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Educational Insights from the Retrospective Analysis of an Annual Training Cycle: Case Study of a Slovak Swimmer's Preparation for the 2023 World Championship in Fukuoka

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Abstract: *The elite swimmer of the Slovak Republic (T.P.), a participant in the 2023 World Swimming Championships in Fukuoka, has since 2012 recorded a gradual increase in performance in the swimming disciplines of 400 m freestyle with a resulting time of 3:49.03 (795 points, SCM) and 800 m freestyle with a resulting with a time of 8:12.87 (771 points, LCM). From the point of view of the annual training macrocycle of ATC 2023, he achieved his best sports performances in the 400m freestyle with a final time of 3:53.88 (747 points, SCM) and in the 800m freestyle with a final time of 8:07.68 (751 points, SCM). We identified the general and special training variables that were most closely related to the swimmer's athletic performance through a retrospective analysis. For interaction identification and prediction, we applied non-parametric techniques (CHAID decision trees and Spearman's correlation coefficient). The available data was analyzed using the technique to examine at the swimmers' workout records from the ATC 2023 annual training cycle. The available data, which include the volume of race pace (STI 105), elemental arm swimming (STI 106), and volume of anaerobic endurance (STI 104), as well as the number of starts (GTI 112) and training units (GTI 111), were analyzed by looking at the swimmers' training diaries from the ATC 2023 annual training cycle.*

Keywords: *performance; training cycle; swimmer; training variables.*

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Introduction

Since the inaugural modern Olympic Games in 1896, swimming has been an integral part of the Olympic program, evolving into one of the largest Olympic sports, with 32 pool events ranging from 50 to 1500 meters. The competitive nature of swimming has led to continuous improvements in training methodologies aimed at enhancing performance, endurance, strength, and technical efficiency. Over the years, advancements in biomechanics, physiology, and sports science have contributed to the optimization of training regimens, allowing athletes to push the limits of human performance. At the 2012 London Olympics, for instance, the winning time in the 50-meter freestyle was 21.34 seconds, while the 1500-meter event was completed in approximately 14 minutes 31.02 seconds, reflecting the remarkable speed and endurance capabilities of elite swimmers. Notably, 26 out of 32 Olympic swimming events (81%) are raced over distances of 200 meters or less, with median times under 2 minutes and 20 seconds (Nugent et al., 2017). These statistics emphasize the need for swimmers to achieve explosive power, efficient energy utilization, and effective race strategies to compete at the highest levels.

Competitive swimming demands a delicate balance between training volume, intensity, and recovery to maximize performance while minimizing physiological and psychological stress. Traditional training programs have focused on high-volume endurance training, emphasizing aerobic capacity and muscular adaptation. However, recent research suggests that low-volume, high-intensity training (HIIT) and periodized approaches can provide similar or even superior performance benefits, reducing the risk of overtraining, chronic fatigue, and injuries (Nugent et al., 2017; Amara et al., 2023). Physiological development, including muscle strength, aerobic endurance, and anaerobic capacity, is essential for swimmers to achieve optimal race performance (Monteiro et al., 2023). However, neuromuscular and mental fatigue, physiological strain, and injuries may occur due to the rigorous demands of training (De Martino & Rodeo, 2018; Chortane et al., 2022). Training loads must therefore be strategically planned to balance progressive overload with sufficient recovery periods to prevent negative adaptations and ensure peak performance.

To achieve optimal readiness for competition, swimmers follow structured periodization models, which systematically vary training volume and intensity across different training phases. Tapering is a widely adopted pre-competition strategy, aimed at reducing training volume while maintaining intensity to optimize physiological and psychological recovery

(Bachelor et al., 2023; Stone et al., 2023). Research indicates that proper tapering techniques can enhance neuromuscular function, reduce physiological fatigue, and improve overall performance on race day (Pla et al., 2019). Additionally, individualized training periodization is crucial, as swimmers have unique physiological profiles and specialization requirements, necessitating customized training regimens (Bompa & Haff, 2009; Platonov, 2019). Despite the growing body of research on training periodization and tapering, there is no universally accepted model for structuring training loads, as event specialization, physiological variability, and adaptive responses differ significantly among athletes (González-Ravé et al., 2021; Hellard et al., 2019).

An essential aspect of swimming preparation is the ability to analyze and interpret training load data to assess general and specific performance indicators. Coaches rely on quantitative performance metrics to predict athletic progress, identify areas for improvement, and make data-driven adjustments to training programs (Chatard & Stewart, 2011; Pollock et al., 2019). The integration of sports analytics and machine learning techniques has enabled coaches and sports scientists to utilize advanced statistical models for training load management and race performance predictions. Classification techniques such as machine learning algorithms, regression models, and decision trees are increasingly being applied to identify key training factors that influence swimming performance (Breiman et al., 1984; Cohen, 1988; Lehmann, 2006). These methods provide valuable insights into individual athlete performance trends, allowing for a more systematic and evidence-based approach to training optimization.

Beyond physical conditioning, technical efficiency and biomechanical improvements play a vital role in maximizing swimming performance. Recent studies have explored the impact of ventilatory responses to varying intensity levels, as well as the risk of multidirectional shoulder instability, particularly among competitive swimmers engaged in high-volume training (Monteiro et al., 2023; De Martino & Rodeo, 2018). Additionally, dry-land training programs incorporating strength, mobility, and core stabilization exercises have been shown to enhance stroke power, endurance, and injury prevention (Amara et al., 2023). The combination of HIIT and dry-land training has demonstrated significant improvements in explosive strength, technical precision, and overall race performance, making it a highly effective training method for age-group and elite swimmers alike (Ravé et al., 2022).

This study aims to examine the intra-individual periodization of training load and its impact on the sports performance of a Slovak swimmer during the 2023 annual training cycle (ATC). By evaluating training periodization strategies, physiological adaptations, and statistical modeling approaches, this research seeks to provide a comprehensive framework for optimizing training methodologies while addressing individual variability in performance development. Additionally, this study contributes to the growing body of knowledge on training load monitoring, physiological adaptations, and race performance predictions, with the goal of enhancing training efficiency and long-term athlete development. Through an integrative analysis of periodization models, data analytics, and training adaptations, this research aims to establish best practices for optimizing training loads, managing fatigue, and improving competitive swimming performance.

Materials and methods

T.P., a Slovak representative competitor in the 2023 World Swimming Championships in Fukuoka (born in 2002) body height 192 mc, body weight 86,4 kg and Vo2 max: 54.3 mL/min/Kg, continues to improve his athletic performance in the disciplines since 2012 (800 m freestyle, 8:12.87, 771 points, LCM, and 400 m free-style, 3:49.03, 795 points, SCM). During the 2023 annual training macrocycle, he set his best times in the 800-meter freestyle race (8:07.68, 751 points, SCM) in the 400-meter freestyle event (3:53.88, 747 points, SCM).

Periodization metrics

The parameters influencing sports performance in the ATC 2023 yearly training cycle are first revealed using non-specific (nsPM) and specific (sPM) periodization metrics from the training diary (Table 1). The weekly volume periodization metrics nsPM 110-115, sPM 101-108, and year-round sports performance (SP), which were translated to point values in accordance with FINA tables, served as the foundation for the analysis (https://www.worldaquatics.com/swimming/points) (Table 1).

The annual time series lasted for fifty-two weeks. Individual weekly micro cycle sports performance was recalculated using point values from 50,100, 200 and 400 meter swimming tests and performances.

Table 1. Volume Metrics of Non-Specific and Specific Periodization in the 2023 Annual Training Cycle

Code		Periodization metrics	Sum	Min	Max	M	SD
PO		Performance output (points)	32203.00	538.00	751.00	619.29	56.50
nsPM	110	Training load days (n)	265.00	3.00	7.00	5.10	0.87
	111	Total training sessions (n)	471.00	5.00	13.00	9.06	1.94
	112	Number of competitions (n)	67.00	0.00	9.00	1.29	2.52
	113	Cumulative training duration (h)	874.50	8.00	22.50	16.82	3.20
	114	Recovery duration (h)	122.00	1.00	4.00	2.35	0.81
	115	Days of medical absence (n)	20.00	0.00	3.00	0.38	0.84
sPM	101	Total distance swum (km)	2133.20	23.50	58.10	41.02	7.97
	102	Warm-up and cool-down volume (km)	351.55	3.80	10.95	6.76	1.77
	103	Aerobic endurance volume (km)	1236.20	12.20	34.90	23.77	5.16
	104	Anaerobic endurance volume (km)	87.80	0.00	4.05	1.69	1.07
	105	Race-pace swimming volume (km)	27.00	0.00	1.60	0.52	0.44
	106	Arm stroke volume (km)	57.65	0.00	3.10	1.11	0.82
	107	Leg kick volume (km)	259.65	2.30	8.35	4.99	1.48
	108	Technical drill volume (km)	115.25	1.30	3.20	2.22	0.50

Methods

We assessed the normality of data distribution across the datasets and employed nonparametric statistical methods for analysis (Breiman et al., 1984; Lehmann, 2006). Given the characteristics of our data, we utilized the Spearman correlation coefficient (r_s) to evaluate the relationship between sports performance and training indicators, as it is particularly effective in identifying monotonic associations in nonparametric datasets (Cohen, 1988).

To further explore variable interactions and performance determinants, we constructed decision trees using the Chi-squared Automatic Interaction Detector (CHAID), a nonparametric algorithm commonly applied in classification, prediction, and interaction analysis (Breiman et al., 1984). This method leverages Chi-square tests to identify significant relationships between independent variables, enabling an automated and structured interpretation of complex interactions. One of the key advantages of CHAID-based Classification and Regression Trees (CART) is their ability to generate binary trees with multiple branching pathways, improving model interpretability and result visualization.

In line with Camp & Slattery (2002), we selected the most influential predictor variable at each stage of the analysis to ensure an accurate classification of dependent variable categories. However, it is important to acknowledge that CHAID does not always determine the optimal variable distribution and may halt category merging when remaining groups are deemed statistically distinct.

Ultimately, our analysis follows a rational, systematic, and unbiased approach, ensuring a scientifically rigorous evaluation of the data and enhancing the validity and reliability of our findings.

Results

The Slovak swimming representative (T.P.) obtained the highest point performance in the 2023 annual training cycle with a value of 751 points in the 800-meter freestyle discipline with a final time of 8:07.68, SCM, thanks to the intra-individual periodization of the training load.

The swimmer's overall load volume for the 2023 annual training cycle was 2133.20 km, or 41.02 km per week on average. The load volume was 23.50 km at the lowest level and 58.10 km at the highest. Over the course of 265 loading days, the swimmer completed 471 training units, or at least 5 and up to 13 training units per week. In terms of regeneration, the swimmer spent 13.90% of the total load time (122 hours) regenerating during the yearly training cycle.

Warm-up and cool-down volume (sPM 102) was 351.55 km (16.48%). At 1236.20 km (57.95%), the swimmer's workload was primarily composed of aerobic endurance (sPM 103). In 87.80 km (4.12%), anaerobic endurance (sPM 104) was achieved. The race-pace swimming volume (sPM 105) at the level of 27 km (1.26%) constituted the least portion of the workload. The volume of leg kick swimming (sPM 107) and arm stroke swimming (sPM 106) achieved 259.65 km (12.17%) and 57.65 km (2.70%), respectively. The final section consisted of technical exercises (sPM 108), which had a volume of 115.25 (5.40%).

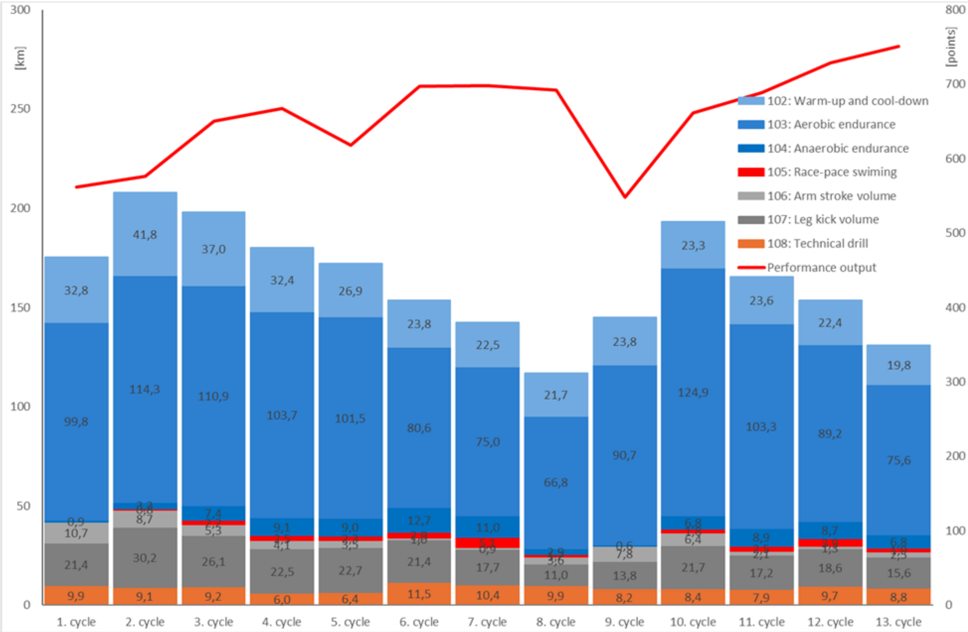

Figure 1. Periodization of training load in annual training cycle 2023 (mesocycles)

We were able to identify the predictors that most significantly impacted the swimmer's average sports performance in ATC 2023, or categorize interactions between training indicators and sports performance, using non-parametric techniques.

Non-specific periodization metrics and performance output showed statistically significant relationships (Table 2) with the number of events (nsPM 112, $r_s = 0.701$, $p<0.01$) and training units (nsPM 111, $r_s = -0.370$, $p=0.007$). The volume of warm-up and swim-out (sPM 102, $r_s = -0.323$, $p = 0.019$), aerobic endurance (sPM 103, $r_s = -0.328$, $p = 0.018$), an-aerobic endurance (sPM 104, $r_s = 0.794$, $p<0.01$), race pace (sPM 105, $r_s = 0.867$, $p<0.01$), elemental arm swimming (sPM 106, $r_s = -0.863$, $p<0.01$), and technical exercises (sPM 108, $r_s = 0.376$, $p = 0.006$) constitute the special training indicators.

The non-parametric CHAID algorithm generated prediction models with high reliability and an acceptable margin of error (Figures 2 and 3, Tables 3 and 4). These models incorporated periodization metrics that exhibited varying degrees of correlation with swimming performance, ranging from low to high associations. The selected periodization metrics function as key nodal variables, each representing specific volume thresholds that help predict performance outcomes at both higher and lower training loads.

As expected with the CHAID algorithm, the resulting decision trees offer multiple branching pathways, reflecting the complexity of performance prediction. The algorithm produced a highly detailed tree structure, where the interactions between periodization metrics determine the variability of performance outcomes. A comprehensive and systematic interpretation of these branches allows for a deeper understanding of how training load distribution impacts performance variability.

Between the key predictors of performance output (Figure 3, Table 4), the analysis identified three specialized periodization metrics: race-pace volume (sPM 105), arm stroke swimming (sPM 106), and anaerobic endurance (sPM 104), each playing a crucial role in optimizing training strategies for competitive swimmers.

Table 2. Correlation of Performance output and Periodization metrics

Code		**Periodization metrics**	**r^s**	**p**
nsPM	110	Training load days (n)	-0.112	0.431
	111	Total training sessions (n)	**-0.370**	**0.007**
	112	Number of competitions (n)	**0.701**	**0.000**
	113	Cumulative training duration (h)	-0.132	0.352
	114	Recovery duration (h)	0.245	0.080
	115	Days of medical absence (n)	-0.224	0.110
sPM	101	Total distance swum (km)	-0.232	0.097
	102	Warm-up and cool-down volume (km)	**-0.323**	**0.019**
	103	Aerobic endurance volume (km)	**-0.328**	**0.018**
	104	Anaerobic endurance volume (km)	**0.794**	**0.000**
	105	Race-pace swimming volume (km)	**0.867**	**0.000**
	106	Arm stroke volume (km)	**-0.863**	**0.000**
	107	Leg kick volume (km)	-0.112	0.429
	108	Technical drill volume (km)	**0.376**	**0.006**

Non-specific periodization metrics and performance output

From a broader perspective of Non-specific periodization metrics (Figure 2, Table 3), two primary predictors of sports performance were identified:

1. Number of events per week (nsPM 112)
2. Number of training units per week (nsPM 111)

Third Branch: The predicted average performance output of 619 points (n = 52 performances) is significantly influenced by participation in more than four events per week (nsPM 112, $F = 29.168$; $p < 0.01$). Additionally, the number of total training units exceeding 8 per week (nsPM

111, $F = \infty$; $p < 0.01$) correlates with the highest observed performance of 751 points ($n = 1$), while swimmers surpassing four weekly events reached an average of 714 points ($n = 5$).

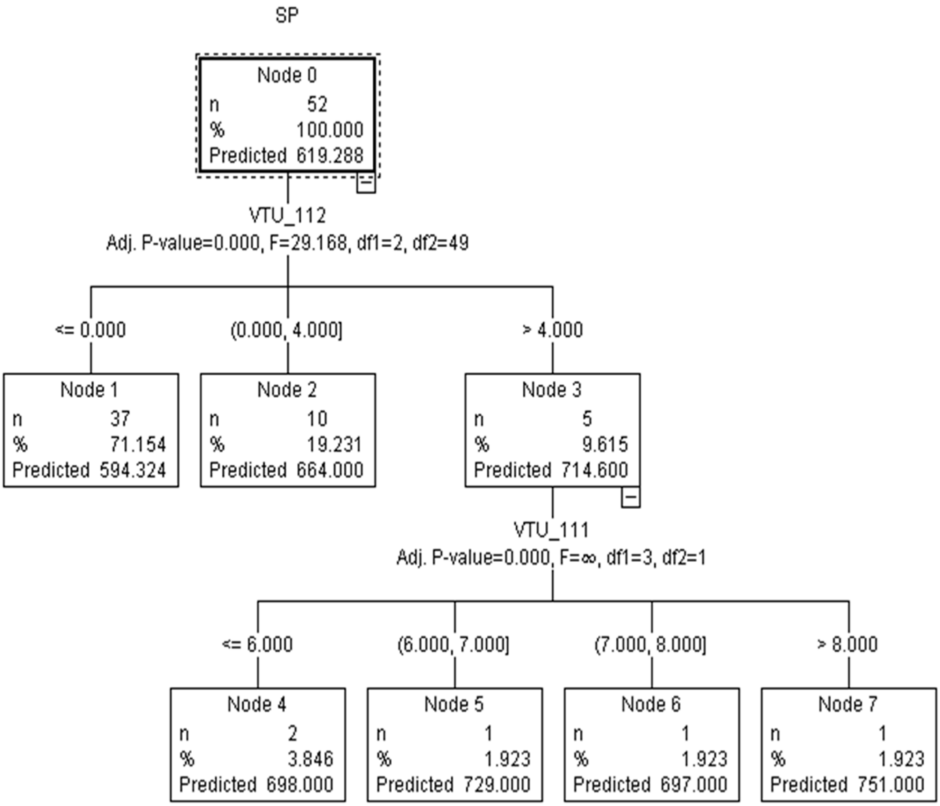

Figure 2. Regression tree of selected non-specific periodization metrics nsPM 110-115 to sports performance by the CHAID method (R: 0.747; SD: 37.553; MAE: 27.801; ME 0.0; MAXE 106.676; MINE -56.324)

Table 3. Prediction model of non-specific periodization metrics for performance output in swimming using the CHAID method

Node	Criterion	Prediction	Effect	N	%
1	nsPM 112 <= 0	594.3	-24.964	37	71.154
2	nsPM 112 > 0 and nsPM _112 <= 4	664.0	44.712	10	19.231
3	nsPM 112 > 4	714.6	95.312	3	9.615
4	nsPM 111 <= 6	698.0	-16.6	2	3.846
5	nsPM 111 > 6 and nsPM_111 <= 7	729.0	14.4	1	1.923
6	nsPM 111 > 7 and nsPM_111 <= 8	697.0	-17.6	1	1.923
7	nsPM 111 > 8	751.0	36.4	1	1.923

Race-Pace Swimming Volume and Performance Predictions

Third Branch: The predicted average performance output is 619 points (based on n = 52 performances) and is primarily influenced by the weekly volume of race-pace swimming exceeding 0.8 km (sPM 105, F = 50.833; p < 0.01). Within this subset, athletes achieving a weekly race-pace volume higher than 0.8 km demonstrated an average performance of 702 points (n = 10).

Second Branch: For swimmers with lower predicted sports performance, a weekly race-pace volume between 0.6 km and 0.8 km (sPM 105, F = 50.833; p < 0.01) is considered sufficient to support performance. Within this range, athletes who combined race-pace swimming with elemental arm swimming at or below 0.2 km (sPM 106, F = ∞; p < 0.01) achieved an average performance of 701 points (n = 1). Meanwhile, a predicted performance of 661 points (n = 5) was observed in cases where race-pace swimming remained within this intermediate range but lacked additional supporting training variables.

First Branch: When the weekly race-pace volume is between 0.5 km and 0.6 km (sPM 105, F = 50.833; p < 0.01; 626 points; n = 10), performance is influenced by elemental arm swimming. Swimmers who completed between 0.3 km and 0.7 km of elemental arm swimming (sPM 106, F = 38.390; p < 0.01; n = 2) demonstrated higher predicted performance outcomes. However, if elemental arm swimming volume is ≤ 0.3 km, a predicted performance of 634 points (n = 3) is achieved only when supported by an anaerobic endurance volume ≤ 2.5 km (sPM 104, F = 0.01; n = 1).

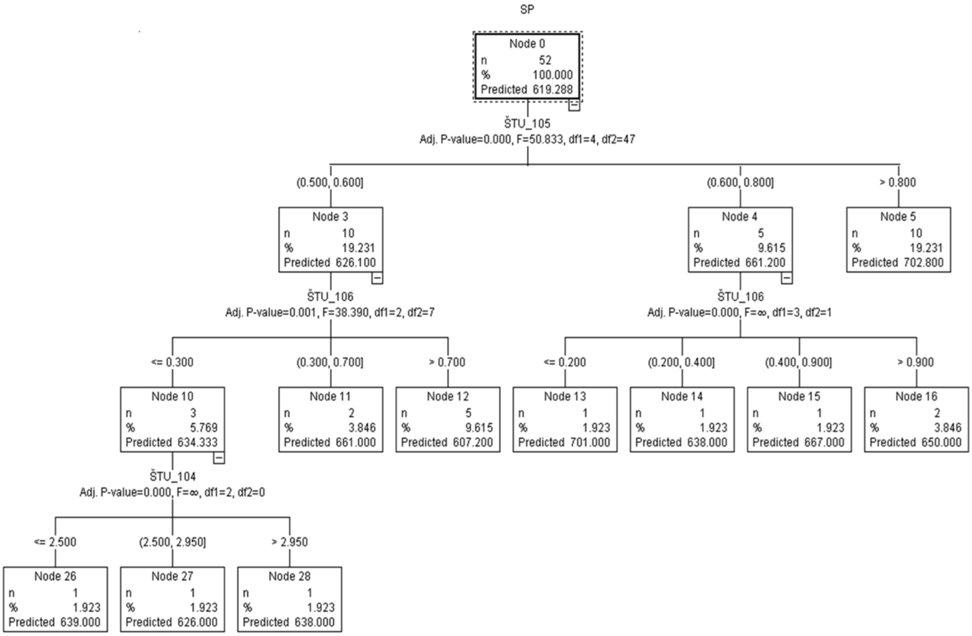

Figure 3. Regression tree of selected specific periodization metrics sPM 101-108 to sports performance by the CHAID method (branches with better predicted performances) (R: 0.981; SD: 10.934; MAE: 5.704; ME 0.0; MAXE 48.2, MINE -26.5)

Table 4. Prediction model of specific periodization metrics for performance output in swimming using the CHAID method

Node	Criterion	Prediction	Effect	N	%
3	sPM 105 > 0.5 and sPM 105 <= 0.6	626.1	6.812	10	19.231
10	sPM 106 <= 0.3	634.33	8.233	3	5.769
26	sPM 104 <= 2	639.0	4.667	1	1.923
27	sPM 104 > 2 and sPM 104 <= 3	626.0	-8.333	1	1.923
28	sPM 104 > 3	638.0	3.667	1	1.923
11	sPM 106 > 0.3 and sPM 106 <= 0.7	661.0	34.9	2	3.846
12	sPM 106 > 0.7	607.2	-18.9	5	9.615
4	sPM 105 > 0.6 and sPM 105 <= 0.8	661.2	41.912	5	9.615
13	sPM 106 <= 0.2	701.0	39.8	1	1.923
14	sPM 106 > 0.2 and sPM 106 <= 0.4	638.0	-23.2	1	1.923
15	sPM 106 > 0.4 and sPM 106 <= 0.9	667.0	5.8	1	1.923
16	sPM 106 <= 0.9	650.0	-11.2	2	3.846
5	sPM 105 > 0.8	702.8	83.512	10	19.231

Discussion

Achieving peak performance in elite swimming competitions requires long-term strategic training planning, often structured over multiple seasonal cycles. To ensure optimal athletic performance at major events, training must be systematically broken down into manageable phases, each focusing on different aspects of physical conditioning, technical refinement, and performance monitoring (Maglischo, 2003). The two-peak season approach adopted in this study aligns with well-established periodization models, in which training load is structured around key competition events. In this case, the swimmer's first peak was observed during the World Championships in Fukuoka (7th mesocycle), while the second peak occurred during the national short course championships (13th mesocycle).

The total training load across the annual training cycle (ATC) 2023 included 471 training units, 874.50 hours of total training time, and a total volume of 2133.20 km. Comparing these values with previous elite-level swimming studies, Mitrenga (2006) found that an Olympic swimmer’s training cycle included 295 load days, 696 training hours, and 1829.80 km of total volume, while Vaňková (2010) reported a total volume of 2511.70 km and a load time of 780 hours for Czech elite swimmers. Additionally, Krčková (2013) documented a higher total volume of 2873 km across 518 training units in an Olympic-level swimmer. These findings emphasize the variability in training demands, with differences likely arising from individualized training approaches, event specialization, and physiological adaptations.

On a weekly basis, the swimmer completed between 5 and 13 training sessions, aligning with Finney’s (2003) recommended range of 10 to 11 sessions per week. Meeusen et al. (2013) suggested that reducing training frequency to 9 sessions per week in British swimmers helped prevent overtraining, highlighting the importance of individualized workload management. In terms of training duration, our results showed weekly microcycle loads ranging from 8 to 22.5 hours, consistent with Finney’s (2013) recommendation of not exceeding 23 training hours per week.

Comparing training volumes, Chatard & Stewart (2011) suggested that elite swimmers typically swim 45-60 km per week, while Bonifazi et al. (2000) and Mujika et al. (2002) reported weekly distances of 50-60 km for the Italian national team and Australian Olympic team, respectively. British swimmers, by contrast, follow a lower-volume approach (43-53 km per week) to mitigate overtraining risks (Meeusen et al., 2013). Gonzalez-Ravé et al. (2021) recommended training volumes between 25 and 90 km per week for swimmers scoring 850-900 FINA points, reflecting a wide range of training loads tailored to performance levels.

A critical aspect of training periodization is the gradual reduction in training intensity in the weeks leading up to competition, allowing for optimal recovery and peak performance (Hermosilla et al., 2021; Solonenco et al., 2021; Chatard & Stewart, 2011). Our findings support this approach, as the highest peak performances were recorded in mesocycles 7 and 13, corresponding with tapering phases leading into major competitions.

In swimming, training periodization adapts the training load to the swimmer's event-specific needs and physiological development. As outlined by Bompa & Haff (2009), a well-designed periodization model integrates multiple training zones, progressively adjusting volume, intensity, and specialization throughout the season. Our study incorporated specific periodization metrics (sPM) such as race-pace swimming volume (sPM 105), arm stroke volume (STI 106), and anaerobic endurance (sPM 104) into performance prediction models.

For swimmers specializing in the 400m freestyle, race-pace volume plays a vital role in simulating competitive conditions during training. The inclusion of arm stroke volume is particularly relevant, as upper-body strength and endurance contribute to maintaining efficiency while conserving lower-body power for the final race stages. The balance between aerobic and anaerobic endurance is another key determinant, as the 400m freestyle is composed of approximately 60% aerobic and 40% anaerobic capacity. Consequently, middle- and long-distance swimmers benefit from training blocks focused on threshold-oriented intensity distribution (Pla et al., 2019; Bonifazi, 2000).

Race-pace swimming volume varied considerably across studies. In our results, weekly race-pace volume peaked at 1.6 km per microcycle, compared to Pollock et al. (2019), who reported 1.3 km per week. However, Maglischo (2003) recommended a significantly higher 3 km per week, while Krčková (2013) documented an annual race-pace training volume of 70 km—far exceeding our swimmer's total of 27 km. Mitrenga (2006) reported 47.90 km of race-pace volume, highlighting variability in distance covered at high-intensity paces. These differences further emphasize the need for individualized periodization models, ensuring that training loads align with the athlete's physiological and technical strengths.

Our findings align with those of Yang et al. (2024), who used a decision-tree model to analyze pacing strategies in elite individual medley (IM) swimmers. Their study revealed that a higher proportion of standardized time allocated to the butterfly leg significantly correlated with successful performance outcomes. Similarly, our decision-tree analysis incorporated key training variables, including race-pace volume, anaerobic endurance, and elemental arm swimming, to predict performance outcomes.

While Yang et al. (2024) focused on within-race pacing distribution, our study explored training periodization over an entire season, identifying weekly and annual training loads associated with peak performance. Both studies emphasize the importance of optimizing energy allocation—Yang et al. (2024) highlighted the significance of stroke efficiency within races, whereas our study underscores the need for balanced periodization to develop both aerobic and anaerobic energy systems in training.

Additionally, Yang et al. (2024) identified front crawl as a critical determinant of 200m IM success, while backstroke and breaststroke played a larger role in 400m IM performance. Similarly, our findings suggest that elemental arm swimming is a key determinant of middle-distance freestyle success, reinforcing the concept that upper-body efficiency is crucial for performance across multiple swimming disciplines.

In summary, both studies support the application of decision-tree models in swimming research, demonstrating their effectiveness in identifying key performance determinants. While our work focused on long-term training adaptations, Yang et al. (2024) provided insights into within-race pacing strategies, highlighting the complementary nature of training and competition analysis in optimizing swimmer performance.

Conclusions

This study examines the intra-individual periodization of training load in a Slovak national swimmer (T.P.) during the 2023 annual training cycle (ATC 2023). Using regression tree analysis with the CHAID method, we identified key periodization metrics that exhibited a strong correlation with the swimmer’s year-round performance outcomes. The optimal training load was subsequently characterized in terms of volume, intensity, and variability, enabling a predictive model for sports performance.

Our findings highlight the significant influence of race-pace swimming volume (sPM 105), Arm stroke volume (sPM 106), and anaerobic endurance (sPM 104) as critical factors in performance development. Additionally, among non-specific periodization metrics, the Number of competitions (nsPM 112) and Total training sessions (nsPM 111) emerged as key contributors to performance enhancement.

Through a retrospective analysis, we classified the training components most effective in optimizing the swimmer’s competitive performance. Accurately identifying these key performance determinants provides a scientific basis for refining training periodization, harmonizing sports training methodologies, and enhancing tapering strategies before major competitions such as the European Championships, World Championships, and the Olympic Games.

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