100m); TSF = Total strokes in fast condition; TSS= Total strokes in slow condition; ASF = Average strokes in 25 meters in fast condition; ASS= Average strokes in 25 meters the slow condition; CI = Confidence interval; * = When compared with Polar $p < 0.05$; # = When compared with Garmim $p < 0.05$.

For the experienced swimmers, there was also a significant difference between the equipment for the variables TDF ($F(2, 64) = 15.73$, $p < 0.05$; $\eta^2_{\text{partial}} = 0.33$), ATF ($F(2, 64) = 18.41$, $p < 0.05$; $\eta^2_{\text{partial}} = 0.37$), APS ($F(2, 64) = 8.13$, $p < 0.05$; $\eta^2_{\text{partial}} = 0.20$) TSF ($F(2, 64) = 53.12$, $p < 0.05$; $\eta^2_{\text{partial}} = 0.62$) and ASF ($F(2, 64) = 24.56$, $p < 0.05$; $\eta^2_{\text{partial}} = 0.43$) (Table 2), with a large effect size for all differences. Between the two smartwatches, in the pairwise comparison, there were significant difference in TDF (Cohen's $d = -0.56$), ATF (Cohen's $d = 0.68$), APS (Cohen's $d = -1.16$), TSF (Cohen's $d = -1.55$) and ASF (Cohen's $d = -1.09$) with medium effect size for TDF and ATF and large effect size for APS, TSF and ATF. In the pairwise comparison between Polar and Video significant differences were found in TDF (Cohen's $d = -1.57$), TSF (Cohen's $d = -2.45$) and ASF (Cohen's $d = -1.59$), with large effect size. And between Garmim and Video there was only one significant difference: ATF (Cohen's $d = 0.73$) (table 2), with medium effect size.

Table 2 – Mean ($\pm$ standard deviation) and 95% confidence interval of the biomechanical variables of the experienced swimmers at 50 m

Variable	Polar		Garmim		Video	
	Mean ($\pm$ SD)	CI (95%)	Mean ($\pm$ SD)	CI (95%)	Mean ($\pm$ SD)	CI (95%)
TDF (m)	35.71 (12.83)	28.30-43.12	48.21 (15.39)*	39.32-57.10	50.00*	-
TDS (m)	53.78(13.32)	46.09-61.47	51.38(9.67)	48.45-54.31	50.00	-
ATF (s)	30.35(9.67)	24.77-35.94	43.20 (8.36)*	38.37-48.02	37.59 (6.90)#	34.86-40.32
ATS (s)	53.00(4.93)	50.15-55.84	56.39(9.58)	50.86-61.93	53.43(5.34)	50.78-56.09
APF (s/100m)	89.21(19.72)	90.23-100.66	97.92(36.20)	77.02-118.83	78.96 (16.94)	70.53-87.39
APS (s/100m)	102.57 (13.16)	94.96-110.17	117.14 (11.79)*	110.33-123.95	109.47 (11.81)	103.59-115.34
TSF	20.78 (13.68)	12.88-28.68	43.42 (15.34)*	34.57-52.28	48.22(7.94)*	44.27-52.17
TSS	42.85(7.55)	38.49-47.21	44.00(9.11)	38.73-49.26	40.50(7.79)	36.62- 44.37
ASF	14.21(6.90)	10.22-18.20	21.28(5.96)*	17.84-24.73	25.50(7.28)*	27.87-29.12
ASS	20.71(4.85)	17.90-23.51	23.92(5.74)	20.61-27.24	20.30(3.98)	18.32-22.28

TDF = Average distance of fast condition in meters; TDS = Average distance of slow condition in meters; ATF = Average time of fast condition in seconds; ATS = Average slow condition time in seconds; APF = Average pace of fast condition (s/100m); APS = Average pace of slow condition (s/100m); TSF = Total strokes in fast condition; TSS= Total strokes in slow condition; ASF = Average strokes in 25 meters in the fast condition; ASS= Average strokes in 25 meters in the slow condition; CI = Confidence interval; * = When compared with Polar $p < 0.05$; # = When compared with Garmim $p < 0.05$.

Distances of 200 Meters

At a distance of 200 m for non-experienced swimmers, there was a significant difference between the equipment for the variables ATF (F (2, 64) = 4.42, $p < 0.05$; $\eta^2_{\text{partial}} = 0.12$), ATS (F (2, 64) = 8.83, $p < 0.05$; $\eta^2_{\text{partial}} = 0.22$), TSF (F (2, 64) = 7.75, $p < 0.05$; $\eta^2_{\text{partial}} = 0.19$), and ASF (F (2, 64) = 5.15, $p < 0.05$; $\eta^2_{\text{partial}} = 0.14$), with medium to large effect size (**Table 3**). In the pairwise comparison, the differences between Polar and Garmim were: ATF (Cohen's $d = 0.23$); ATS (Cohen's $d = -0.54$) and TSF (Cohen's $d = 0.63$), with small effect sizes for ATF and medium effect sizes for ATS and TSF. In the pairwise comparison between Garmim and Video they were at ATF (Cohen's $d = 0.23$); TSF (Cohen's $d = 0.63$) and ASF (Cohen's $d = 0.43$), with ATF and ASF having small effect sizes and TSF having a medium effect size. However, there were no significant differences between the Polar and the video analyses, indicating possible accuracy for this distance in non-experienced swimmers and at different swimming intensities.

Table 3 - Mean ($\pm$ standard deviation) and 95% confidence interval of the biomechanical variables measured of the non-experienced swimmers at 200 m

Variable	Polar		Garmim		Video	
	Mean ($\pm$ SD)	CI (95%)	Mean ($\pm$ SD)	CI (95%)	Mean ($\pm$ SD)	CI (95%)
TDF (m)	189.47 (28.03)	165.56 - 204.43	201.31 (10.11)	196.43 - 206.19	- 200.00	-
TDS (m)	182.89 (38.23)	169.19 - 254.13	201.31 (5.73)	198.55 - 204.08	- 200.00	-
ATF (s)	215.10 (38.38)	173.79 - 229.40	226.88 (35.35)*	209.84 - 243.93	- 218.29 (36.46) [#]	202.89 - 233.69
ATS (s)	235.94 (55.17)	197.69 - 251.95	261.02 (34.28)*	244.50 - 277.54	- 253.46 (39.90)	236.62 - 270.31
APF (s/100m)	115.44 (26.69)	96.64 - 116.82	111.74 (18.04)	103.04 - 120.43	- 112.93 (23.07)	103.19 - 122.68
APS (s/100m)	125.21 (22.01)	98.73 - 125.75	129.47 (17.06)	121.24 - 137.69	- 131.04 (24.84)	120.55 - 141.53
TSF	207.84 (48.46)	160.01 - 215.45	235.15 (44.67)*	213.62 - 256.69	- 208.62 (38.93) [#]	192.18 - 225.06
TSS	190.00 (85.73)	157.32 - 210.06	205.57 (54.97)	179.08 - 232.07	- 186.08 (43.28)	167.80 - 204.36
ASF	27.20 (4.78)	22.24 - 27.08	27.89 (5.09)	25.43 - 30.15	25.82 (4.49) [#]	23.92 - 27.72
ASS	25.31 (5.53)	19.53 - 29.93	26.31 (5.58)	23.62 - 29.00	24.47 (4.09)	22.74 - 26.20

TDF = Average distance of fast condition in meters; TDS = Average distance of slow condition in meters; ATF = Average time of fast condition in seconds; ATS = Average slow condition time in seconds; APF = Average pace of fast condition (s/100m); APS = Average pace of slow condition (s/100m); TSF = Total strokes in fast condition; TSS= Total strokes in slow condition; ASF = Average strokes in 25 meters in fast condition; ASS= Average strokes in 25 meters in slow condition; CI = Confidence interval; * = When compared with Polar $p < 0.05$; # = When compared with Garmim $p < 0.05$.

For the experienced 200 m distance (**Table 4**), there were only significant differences in the TSS variable (F (2, 64) = 6.38, $p < 0.05$; $\eta^2_{\text{partial}} = 0.17$), with large effect size. These differences were verified between Polar and Garmim (Cohen's $d = -0.83$) and from Garmim to Video (Cohen's $d = 0.77$), both with large effect sizes.

Table 4 - Mean ($\pm$ standard deviation) and 95% confidence interval of the biomechanical variables of the experienced swimmers at 200 meters.

Variables	200 m Polar		Garmim		Video	
	Mean ($\pm$ SD)	CI (95%)	Mean ($\pm$ SD)	CI (95%)	Mean ($\pm$ SD)	CI (95%)
TDF (m)	185.00 (35.10)	165.56 - 204.43	201.66 (6.45)	198.09 - 205.24	- 200.00	-
TDS (m)	211.66 (76.68)	169.19 - 254.13	203.33 (8.79)	198.46 - 208.20	- 200.00	-
ATF (s)	201.60 (50.21)	173.79 - 229.40	227.80 (37.78)	206.87 - 248.73	- 221.61 (35.27)	203.47 - 239.74
ATS (s)	224.82 (48.99)	197.69 - 251.95	247.41 (24.49)	233.85 - 260.98	- 247.80 (28.45)	233.17 - 262.43
APF (s/100m)	106.73 (18.22)	96.64 - 116.82	111.60 (16.02)	102.72 - 120.47	- 110.80 (17.63)	101.73 - 119.87
APS (s/100m)	112.26 (24.42)	98.73 - 125.75	130.60 (39.07)	108.96 - 152.23	- 122.97 (15.27)	115.12 - 130.82
TSF	187.73 (50.05)	160.01 - 215.45	213.06 (31.92)	195.38 - 230.74	- 208.64 (42.11)	186.99 - 230.30
TSS	184.00 (48.17)	157.32 - 210.06	219.60 (36.64)*	199.19 - 240.00	- 191.88 (34.42)	174.18 - 209.58
ASF	24.66 (4.36)	22.24 - 27.08	26.40 (3.56)	24.42 - 28.37	26.07 (5.26)	23.37 - 28.78
ASS	24.73 (9.38)	19.53 - 29.93	26.13 (4.17)	23.82 - 28.44	23.97 (4.30)	21.76 - 26.19

TDF = Average distance of fast condition in meters; TDS = Average distance of slow condition in meters; ATF = Average time of fast condition in seconds; ATS = Average slow condition time in seconds; APF = Average pace of fast condition (s/100m); APS = Average pace of slow condition (s/100m); TSF = Total strokes in fast condition; TSS= Total strokes in the slow condition; ASF = Average strokes in 25 meters in fast condition; ASS= Average strokes in 25 meters in the slow condition; CI = Confidence interval; * = When compared with Garmin $p < 0.05$; # = When compared with Video $p < 0.05$; † = When compared with Polar and Video $p < 0.05$.

Discussion

Distances of 50 Meters

In non-experienced swimmers, smartwatches showed discrepancies varying from temporal to technique-related biomechanics parameters (ATF, ATS, APF, APS, TSF and ASF). In Garmin, variables with significant differences are characterized as time-related metrics (e.g.: total time in slow condition and average pace, regardless of speed conditions). These discrepancies may stem from variations in swimming speed during tests, and unmeasured variables like swimming efficiency and distance per stroke, which could affect performance and contribute to differences observed, particularly among less experienced swimmers (Seifert et al., 2010). Furthermore, as the Garmin model recommends, for a more accurate length measurement, a “strong push off the wall and glide before the first stroke”, the inability of the non-experienced swimmers to use the proper wall push off and glide can interfere in time related metrics such as pace. Otherwise, as the Polar’s watch seems to not need this markedly push off and glide before the first stroke, the pacing estimation was more precise at the same subjects, wherein both speed conditions matched the video’s analyses. In accordance with Weimar et al. (2019) the flip-turn technique contributes significantly to the swimmer’s performance, being the wall contact phase the most important of its components. Thus, in the present study the participants performed the open turn, which also involves the wall contact phase, so if a watch requires a proper push off and glide, it is possible that variations in the open turn performance within non-experienced may have distressed the watch readings, justifying the pace-related differences found between the two smartwatches.

In experienced swimmers, fewer measurement discrepancies among the smartwatches and video analysis were found. Perhaps, the more consistent technique presented by the experienced swimmers is followed by less interference in the smartwatches reading (one for Garmin; three for Polar). When comparing non-experienced and experienced swimmers, non-experienced swimmers displayed greater variability in biomechanical parameters, as reflected by larger partial eta squared values. For the average time in the fast condition (ATF), η^2_{partial} was 0.36 for non-experienced swimmers and 0.37 for experienced swimmers, indicating a large effect size in both groups. For the total strokes in the fast condition (TSF), η^2_{partial} was equally high at 0.62 in both groups, emphasizing the significant impact of this variable on the measurements. These results highlight that non-experienced swimmers’ inconsistent techniques amplify discrepancies in smartwatch measurements, whereas experienced swimmers show more reliable data due to their refined stroke mechanics. Effect size analysis further highlighted that while TDM showed a medium effect, other variables had large effect sizes, potentially indicating measurement limitations in the devices.

Taken together, our 50 meter results demonstrate that both devices performed reliable distances measurement, wherein Garmin disposal showed to be more assertive in mechanic-related metrics, regardless subject experience, while Polar in pacing estimates only for non-experience subjects. These discrepancies may result from variations in swimming speed during tests, and unmeasured variables such as swimming efficiency and distance per stroke, which could affect performance and contribute to differences observed, particularly among less experienced swimmers (Seifert et al., 2010).

Distances of 200 Meters

At the 200 m distance, there were no significant differences between the Polar smartwatch and video analysis in non-experienced swimmers, indicating potential accuracy at this distance and across different intensities. Conversely, for Garmin, three variables (ATF, TSS and ATSS) showed no agreement with video analysis in this group. For experienced swimmers, no differences were found between both smartwatches and the video analysis, and fewer significant differences were found between devices. The differences in fewer variables between smartwatches (200 m - ATF, ATS, TSF; 50 m - ATF, ATS, APF, TSF, and ATSF) suggest that longer distances and lower pace allow swimmers to maintain a more consistent movement pattern than at short distance and higher-paced distances (Samson et al., 2015). Also, some of them could be influenced by uncontrolled factors such as anthropometric differences and fatigue levels in this study (Seifert et al., 2015).

Comparing the two groups, non-experienced swimmers showed greater discrepancies across devices, though fewer variables were affected compared to the shorter distance. The partial eta squared (η^2_{partial}) for total strokes in the slow condition (TSS) was 0.17, indicating a moderate effect size. In contrast, the other variables, such as ATF, had smaller effect sizes compared to the 50-meter trials. This suggests that longer distances allow swimmers to maintain a more stable movement pattern, reducing the impact of inconsistencies in stroke technique on smartwatch accuracy. According to Lee (2018), the precision of lap and stroke counts in wearables such as Apple and Garmin increases along with the exercise intensity. However, the precision seems to be related to volume, where both smartwatches showed satisfactory accuracy. Thus, we hypothesize that as most

of the variables have used a pool segment in their calculations, short distances (e.g 50 m) do not allow proper watches settings.

Our findings indicate that smartwatch technology may still lack the precision needed to measure certain parameters accurately, especially in non-experienced swimmers, who often exhibit inconsistent swimming patterns. In general, the smartwatches do not have their monitoring mechanism algorithms disclosed by their respective companies. Without this information, it is difficult to identify why smartwatches have errors in their monitoring. Furthermore, in the user manual, the requirements, and procedures for the best functioning during the training session are scarce. An example is that in a practical swimming environment both smartwatches are factory configured to automatically pause every time the swimmer stops moving around the pool. At that point they record the laps, the number of strokes, travel time, swimming rhythm, etc. However, during the break interval, the swimmer naturally takes the water bottle to hydrate, adjusts their swimming cap and goggles, interacts with their coach, etc. With these movements, the accelerometers can be activated and begin to record all the variables mentioned previously, consequently measuring the training session incorrectly.

Conclusions

Our results demonstrate that the Polar Vantage M2 and Garmin Fenix 6 Pro smartwatches hold considerable potential as accessible and user-friendly tools for measuring biomechanical parameters in swimming, particularly in training and long-term monitoring contexts. However, their accuracy was shown to be dependent on swimmers' expertise level and on test distance/intensity. This indicates that technical proficiency is a critical factor on the reliability of smartwatch-derived metrics.

At shorter distances (50 m), especially under maximal intensities, both devices displayed notable discrepancies when compared with video analysis, considered the gold standard. These differences were more pronounced in non-experienced swimmers, supporting the notion that inconsistent technical patterns and greater execution variability negatively affect sensor detection and measurement accuracy.

Conversely, at longer distances (200 m), regardless of swimming intensity, both smartwatches produced more consistent results, with closer agreement to video analysis, particularly among experienced swimmers. This suggests that greater swimming volume and technical stability during prolonged efforts enhance measurement reliability. From a practical standpoint, these findings indicate that smartwatches may serve as valid monitoring instruments for recreational swimmers and in early training programs, but require more rigorous validation before being applied to elite athletes, whose performance relies on highly precise and reliable data.

In summary, despite their limitations, smartwatches represent a promising, low-cost, and practical alternative, particularly in contexts where traditional assessment methods (e.g., video analysis) are not feasible. With continued improvements in embedded algorithms and greater standardization of measurement protocols, these devices may become reliable tools for biomechanical monitoring in swimming across different levels of expertise.

Conflicts of interest - The authors declare no conflicts of interest.

References:

- Bächlin, M., & Tröster, G. (2012). Swimming performance and technique evaluation with wearable acceleration sensors. *Pervasive and Mobile Computing*, 8(1), 68–81. <https://doi.org/10.1016/j.pmcj.2011.05.003>
- Barbosa, T. M., Goh, W. X., Morais, J. E., & Costa, M. J. (2017). Variation of Linear and Nonlinear Parameters in the Swim Strokes According to the Level of Expertise. *Motor Control*, 21(3), 312–326. <https://doi.org/10.1123/mc.2015-0097>
- Brunner, G., Melnyk, D., Sigfússon, B., & Wattenhofer, R. (2019). Swimming style recognition and lap counting using a smartwatch and deep learning. *Proceedings of the 23rd International Symposium on Wearable Computers*, 23–31. <https://doi.org/10.1145/3341163.3347719>
- Budig, M., Keiner, M., Stoohs, R., Hoffmeister, M., & Höltke, V. (2022). Heart Rate and Distance Measurement of Two Multisport Activity Trackers and a Cellphone App in Different Sports: A Cross-Sectional Validation and Comparison Field Study. *Sensors*, 22(1), Article 1. <https://doi.org/10.3390/s22010180>
- Correia, R. de A., Feitosa, W. G., & Castro, F. A. de S. (2023). Kinematic, arm-stroke efficiency, coordination, and energetic parameters of the 400-m front-crawl test: A meta-analysis. *Frontiers in Sports and Active Living*, 5. <https://www.frontiersin.org/articles/10.3389/fspor.2023.977739>
- Cortesi, M., Giovanardi, A., Gatta, G., Mangia, A. L., Bartolomei, S., & Fantozzi, S. (2019). Inertial Sensors in Swimming: Detection of Stroke Phases through 3D Wrist Trajectory. *Journal of Sports Science & Medicine*, 18(3), 438–447.
- Cosoli, G., Antognoli, L., Veroli, V., & Scalise, L. (2022). Accuracy and Precision of Wearable Devices for Real-Time Monitoring of Swimming Athletes. *Sensors*, 22(13), Article 13. <https://doi.org/10.3390/s22134726>
- Cosoli, G., Spinsante, S., & Scalise, L. (2020). Wrist-worn and chest-strap wearable devices: Systematic review on accuracy and metrological characteristics. *Measurement*, 159, 107789. <https://doi.org/10.1016/j.measurement.2020.107789>

-
- Costa, J., Silva, C., Santos, M., Fernandes, T., & Faria, S. (2021). Framework for Intelligent Swimming Analytics with Wearable Sensors for Stroke Classification. *Sensors (Basel, Switzerland)*, 21(15), 5162. <https://doi.org/10.3390/s21155162>
- Dadashi, F., Millet, G. P., & Aminian, K. (2016). Front-crawl stroke descriptors variability assessment for skill characterisation. *Journal of Sports Sciences*, 34(15), 1405–1412. <https://doi.org/10.1080/02640414.2015.1114134>
- Ellens, S., Carey, D. L., Gastin, P. B., & Varley, M. C. (2024). Effect of Data-Processing Methods on Acceleration Summary Metrics of GNSS Devices in Elite Australian Football. *Sensors*, 24(13), Article 13. <https://doi.org/10.3390/s24134383>
- Engel, A., Schaffert, N., Ploigt, R., & Mattes, K. (2021). Intra-cyclic analysis of the front crawl swimming technique with an inertial measurement unit. *Journal of Human Sport and Exercise*, 17(3). <https://doi.org/10.14198/jhse.2022.173.17>
- Fantozzi, S., Coloretti, V., Piacentini, M. F., Quagliarotti, C., Bartolomei, S., Gatta, G., & Cortesi, M. (2022). Integrated Timing of Stroking, Breathing, and Kicking in Front-Crawl Swimming: A Novel Stroke-by-Stroke Approach Using Wearable Inertial Sensors. *Sensors (Basel, Switzerland)*, 22(4), 1419. <https://doi.org/10.3390/s22041419>
- Hagem, R. M., Thiel, D. V., O’Keefe, S., & Fickenscher, T. (2013). Real-time swimmers’ feedback based on smart infrared (SSIR) optical wireless sensor. *Electronics Letters*, 49(5), 340–341. <https://doi.org/10.1049/el.2012.3222>
- Haghi, M., Thurow, K., & Stoll, R. (2017). Wearable Devices in Medical Internet of Things: Scientific Research and Commercially Available Devices. *Healthcare Informatics Research*, 23(1), 4–15. <https://doi.org/10.4258/hir.2017.23.1.4>
- Kos, A., & Umek, A. (2019). Wearable Sensor Devices for Prevention and Rehabilitation in Healthcare: Swimming Exercise With Real-Time Therapist Feedback. *IEEE Internet of Things Journal*, 6(2), 1331–1341. *IEEE Internet of Things Journal*. <https://doi.org/10.1109/JIOT.2018.2850664>
- Lee, M. (2018). Accuracy of swimming wearable watches for estimating energy expenditure. *IJASS(International Journal of Applied Sports Sciences)*, 30(1), 80–90. <https://doi.org/10.24985/ijass.2018.30.1.80>
- Lopes, T., Sampaio, T., Oliveira, J., Pinto, M., Marinho, D., & Morais, J. (2023). Using Wearables to Monitor Swimmers’ Propulsive Force to Get Real-Time Feedback and Understand Its Relationship to Swimming Velocity. *Applied Sciences*, 13. <https://doi.org/10.3390/app13064027>
- Magalhaes, F. A. de, Vannozzi, G., Gatta, G., & Fantozzi, S. (2015). Wearable inertial sensors in swimming motion analysis: A systematic review. *Journal of Sports Sciences*, 33(7), 732–745. <https://doi.org/10.1080/02640414.2014.962574>
- Mooney, R., Quinlan, L. R., Corley, G., Godfrey, A., Osborough, C., & ÓLaighin, G. (2017). Evaluation of the Finis Swimsense® and the Garmin Swim™ activity monitors for swimming performance and stroke kinematics analysis. *PLOS ONE*, 12(2), e0170902. <https://doi.org/10.1371/journal.pone.0170902>
- Morais, J. E., Oliveira, J. P., Sampaio, T., & Barbosa, T. M. (2022). Wearables in Swimming for Real-Time Feedback: A Systematic Review. *Sensors (Basel, Switzerland)*, 22(10), 3677. <https://doi.org/10.3390/s22103677>
- Newsome, A. M., Batrakoulis, A., Camhi, S. M., McAvoy, C., Sansone, J. (Sudock), Reed, R., & Contributors. (2024). 2025 ACSM Worldwide Fitness Trends: Future Directions of the Health and Fitness Industry. *ACSM’s Health & Fitness Journal*, 28(6), 11. <https://doi.org/10.1249/FIT.0000000000001017>
- Olstad, B. H., & Zinner, C. (2020). Validation of the Polar OH1 and M600 optical heart rate sensors during front crawl swim training. *PLOS ONE*, 15(4), e0231522. <https://doi.org/10.1371/journal.pone.0231522>
- Pratama, A. B., & Yimlamai, T. (2020). Effects of Active and Passive Recovery on Muscle Oxygenation and Swimming Performance. *International Journal of Sports Physiology and Performance*, 1–8. <https://doi.org/10.1123/ijspp.2019-0537>
- Ruiz-Navarro, J. J., López-Belmonte, Ó., Gay, A., Cuenca-Fernández, F., & Arellano, R. (2023). A new model of performance classification to standardize the research results in swimming. *European Journal of Sport Science*, 23(4), 478–488. <https://doi.org/10.1080/17461391.2022.2046174>
- Seifert, L., Toussaint, H. M., Alberty, M., Schnitzler, C., & Chollet, D. (2010). Arm coordination, power, and swim efficiency in national and regional front crawl swimmers. *Human Movement Science*, 29(3), 426–439. <https://doi.org/10.1016/j.humov.2009.11.003>
- Shell, S. J., Clark, B., Broatch, J. R., Slattery, K., Halson, S. L., & Coutts, A. J. (2021). Is a Head-Worn Inertial Sensor a Valid Tool to Monitor Swimming? *International Journal of Sports Physiology and Performance*, 16(12), 1901–1904. <https://doi.org/10.1123/ijspp.2020-0887>
- Zacca, R., Neves, V., da Silva Oliveira, T., Soares, S., Rama, L. M. P. L., de Souza Castro, F. A., Vilas-Boas, J. P., Pyne, D. B., & Fernandes, R. J. (2020). 5 km front crawl in pool and open water swimming: Breath-by-breath energy expenditure and kinematic analysis. *European Journal of Applied Physiology*, 120(9), 2005–2018. <https://doi.org/10.1007/s00421-020-04420-7>
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