

PACING STRATEGIES AND PERFORMANCE DETERMINANTS IN 200M FREESTYLE: A CLUSTER ANALYSIS OF WORLD CHAMPIONSHIP FINALISTS

Andreea Natalia JURESCHI (GHEORGHE)¹, Luciela Maria VASILE¹

¹ National University of Physical Education and Sports, Faculty of Physical Education and Sport, Bucharest, Romania

* Corresponding author: njureschi@gmail.com

<https://doi.org/10.52846/46.2025.1.12>

Abstract: Background: World Swimming Championships bring together elite swimmers globally. The 200m freestyle demands optimal pacing strategy due to speed and metabolic control requirements. Data from three World Championships (2022, 2023, 2024) provided opportunity to analyze elite performance patterns. Previous research suggests the third 50m segment significantly impacts outcomes.

Materials and Methods: Data from 24 finalists across three championships were collected from World Aquatics website, including reaction times, intermediate times, and final times. Swimming velocities were calculated for each 50m section. Athletes were categorized into three pacing strategies: A (positive pacing, fourth 50m equal/faster than third), B (positive pacing progressively slower), and C (negative pacing with fast finish). K-means cluster analysis was performed using SPSS, with final time and third 50m speed as clustering criteria.

Results: Cluster analysis revealed three performance groups. Cluster 1 (62.5%, n=15) showed superior performance occupying positions 1-5. Cluster 2 (33.33%, n=8) demonstrated slower performance (106.14s, 1.82 m/s), typically finishing 6th-8th. Cluster 3 contained only David Popovici with exceptional performance (103.21s, 1.90 m/s). Strategy A proved most effective for top-3 placements. ANOVA confirmed statistically significant differences between clusters, $F(2,21) = 48.10, p < .001$. Reaction time showed no correlation with final performance.

Conclusions: Third 50m segment speed emerges as the primary differentiating factor among 200m freestyle finalists. Positive pacing strategies, particularly maintaining speed in the final 50m, prove most successful for top-3 positions. Start reaction time does not impact race results. These findings provide coaches with evidence-based insights for targeted training programs.

Keywords: swimming competitive performance, freestyle events, predictive modelling

Introduction

Investigating the performance metrics of 200 m freestyle finalists across the World Swimming Championships (WSC) held in Budapest 2022, Fukuoka 2023, and Doha 2024 - a series of consecutive competitions unprecedented in the history of the event - is essential for understanding the intricate link between athletes' behaviors and their competitive outcomes. In the realm of competitive sports, comprehending athletes' behavior and its connection to their competitive results is crucial for enhancing future performance. Thus, performance analysis plays a vital role in supporting athletes' development through a scientific lens. Performance analysis is characterized as an unbiased evaluation of real sports performance that does not rely on self-reports or laboratory conditions (Gonjo & Olstad, 2021). The analysis of race strategy holds significant importance in an athlete's performance, particularly in races where each segment of the race contributes to the final outcome, potentially determining the margin between victory and second place (de Souza Castro et al., 2017). Race strategy entails the way athletes regulate their

speed and energy usage during the competition, with the timing of different segments playing a vital role (da Silva et al., 2020).

Typically, race analyses in swimming rely on official race data, such as reaction time, lap times, and finishing times, often supplemented by video recordings. Official race results provide valuable insights into swimmers' pacing strategies, while video footage becomes crucial for obtaining detailed information on various aspects of the race, including the start, clean swimming, turns, and finish duration (Morais et al., 2021).

The following data was used in the analysis: reaction time, intermediate times for each length of the race, and the final time. Additionally, the swimming speed for each 50 meters swum separately was also considered.

While pacing is readily apparent in the 400 m events, it is important to consider pacing strategies in the shorter 100 m and 200 m events as well, despite the variations in component parts being relatively smaller (Maglischo, 2010). The 200 m freestyle event requires an appropriate strategy due to the demands of increased speed and metabolic control required for energy

conservation (Cuenca- Fernandez et al., 2023). The 200 m freestyle event arouses interest for both 100 m sprinters and middle-distance swimmers. There are 3 pacing strategies recognized by specialists in the field (Huot-Marchand et al., 2005; Maglischo, 2010; Veiga & Roig, 2016):

- Even pacing: the swimming speed is relatively uniform, but the first 50 is swum in a better time due to the start. The dive, being the swiftest phase of the race, is attributed to the initial acceleration and the propulsion in the air, unlike the subsequent segments of the race where propulsion predominantly takes place in water (Menting et al., 2019);
- Positive pacing: with a rapid initial acceleration followed by deceleration at subsequent intermediate distances;
- Negative pacing: the second half of the race is swum faster than the first (de Oliveira et al., 2022).

Taking these aspects into consideration, we chose to examine the factors that affect the ultimate result, drawing on the findings of McGibbon et al. (2018) and Robertson et al. (2009), which suggest a significant correlation between the performance in the third 50 meters of the race and the final outcome.

Method

Purposes: In this study, our aim is to ascertain whether there is a connection between start reaction times and the ultimate outcome, as well as to assess the impact of the selected race strategy on the resulting performance. The objective of this research was to compare the reaction time, swimming velocity, as well as partial and final times among freestyle finalists in the WSC held in Budapest 2022, Fukuoka 2023, and Doha 2024.

Participants: The sample consisted of 24 male swimmers who competed in the 200m freestyle finals across three consecutive World Swimming Championships: Budapest 2022, Fukuoka 2023, and Doha 2024. All finalists (eight per championship) were included in the analysis.

Inclusion criteria:

- participation in 200m freestyle finals at WSC 2022, 2023, or 2024;
- complete race data available (reaction time, all intermediate splits, final time).

Exclusion criteria:

- disqualifications;
- incomplete data.

Since all data were publicly available through World Aquatics official records and do not contain sensitive personal information beyond

athletic performance, no explicit informed consent was required from participants, consistent with ethical standards for secondary analysis of public sports data.

Data Sources and Measures: all race data were obtained from the World Aquatics official website (<http://www.worldaquatics.com>), the international governing body for aquatic sports. The following variables were extracted for each race:

Temporal variables:

- start reaction time (seconds): time from starting signal to athlete movement
- intermediate times (seconds): cumulative time at 50m, 100m, 150m, and 200m
- final time (seconds): total race duration

Performance variables:

- swimming velocity (m/s): calculated for each 50m segment using the formula:

$$velocity = distance (50m) / time for segment$$

- average speed of third 50m (m/s): velocity achieved during 100m-150m segment, calculated as:

$$V_3 = 50 / (T_{150} - T_{100})$$

where T_{150} = time at 150m and T_{100} = time at 100m

Pacing Strategy Classification:

Based on velocity distribution across the four 50m segments, each race was categorized into one of three pacing strategies:

- strategy A (positive-controlled): positive pacing with fourth 50m velocity equal to or faster than third 50m ($V_4 \geq V_3$);
- strategy B (positive-progressive): positive pacing with each successive 50m slower than previous ($V_1 > V_2 > V_3 > V_4$);
- strategy C (negative split): negative pacing with accelerated finish, fourth 50m substantially faster than third ($V_4 \gg V_3$).

Procedure

Data collection and preparation involved the following steps:

1. data extraction: race results for all 24 finals were manually extracted from the World Aquatics website between February and March 2024;
2. data entry: start times, intermediate splits (50m, 100m, 150m), and final times were entered into Microsoft Excel (Version 2021);
3. data validation: all entries were cross-checked against original source data to minimize transcription errors. A second researcher independently verified 25% of entries (randomly selected), with 100% agreement achieved;
4. variable computation: swimming velocities for each 50m segment were calculated using Excel formulas;

5. data import: the validated dataset was imported into IBM SPSS Statistics (Version 27.0) for analysis;

6. pacing strategy coding: each race was independently coded by the authors.

Results and Discussions

Regarding our research performed on the male athletes (see Table 1), we used a cluster analysis to explore the patterns and grouping that emerged among these elite swimmers. Through a detailed examination of these findings, we aim to uncover

nuanced insights that shed light on the diverse performance profiles within this highly competitive field, ultimately contributing to a deeper understanding of the factors influencing success in the 200 m freestyle event at the world-class level.

Figures 1 and 2 depict the distribution of start reaction times and the average speed of the third 50 m in each of the 24 races examined, and the frequency of the three strategies adopted by the world finalists.

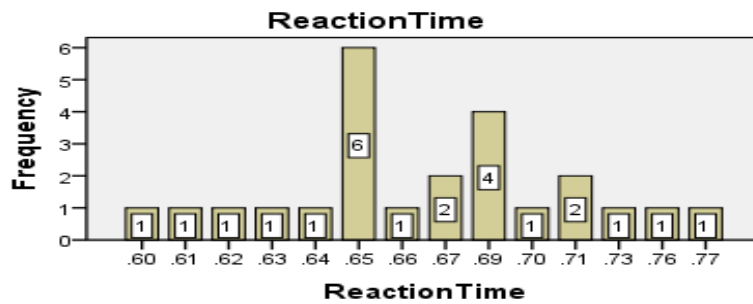


Figure 1. Frequency of the reaction time of the 24 analyzed races

It can be seen how the average reaction time is the most common and the extremes (slowest and fastest) have a low frequency.

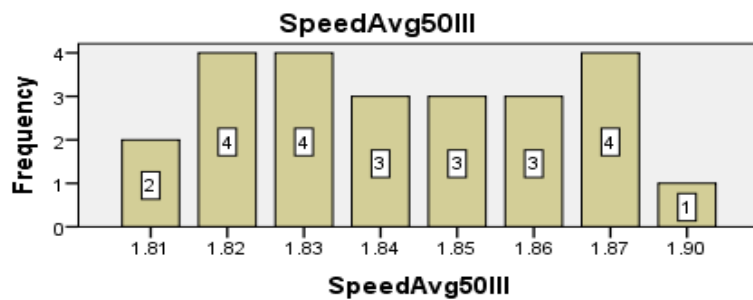


Figure 2. Frequency of the average speed of the third 50 m swim in the 24 analyzed races

As illustrated in figure 3, the top performances were recorded during the Budapest championships, while the poorest performances were observed in Doha, in 2024. This phenomenon can be attributed to 2024 being an Olympic year, with athletes typically aiming to be at their peak performance levels by the end of July in preparation for the prestigious event.

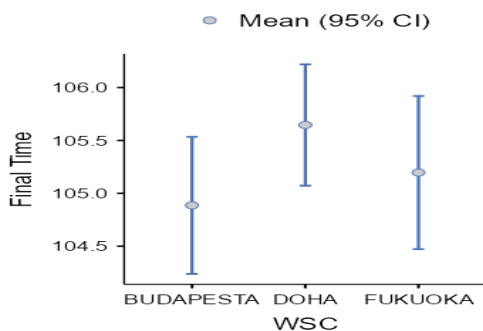


Figure 3. Mean final time

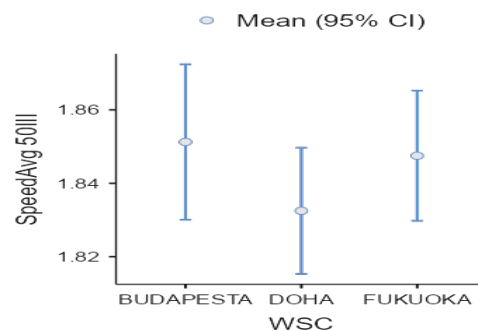


Figure 4. Mean of average speed on the third 50 m

In figure 4, the intermediate time averages for the third 50 meters of the swim are depicted. The data reveals that the swiftest speed was realized during the 2022 final, primarily attributable to David Popovici's

exceptional performance. On the contrary, the slowest speeds were observed during the Doha-2024 event, where the recorded times serve as a precursor to the anticipated performances in the upcoming 200 meters freestyle event at the Olympic Games slated to occur later in the year.

In table 1 are presented the values of all participants in WSC, such as start reaction time, final time, average speed for every 50 m swum and pacing strategy.

Table 1: *Start time, average lap speed, final times and type of pacing strategy in the 200 freestyle events at the WSC in Doha 2024, Fukuoka 2023 and Budapesta 2022*

World Swimming Championship	Place	Name	Country	Start reaction time (seconds)	Average speed 1st 50 (m/sec)	Average speed 2nd 50 (m/sec)	Average speed 3rd 50 (m/sec)	Average speed 4th 50 (m/sec)	Final time (seconds)	Average speed (m/sec)	Pacing strategy
DOHA	1	HWANG	KOR	0.62	2.06	1.89	1.83	1.85	104.75	1.909	A
DOHA	2	RAPSYS	LTU	0.65	2.03	1.87	1.85	1.85	105.05	1.903	A
DOHA	3	HOBSON	USA	0.73	2.05	1.89	1.87	1.79	105.26	1.900	B
DOHA	4	MARTENS	GER	0.69	2.03	1.86	1.84	1.86	105.33	1.898	C
DOHA	5	MIROSLAW	GER	0.65	2.04	1.88	1.83	1.81	105.84	1.889	A
DOHA	6	SCOTT	GBR	0.65	2.03	1.87	1.82	1.83	105.87	1.889	A
DOHA	7	WINNINGTON	AUS	0.65	2.00	1.84	1.81	1.87	106.20	1.883	C
DOHA	8	COSTA	BRA	0.69	1.98	1.84	1.81	1.85	106.87	1.871	C
FUKUOKA	1	RICHARDS	GBR	0.60	2.06	1.87	1.85	1.88	104.30	1.917	C
FUKUOKA	2	DEAN	GBR	0.67	2.03	1.88	1.86	1.89	104.32	1.917	C
FUKUOKA	3	HWANG	KOR	0.63	2.06	1.88	1.86	1.86	104.42	1.915	A
FUKUOKA	4	POPOVICI	ROM	0.69	2.10	1.89	1.87	1.77	104.90	1.906	B
FUKUOKA	5	HOBSON	USA	0.77	2.01	1.88	1.87	1.83	105.09	1.903	B
FUKUOKA	6	LEE	KOR	0.65	2.01	1.85	1.83	1.84	106.04	1.886	A
FUKUOKA	7	SMITH	USA	0.69	2.05	1.89	1.82	1.78	106.10	1.885	B
FUKUOKA	8	AUBOECK	AUT	0.76	1.98	1.86	1.82	1.85	106.40	1.879	A
BUDAPESTA	1	POPOVICI	ROM	0.67	2.10	1.90	1.90	1.85	103.21	1.937	A
BUDAPESTA	2	HWANG	KOR	0.61	2.05	1.89	1.87	1.84	104.47	1.914	B
BUDAPESTA	3	DEAN	GBR	0.66	2.10	1.91	1.84	1.78	104.98	1.905	B
BUDAPESTA	4	KIBLER	USA	0.64	2.05	1.89	1.86	1.82	105.01	1.904	B
BUDAPESTA	5	AUBOECK	AUT	0.71	2.03	1.87	1.85	1.86	105.11	1.902	A
BUDAPESTA	6	SMITH	USA	0.71	2.06	1.91	1.84	1.79	105.16	1.901	B
BUDAPESTA	7	MARTENS	GER	0.70	2.02	1.88	1.83	1.83	105.33	1.898	A
BUDAPESTA	8	WINNINGTON	AUS	0.65	2.04	1.88	1.82	1.82	105.82	1.890	A

Based on these strategies we designed a cluster analyses. In the sample, a single swimmer maintains an average speed of 1.9 m/s (David Popovici at Budapest when he broke the World Junior Record), while the remaining participants exhibit speeds under 1.87 m/s. The two instances recording 1.81 m/s align with the competitors securing the lowest rankings at the Doha 2024 event, specifically 7th and 8th places. Regarding the frequency of the selected strategies across the 24 races, figure 5 indicates their distribution. The most common pacing strategy chosen by the swimmers of the last 3 WSC is the one with last 50 m equal or faster than third, A. The least commonly chosen strategy is the negative split, C, demanding a heightened blend of aerobic and anaerobic capacity. This approach is notably challenging to execute as it necessitates specific physical and physiological attributes along with specialized training (Breen et al., 2020; de Souza Castro et al., 2010).

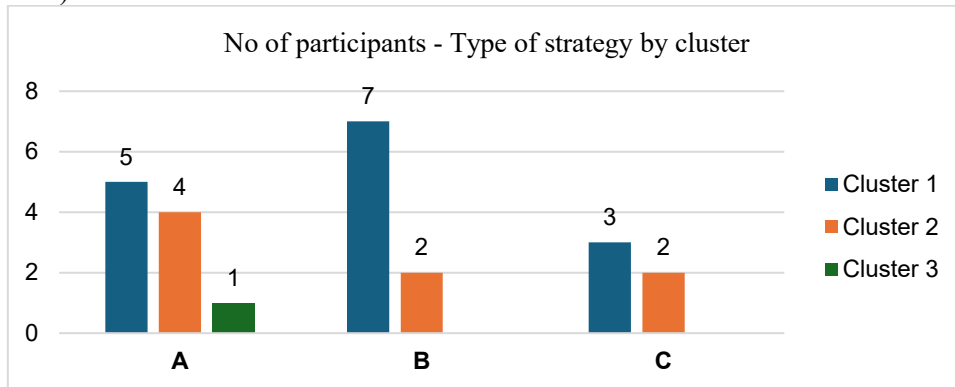


Figure 5. Frequency of the chosen pacing strategy

Figures 6 and 7 display the mean speeds of the split times documented across the analysis of 24 races, along with the average split times. The noticeable discrepancy in speeds between the initial 50 meters and the subsequent three pool lengths is attributed to enhancements in race starts, which have become increasingly efficient in recent years.

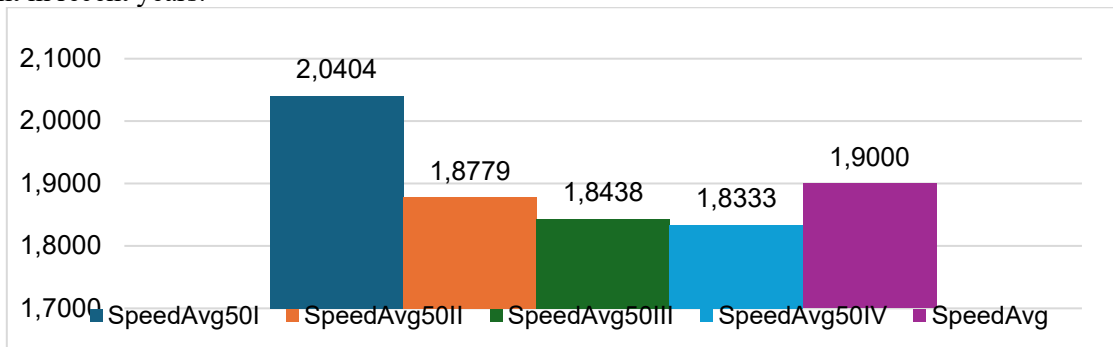


Figure 6. The average speed on each of the 4 50 m laps and the average speed of the entire race

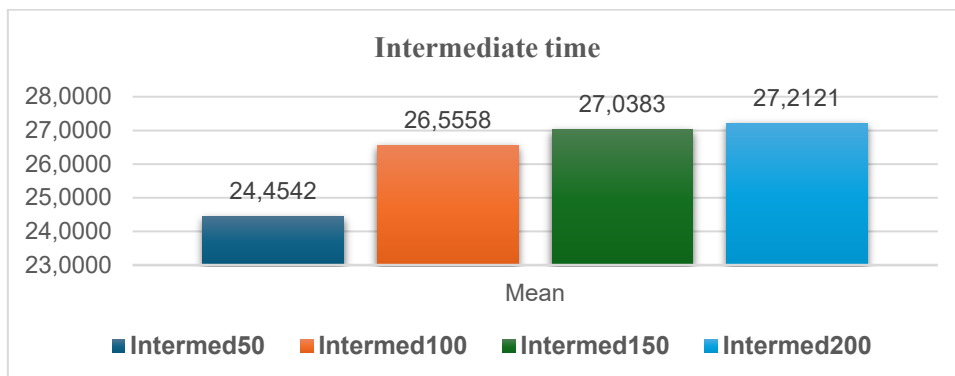


Figure 7. The mean intermediate time for the 24 races examined

Cluster analysis

K-Means is a partition-based clustering technique that uses Euclidean distances between points as a criterion for cluster formation. Each cluster has an assigned center and each cluster is placed at larger distances. Each received data point is placed in the cluster with the closest cluster center. This process is repeated until all data points are assigned to a cluster. Once all data points are covered, the cluster centers or centers are recalculated (Everitt 2005; Krieger et al., 2011). We chose to split the data source into 3 clusters, as the dendrogram shows that this would be a

suitable solution. As clustering criteria, we chose the final time obtained by the athletes and the average speed of the third 50 m, because in the 200 m freestyle event, considering the 2009 study conducted by Robertson, Pyne, Hopkins, and Anson, which emphasizes that the swimming speed during the third 50 meters in the 200 m freestyle significantly impacts the ultimate outcome, these are the most important. SPSS displays the center of the initial clusters, the changes after 3 iterations and the centers of the final clusters (Fig. 8).

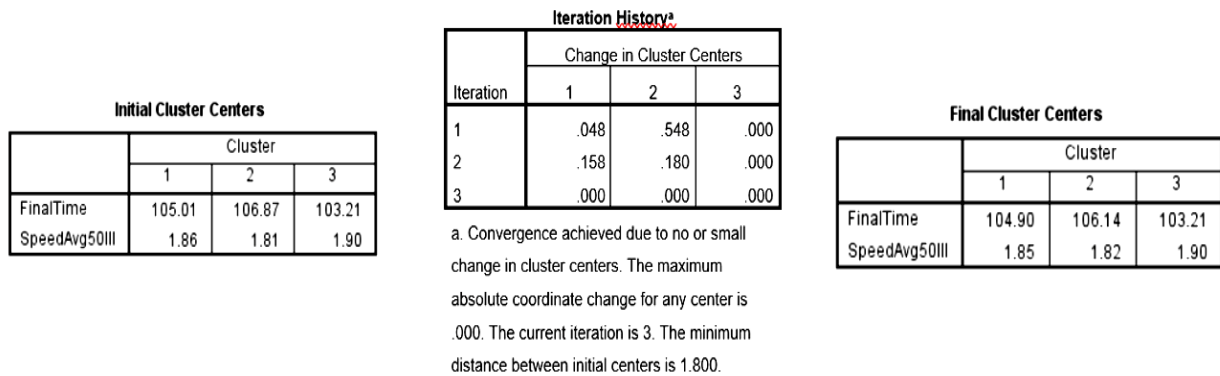


Figure 8. Cluster centers

It can be seen that the athletes in cluster 1 have on average a better final time (104.9) and a higher average speed of the third 50 m (1.85), as shown in Fig.1. 15 athletes belong to this cluster, with a preference for places 1-5. This cluster is the largest in terms of the number of athletes (62.5%), as shown in Fig. 8. The names of the athletes and the values obtained at the championships are shown in Table 2. Of these, 7 applied strategy type B, which involves swimming the race at a positive pace, each 50 being slower than the previous - usually undertaken by strong swimmers with high power but lower endurance, and 5 applied strategy type A, which also involves a positive pacing, but with a fourth 50 m equal to or faster than the third, a strategy that can be assimilated to the even pacing. Those who applied strategy A generally placed 1-3, so it is a relatively good strategy. Only 3 athletes applied strategy C which involves a relatively slower start, but an extremely fast finish, requiring extremely high-speed endurance, which is recommended, as they occupied places 1, 2 and 4.

Athletes in cluster 2 have on average a slower final time (106.14) and a lower average speed of the third 50 m (1.82 m/s), as shown in Fig.8. 8 athletes (33.33%) belong to this cluster, with a preference for places 6-7 as shown in Fig.9 and Table 2. The names of the athletes and the values obtained at the championships are shown in Table 1. Of these, 4 applied strategy type A, 2 applied strategy type B and 2 applied strategy type C. Cluster 3 contains only 1 athlete, the Romanian David Popovici, a phenomenon in the swimming world, obtaining the best final time (103.21) and the best average speed of the third 50 m (1.9). The race that is included in cluster 3 is the world junior record race from Budapest in 2022 and is an example of an even pacing. Although the fourth 50 m was not the fastest swum by any of the World Championship finalists, the middle laps were swum at a speed faster than any other swimmers and were equal to each other, demonstrating exceptional training and physical fitness (table 2, figure 9).

Number of Cases in each Cluster

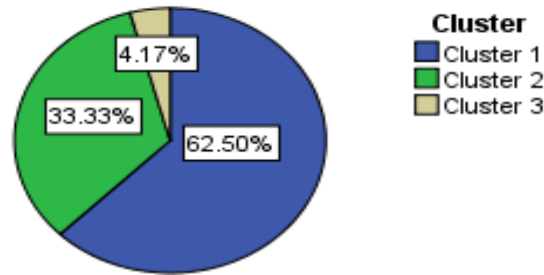


Figure 9. Percentage of cases in each cluster

Table 2 – Cluster member

PACING STRATEGIES	CLUSTER	DISTANCE	WORLD SWIMMING CHAMPIONSHIP	PLACE	NAME	COUNTRY	AVERAGE SPEED OF 3 RD 50 M	FINAL TIME
1	1	.150	DOHA	1	HWANG	KOR	1.83	104.75
1	1	.151	DOHA	2	RAPSYS	LTU	1.85	105.05
2	1	.362	DOHA	3	HOBSON	USA	1.87	105.26
3	1	.432	DOHA	4	MARTENS	GER	1.84	105.33
3	1	.599	FUKUOKA	1	RICHARDS	GBR	1.85	104.30
3	1	.579	FUKUOKA	2	DEAN	GBR	1.86	104.32
1	1	.479	FUKUOKA	3	HWANG	KOR	1.86	104.42
2	1	.017	FUKUOKA	4	POPOVICI	ROM	1.87	104.90
2	1	.192	FUKUOKA	5	HOBSON	USA	1.87	105.09
2	1	.429	BUDAPESTA	2	HWANG	KOR	1.87	104.47
2	1	.082	BUDAPESTA	3	DEAN	GBR	1.84	104.98
2	1	.112	BUDAPESTA	4	KIBLER	USA	1.86	105.01
1	1	.211	BUDAPESTA	5	AUBOECK	AUT	1.85	105.11
2	1	.262	BUDAPESTA	6	SMITH	USA	1.84	105.16
1	1	.432	BUDAPESTA	7	MARTENS	GER	1.83	105.33
2	2	.303	DOHA	5	MIROSLAW	GER	1.83	105.84
1	2	.273	DOHA	6	SCOTT	GBR	1.82	105.87
3	2	.058	DOHA	7	WINNINGTON	AUS	1.81	106.20
3	2	.728	DOHA	8	COSTA	BRA	1.81	106.87
1	2	.103	FUKUOKA	6	LEE	KOR	1.83	106.04
1	2	.043	FUKUOKA	7	SMITH	USA	1.82	106.10
2	2	.257	FUKUOKA	8	AUBOECK	AUT	1.82	106.40
1	2	.323	BUDAPESTA	8	WINNINGTON	AUS	1.82	105.82
1	3	0.000	BUDAPESTA	1	POPOVICI	ROM	1.90	103.21

SPSS displays the distance between cluster centers as small (1.24) between cluster 1 and cluster 2, medium (1.689) between cluster 1 and cluster 3, and large (2.934) between cluster 2 and cluster 3. This distance highlights the fact that the result (final time) obtained by David Popovici (cluster 3) differs greatly from the athletes in cluster 2 (table 3).

Table 3. Distances between Final Cluster Centers

Cluster	1	2	3
1		1.244	1.689
2	1.244		2.934
3	1.689	2.934	

The Anova table (table 4) shows us that there are statistically significant differences ($p < .001$) between the 3 clusters, both in terms of final time (calculated $F(2,21)=48.10$, $p < .001$) and in terms of average speed of the third 50 (calculated $F(2, 21)=28.28$, $p < .001$), so we can rely on the clustering/sorting of the athletes. The F-test was used to maximize the differences between athletes placed in different clusters, so the cluster means are not equal. Our analysis is statistically representative.

Table 4. ANOVA- clusters

	Cluster		Error		F	p
	Mean Square	df	Mean Square	df		
Final Time	6.192	2	.129	21	48.102	.000
SpeedAvg 50 III	.004	2	.000	21	28.277	.000

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal

If we analyze from the point of view of the strategy, we observe that those who apply strategy 1 generally have a final time between 105-106, with the exception of David Popovici who obtains the best time (103.21) and an average speed of approximately (1.825 -1.86). This is the steepest slope on the graph, thanks to David. Those who apply strategy 2 generally have a final time of approximately 104.9-106, and average speed of approximately (1.82 -1.87). Those who apply strategy C generally have a final time of approximately 104-106.87, and average speed of approximately (1.81 -1.86). Athlete Costa from Brazil had the slowest final time 106.87 and the lowest speed (1.81). Similarly, Australia's Wington had a poor final time of 106.2 and the lowest speed (1.81). They are the ones pulling down the graph curve (Figure 10).

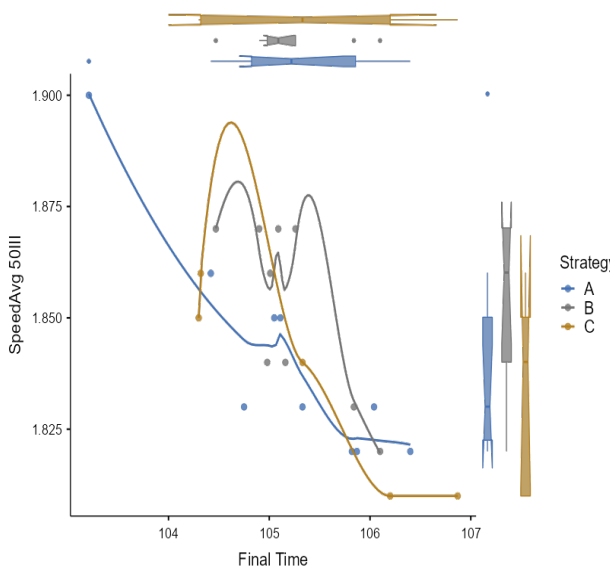


Figure 10. Final time and average speed by strategy

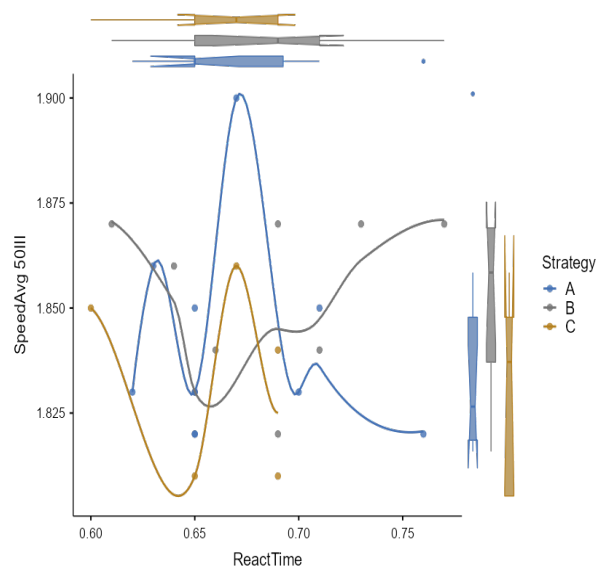


Figure 11. Reaction time, average speed of the third 50 m swum by strategy

Regarding the analysis of data in terms of reaction time, no statistically relevant correlations were found. Reaction time is generally better for those applying strategy C, compensating for a low average speed. For athletes who applied strategy A or B the reaction time takes the whole range of values, so we cannot say that it correlates with strategy (Figure 11).

Having in mind that we observed that there is difference between clusters, we further decided to analyse if there is significant statistical difference between athletes regarding reaction time.

Anova (table 5) shows that there are significant differences between athletes if we analyze the reaction time, but it does not correlate with the final time, so it is not decisive, in this type of event. According to Maglischo, enhancing the start reaction can result in a time improvement of .1 seconds, a significant impact in a 50 m race. However, this improvement is less influential in a 200 m race due to the longer distance involved (Takeda et al., 2009). Despite the data indicating that the start reaction time does not have a statistical impact on the outcome, we advocate for a comprehensive examination of variables such as flight time, underwater distance covered, and underwater speed as factors that should be thoroughly investigated.

Table 5. ANOVA-reaction time

	sum of squares	df	mean square	f	p	η^2
Name	0.04070	15	0.00271	8.51	0.02	0.941
Residuals	0.00255	8	3.19e-4			

The study examined the patterns that emerged in the race strategy choices adopted by the winners of the last 3 World Swimming Championships. The results revealed there is not a consistency in the split times recorded across three different championships, showcasing how athletes tended to favor one of three distinct race strategies, emphasizing the diverse approaches employed during competition. This highlighted the strategic planning and execution that defined their performances. This analysis provides valuable insights into the decision-making processes of elite swimmers as they navigate the complexities of competition at the highest level.

The variables analyzed in this study included lap times, final time, average swimming speed, and intermediate distance speeds. According to Haljand & Saagpakk (1994), it is essential to conduct a thorough analysis of competitions by measuring various elements of the event. This complex approach is crucial for gaining a comprehensive understanding of the dynamics at play during the competition, providing deeper insights into performance nuances and the factors that contribute to success in swimming races. By examining these different variables, researchers can better grasp the complexities involved in competitive swimming and improve training strategies accordingly. The differences

observed in the times of the finalists arise from the distribution of energy expenditure, reflecting each athlete's choice of a strategy that best suits their performance (Damasceno, 2013). Santos et al. (2023) documented similar performance variability across rounds at the 2022 World Championships, attributing within-athlete differences to tactical pacing adjustments and energy management strategies.

Da Silva et al. (2020) demonstrates that the 200 m freestyle race is more complex than shorter distances due to the high speeds involved and the additional components it entails, such as turns, underwater swimming phases, and laps. In contrast to the 50 m and 100 m freestyle events, the 200 m race incorporates more elements that require strategic energy management. With a duration of approximately 2 minutes, this race primarily utilizes the glycolytic energy system, leading to a significantly high level of fatigue by the end of the event (Thompson et al., 2003). This complexity requires a careful balance of speed and endurance, making the 200 m freestyle a unique challenge for competitors.

Advancements in technology and innovative training methods have contributed to an evolution in performance. This enhancement can be attributed to both an increase in the quality of swimming skills and the

development of swimming methodologies (Maglischo, 2003; O'Connor & Vozenilik, 2011; McGibbon et al., 2020). As these elements have evolved, they have significantly impacted athletes' overall effectiveness and competitiveness in the sport.

Limitations

This study has several limitations that should be acknowledged:

1. **Sample size:** while our sample includes all finalists (N=24) from three consecutive World Championships, the relatively small sample size limits statistical power, particularly for between-strategy comparisons. Additionally, our findings represent only male elite swimmers; generalization to female athletes or developmental-level swimmers requires caution.
2. **Single-athlete cluster:** cluster 3 contained only David Popovici, limiting statistical interpretation. While his performance is theoretically meaningful as an exemplar of exceptional pacing, single-case clusters cannot inform population-level patterns.
3. **Contextual factors:** we could not control for external variables such as competition scheduling, prior race load, individual training phases, or strategic race goals (e.g., qualifying vs. winning). The Doha 2024 performances, occurring in an Olympic year, may reflect deliberate underperformance relative to athletes' true capabilities.

Future Research Directions

This study highlights several avenues for future investigation:

1. **Longitudinal analysis:** Tracking individual swimmers across multiple championships would reveal whether pacing patterns are stable traits or adaptive strategies that evolve with experience and conditioning.
2. **Biomechanical integration:** Combining split time analysis with video-based stroke mechanics (stroke rate, stroke length, underwater distance, turn times) would provide a more comprehensive understanding of how technical execution contributes to optimal pacing.

3. **Female swimmers:** Replicating this analysis with female 200m freestyle finalists would determine whether gender-specific pacing patterns exist, potentially related to differences in anthropometry, muscle fiber distribution, or fatigue resistance.

4. **Predictive modeling:** Machine learning approaches could develop algorithms that recommend optimal pacing strategies based on individual swimmer characteristics, training status, and competitive goals.

5. **Turn and underwater analysis:** Detailed examination of turn times, push-off velocity, underwater distances, and breakout efficiency would identify whether these technical elements interact with pacing strategy to influence overall performance.

Conclusions

Understanding the different approaches to competitive racing is crucial for swimmers. Based on their preferences, swimmers will adopt specific strategies that they will diligently and continuously prepare for, that will allow an appropriate dosage of effort, an efficient distribution of the swimmer's bio-psycho-motor resources. This constant and thorough preparation is key to their success in achieving optimal performance in races.

In our evaluation of the three World Championship finals examined, we have found that the start reaction does not influence the ultimate race outcome. Through cluster analysis, it has been revealed that the speed at which the third 50 m is completed holds a beneficial effect on the final result in a 200 m freestyle race. We believe that delving into split times can offer coaches valuable insights into the pacing tactics of both their own athletes and competitors, serving as a useful tool in race preparation and strategy.

Author contributions: All authors have equally contributed to the article.

References

- Breen, D., Powell, C., & Anderson, R. (2020). Pacing During 200-m Competitive Masters Swimming. *The Journal of Strength & Conditioning Research*, 34(7), 1903-1910. DOI: 10.1519/JSC.0000000000003621
- Cuenca-Fernández, F., Ruiz-Navarro, J. J., Polach, M., Arellano, R., & Born, D. P. (2023). Short-course performance variation across all race sections: How 100 and 200 m elite male swimmers progress between rounds. *Frontiers in Sports and Active*

- Living*, 5, 1146711. <https://doi.org/10.3389/fspor.2023.1146711>.
- Damasceno, M., Correia-Oliveira, C. R., Narita, T., Pasqua, L., Bueno, S., Lima-Silva, A. E., & Bertuzzi, R. (2013). Estratégia adotada em provas de natação estilo crawl: uma análise das distâncias de 800 e 1500m. *Revista Brasileira de Cineantropometria & Desempenho Humano*, 15, 361-370. <https://doi.org/10.5007/1980-0037.2013v15n3p361>
- Everitt, B. S. (2005). Cluster analysis of subjects, hierarchical methods. *Encyclopedia of biostatistics*, <https://doi.org/10.1002/0470011815.b2a13008>
- Gonjo, T., & Olstad, B. H. (2021). Race analysis in competitive swimming: A narrative review. *International Journal of Environmental Research and Public Health*, 18(1), 69. <https://doi.org/10.3390/ijerph18010069>
- Haljand, R., & Saagpakk, R. (1994). Swimming competition analysis of the European Sprint Swimming Championship. *LEN, Stavanger*.
- Huot-Marchand, F., Nesi, X., Sidney, M., Alberty, M., & Pelayo, P. (2005). Swimming: Variations of stroking parameters associated with 200 m competitive performance improvement in top-standard front crawl swimmers. *Sports biomechanics*, 4(1), 89-100. <https://doi.org/10.1080/14763140508522854>
- Kriegel, H. P., Kröger, P., Sander, J., & Zimek, A. (2011). Density-based clustering. *Wiley interdisciplinary reviews: data mining and knowledge discovery*, 1(3), 231-240. <https://doi.org/10.1002/widm.30>
- Maglischo, E. W. (2003). Swimming fastest. *Human Kinetics*.
- McGibbon, K. E., Pyne, D. B., Shephard, M. E., & Thompson, K. G. (2018). Pacing in Swimming: A Systematic Review. *Sports Medicine*, 48(7), 1621-1633. <https://doi.org/10.1007/s40279-018-0901-9>
- McGibbon, K. E., Pyne, D. B., Shephard, M. E., Osborne, M. A., & Thompson, K. G. (2020). Contemporary practices of high-performance swimming coaches on pacing skill development and competition preparation. *International Journal of Sports Science and Coaching*, 15(4), 495-505. <https://doi.org/10.1177/1747954120926643>
- Menting, S. G. P., Elferink-Gemser, M. T., Huijgen, B. C., & Hettinga, F. J. (2019). Pacing in lane-based head-to-head competitions: A systematic review on swimming. *Journal of sports sciences*, 37(20), 2287-2299. <https://doi.org/10.1080/02640414.2019.1627989>
- Moraes, J. E., Barbosa, T. M., Forte, P., Pinto, J. N., & Marinho, D. A. (2021). Assessment of the inter-lap stability and relationship between the race time and start, clean swim, turn and finish variables in elite male junior swimmers' 200 m freestyle. *Sports Biomechanics*, 1-14. <https://doi.org/10.1080/14763141.2021.1952298>
- O'Connor, L. M., & Vozenilek, J. A. (2011). Is It the Athlete or the Equipment? An Analysis of the Top Swim Performances from 1990 to 2010. *The Journal of Strength and Conditioning Research*, 25(12), 3239-3241. <https://doi.org/10.1519/jsc.0b013e3182392c5f>
- de Oliveira, L. L., Soares, E. R., de Oliveira, G. T., & Ferreira, R. M. (2023). What pacing is used by the best swimmers in the 200m freestyle?. *Motricidade*, 19(1). <https://doi.org/10.6063/motricidade.27905>
- Robertson, E. Y., Pyne, D. B., Hopkins, W. G., & Anson, J. M. (2009). Analysis of lap times in international swimming competitions. *Journal of Sports Sciences*, 27(4), 387-395. <https://doi.org/10.1080/02640410802641400>
- Santos, C. C., Fernandes, R. J., Marinho, D. A., & Costa, M. J. (2023). From Entry to Finals: Progression and Variability of Swimming Performance at the 2022 FINA World Championships. *Journal of sports science & medicine*, 22(3), 417-424. <https://doi.org/10.52082/jssm.2023.417>
- Da Silva, J., K.F., Enes, A. A. N., Sotomaior, B. B., Barbosa, M. A. R., De Souza, R., O., & Osiecki, R. (2020). Analysis of the performance of finalist swimming athletes in olympic games: Reaction time, partial time, speed, and final time. *Journal of Physical Education and Sport*, 20(2), 539-545. <https://doi.org/10.7752/jpes.2020.02080>
- de Souza Castro, F., & Mota, C. B. (2010). Energética e desempenho em 200 m nado crawl realizado sob máxima intensidade. *Revista Brasileira de Ciência e Movimento*, 18(2), 67-75. <https://doi.org/10.18511/rbcm.v18i2.1347>
- De Souza Castro, F. A., Diefenthaler, F., Colpes, F., Silveira, R. P., & Franken, M. (2017). Desempenho e pacing na prova de 200 m nado borboleta: variabilidade e relações dos tempos parciais de 50 m com o tempo final. *Revista Andaluza de Medicina del Deporte*, 10(4), 197-201. <https://doi.org/10.1016/j.ramd.2016.02.007>
- Takeda, T., Ichikawa, H., Takagi, H., & Tsubakimoto, S. (2009). Do differences in initial speed persist to the stroke phase in front-crawl swimming?. *Journal of sports sciences*, 27(13), 1449-1454. <https://doi.org/10.1080/02640410903046228>
- Thompson, K., MacLaren, D., Lees, A., & Atkinson, G. (2003). The effect of even, positive and negative pacing on metabolic, kinematic and temporal variables during breaststroke swimming. *European Journal of Applied Physiology*, 88(4), 438-443. <https://doi.org/10.1007/s00421-002-0715-0>
- Veiga, S., & Roig, A. (2016). Underwater and surface strategies of 200 m world level swimmers. *Journal of sports sciences*, 34(8), 766-771. <https://doi.org/10.1080/02640414.2015.1069382>