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Original Article

Training load determining sports performance of swimmer in preparation for top events

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Abstract
A representative of the Slovak Republic, T. P., and a participant in the 2024 World Championships in Doha and the European Championships in Belgrade, has shown progressive improvement in athletic performance since 2012 in the disciplines of 400 m freestyle (3:49.03, 795 points, SCM) and 800 m freestyle (8:12.87, 771 points, LCM). In the 2024 annual training macrocycle, he achieved his best performance in the 400 m freestyle with a time of 3:55.19, scoring 735 points. A retrospective analysis classified specific and general training means that showed the highest correlation with swimming performance. Non-parametric methods such as Spearman's rank correlation coefficient and CHAID decision trees were used to detect interactions and make predictions. The data analysis was based on the study of the athlete's training diaries from the 2024 annual training cycle. Among the specific training indicators, the determinants of sports performance included volume swum at race pace (STI 105), arm technique drills (STI 106), and technical drills (STI 108). Among general training means, performance was determined by recovery time (GTI 114), number of training sessions (GTI 111), and load time (GTI 113). The contribution is part of the UGA project V/4/2025 Training load determining sports performance in swimming
Key Words: World Championships, European Championships, swimming, performance, load, predictors

Introduction

Changes in the level of athletic performance are inconceivable without the purposeful use and manipulation of training load. Based on this, sports performance is limited by factors that can be more or less influenced through the training process. Additionally, the applied load during athletic preparation and the athlete's adaptation to it play a crucial role in enhancing abilities or qualities.

Over the past few decades, the swimming world has witnessed a steady rise in swimmers' performance levels. Between 2008 and 2009, more than 130 world records were broken. This high number was largely attributed to swimsuits that had undergone significant innovations. These suits were later banned by the International Swimming Federation (FINA). At the time, the sports community believed that many of the records set in these suits would remain unbroken. However, the reality is that many of those records have since been surpassed. The continuous improvement in swimming performance has pushed coaches to develop new training principles or to optimize existing training methods. For elite swimmers, the primary goal is to swim faster and achieve better times compared to their competitors, or to become the fastest swimmer in the world and break personal, national, or even world records. According to Bompa (1999), the training process is characterized by its complexity and versatility, as it constantly changes based on the application of selected training loads. The main goal of training load is to influence and enhance specific activities, abilities, and attributes.

With properly selected periodization of training load, athletes are capable of reaching an optimal level of readiness for peak events (Platonov, 2019). Through careful analysis of training loads, we can assess and identify general and specific indicators of training. These insights allow coaches to predict athletes' performance throughout the training process. Each swimming discipline is unique in terms of its training load, aerobic and anaerobic volume, and especially the volume performed at race pace. The volumes of these characteristics can vary significantly even among swimmers specializing in the same events.

In the literature, we find numerous recommendations for weekly training volumes, such as those by Chatard and Stewart (2011), Hellard et al. (2019), Pollock et al. (2019), Pla et al. (2019), Solonec et al. (2021), María Gonzalez Rave et al. (2021), Hermosilla et al. (2021), and Ravé et al. (2022). These recommendations help in creating an accurate model of training load structure. Based on the literature review, we expect specific training indicators such as STI 103 (aerobic endurance), STI 104 (anaerobic endurance), and STI 105 (race-pace volume) to be dominant in predictive models. However, it is essential to remember that these recommendations and the ratio of individual characteristics may not suit every swimmer. The volumes of each characteristic will vary for each individual.

Therefore, there is no exact template or formula for applying training load in athletic preparation that fits all. What we currently have are generalizations and findings based on available knowledge.

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Materials & methods

The representative of the Slovak Republic, T. P. (born in 2002) and participant in the 2024 World Championships in Doha and the European Championships in Belgrade, has shown progressive growth in sports performance since 2012 in the disciplines of 400 m freestyle (3:49.03, 795 points, SCM) and 800 m freestyle (8:12.87, 771 points, LCM). In the 2024 annual training macrocycle, he achieved his best performance in the 400 m freestyle with a time of 3:55.19, scoring 735 points.

General (GTI) and special (STI) training indicators from the training log (Table 1) serve as the basis for identifying factors determining sports performance in the 2024 annual training cycle (ATC 2024). The core of the analysis consisted of weekly training volume indicators: GTI 110–116, STI 101–108, and overall annual sports performance (SP), recalculated into point values according to the FINA scoring tables (Table 1). The annual time series length was 52 weeks. Sports performance in each weekly microcycle was recalculated into point values based on swimming results and tests at 50 m, 100 m, 200 m, and 400 m distances.

Non-parametric methods (Breiman et al. 1984, Lehmann 1975) were selected based on assessments of the normality of the data distribution. The interaction between sports performance and training indicators was assessed using Spearman's correlation coefficient *rs* (Cohen, 1988).

To construct decision trees, the non-parametric CHAID (Chi-squared Automatic Interaction Detector) algorithm and Classification and Regression Trees (CART; Breiman et al., 1994) were used. This technique can be applied for prediction (as an alternative to parametric multiple regression), classification, and detection of interactions between variables. Results are achieved by automatically detecting relationships between independent variables using chi-square tests. The advantage of the CHAID technique (Classification and Regression Trees) lies in better summarization, interpretation, and presentation of binary trees. CHAID tends to produce trees with multiple branches (options).

In each analysis step, the algorithm searches for the single predictor that has the greatest impact on the dependent variable categories (Camp & Slattery, 2002). However, CHAID does not always find the optimal split for variables. Once it determines that all remaining categories are statistically distinct, it stops merging them.

The models also include regression parameters (Linear Correlation R, Standard Deviation SD, Mean Absolute Error MAE, Mean Error ME). These allow us to define the predictive reliability of the non-parametric model similarly to linear regression.

The findings and conclusions are formulated based on a factual and logical evaluation of the results obtained.

Table 1 Volume of General and Special Training Indicators in the Annual Training Cycle ATC 2024

Code	Training Indicators	Sum	M	Max	Min	SD
SP	Sports Performance (points)	32557.00	626.10	735.00	540.00	59.48
GTI 110	Load Days (n)	285.00	5.48	6.00	3.00	0.64
111	Training Sessions - Water (n)	415.00	7.98	10.00	3.00	1.95
112	Number of Starts (n)	45.00	0.87	2.00	0.00	1.96
113	Load Time (h)	734.00	14.12	20.00	6.00	3.94
114	Recovery Time (h)	36.00	0.69	3.00	0.00	0.81
115	Sick Days (n)	12.00	0.23	2.00	0.00	0.43
116	Training Sessions - Land (n)	71.00	1.37	2.00	0.00	0.66
STI 101	Total Distance Swum (km)	1795.00	34.52	55.30	16.50	9.63
102	Warm-Up and Cool-Down (km)	229.45	4.41	5.80	3.10	0.75
103	Aerobic Endurance (km)	1145.00	22.02	38.60	10.60	6.85
104	Anaerobic Endurance (km)	59.40	1.14	2.30	0.00	0.97
105	Distance Swum at Race Pace (km)	18.80	0.36	1.10	0.00	0.32
106	Arm Technique Drills (km)	75.70	1.46	2.60	0.60	0.56
107	Leg Technique Drills (km)	150.80	2.90	4.30	1.20	0.88
108	Technical Drills (km)	117.85	2.27	3.50	0.90	0.68

Results

Intra-individual periodization of training load enabled the Slovak swimming representative (T.P.) to achieve his highest point performance in the 2024 Annual Training Cycle (ATC 2024) with a score of 735 points in the 400 m freestyle event, with a recorded time of 3:55.19.

During the ATC 2024, the swimmer completed a total training volume of 1795.00 km, which corresponds to an average of 34.52 km per week (Min. 16.50 km; Max. 55.30 km). The total number of water-based training sessions was 415, distributed over 285 training days (Min. 3; Max. 10 sessions per week). Over the course of the annual training cycle, the swimmer spent 36 hours on recovery, representing 4.9% of the total training time.

From the perspective of total training load over the calendar year, the volume of warm-up and cool-down swimming (STI 102) reached 229.45 km (12.87%). The highest training volume was achieved in aerobic endurance (STI 103) at 1145.00 km (63.79%). Anaerobic endurance (STI 104) accounted for 59.40 km (3.31%). The distance swum at race pace (STI 105) was the smallest, totaling 18.8 km (1.05%).

Arm technique drills (STI 106) reached a volume of 75.70 km (4.22%), and leg technique drills (STI 107) amounted to 150.80 km (8.4%). The final component was technical drills (STI 108), with a total volume of 117.85 km (6.57%).

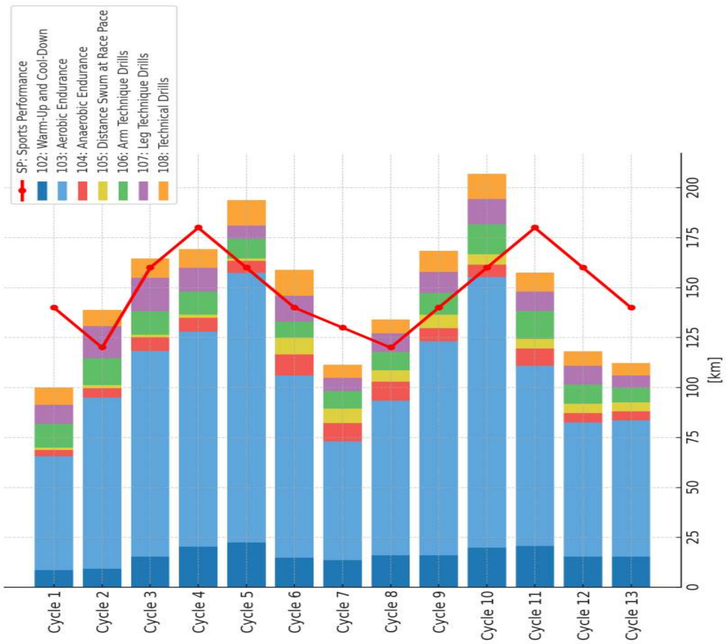

Figure 1. Periodization of Training Load in the 2024 Annual Training Cycle (Mesocycles)

Through non-parametric methods, we were able to classify the interactions between athletic performance and training indicators, or to detect predictors that most significantly influenced the average athletic performance of swimmers in the RTC 2024. Statistically significant correlations (Table 2) between general technical indicators and athletic performance were demonstrated for the number of starts (GTI 112, r^s= 0.460, p= 0.001) and recovery time (GTI 114, r^s= 0.616, p< 0.01). Among the specific training indicators, the following showed significant correlations with athletic performance: total distance swum (STI 101, r^s= -0.327, p= 0.018), volume of warm-up and cool-down (STI 102, r^s= -0.327, p= 0.018), aerobic endurance (STI 103, r^s= -0.442, p= 0.001), anaerobic endurance (STI 104, r^s= 0.434, p= 0.001), race-pace volume (STI 105, r^s= 0.779, p< 0.01), arm technique drills (STI 106, r^s= -0.509, p< 0.01), and technical drills (STI 108, r^s = -0.467, p< 0.01).

Table 2 Correlations between Sports Performance and Training Indicators

Code	**Training Indicators**	**r^s**	**p**
GTI			
110	Load Days (n)	0.017	0.903
111	Training Sessions – Water (n)	-0.173	0.219
112	Number of Starts (n)	**0.460**	**0.001**
113	Load Time (h)	-0.168	0.234
114	Recovery Time (h)	**0.616**	**0.000**
115	Sick Days (n)	-0.010	0.944
116	Training Sessions – Land (n)	-0.069	0.625
STI			
101	Total Distance Swum (km)	**-0.327**	**0.018**
102	Warm-up and Cool-Down (km)	**-0.327**	**0.018**
103	Aerobic Endurance (km)	**-0.442**	**0.001**
104	Anaerobic Endurance (km)	**0.434**	**0.001**
105	Distance Swum at Race Pace (km)	**0.779**	**0.000**
106	Arm Technique Drills (km)	**-0.509**	**0.000**
107	Leg Technique Drills (km)	-0.074	0.604
108	Technical Drills (km)	**-0.467**	**0.000**

The non-parametric CHAID algorithm constructed predictive models that demonstrate high reliability with an acceptable prediction error (Figures 2 and 3, Tables 3 and 4). The models incorporated training indicators that showed low to high correlation with swimming performance. These indicators formed node variables, each with defined threshold values, enabling the prediction of performance count based on higher or lower training loads.

As mentioned in the methodology, the CHAID algorithm generates trees with multiple branches. In this case, the algorithm created a multi-branch decision tree. Based on a substantive and logical evaluation, we interpret the branches of the regression tree that predict greater variability in athletic performance when specific combinations of training indicators are present.

Among the predictors of swimming performance (Figure 3, Table 4), the algorithm selected **special training indicators:** race pace volume (STI 105), arm drills (STI 106) and technical exercises (STI 108).

Third branch: The predicted average sports performance of 626 points (for n= 52 performances) is determined by the volume swum at race pace, when the weekly volume exceeds 0.5 km (STI 105, F= 45.739; p< 0.01; 686 points; n= 18), supported by arm technique drills volume less than or equal to 1.2 km (STI 106, F= 11.531; p= 0.030; 703 points; n= 12).

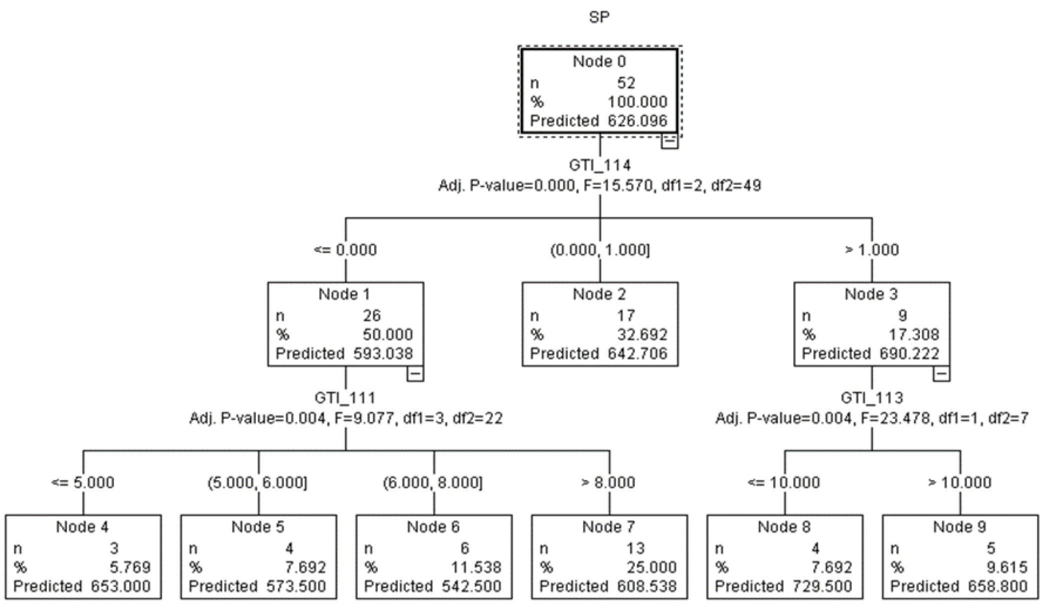

Figure 2. Regression tree of selected general training indicators GTI 110–116 in relation to sports performance using the CHAID method
(R: 0.788; SD: 36.637; MAE: 26.081; ME -0.0; MAXE 94.462; MINE -94.706)

Table 3. Predictive model of general training indicators for sports performance in swimming selected using the CHAID method

Node		Criterium	Prediction	Effect	N	%
1		GTI 114 <= 0	593	-33.058	26	50
	4	GTI 111 > 5 and GTI 111<= 6	653	59.962	3	5.769
	5	GTI 111 > 6 and GTI 111 <= 7	573.5	-19.538	4	7.692
	6	GTI 111 > 6 and GTI 111 <= 8	542.5	-50.538	6	11.538
	7	GTI 111 > 8	608.538	15.5	13	25.000
2		GTI 114 > 0 and GTI 114 <= 1	642.706	16.61	17	32.682
3		GTI 114 > 1	690.222	64.126	9	17.308
	8	GTI 113 <= 10	729.5	39.278	4	7.692
	9	GTI 113 > 10	658.8	-31.422	5	9.615

Second branch: For lower predicted sports performance, a race-pace volume ranging from 0.2 to 0.5 km is sufficient (STI 105, F= 45.739; p< 0.01; 619 points; n= 14), supported by arm technique drills with a volume less than or equal to 1.3 km (STI 106, F= 20.019; p= 0.005; 648 points; n= 5).

First branch: If the race-pace volume is less than or equal to 0.2 km (STI 105, F= 45.739; p< 0.01; 575 points; n= 20), and supported by technical drills with a volume less than or equal to 1.6 km (STI 108, F= 20.428; p= 0.002; 624 points; n= 5).

From the perspective of **general training indicators** (Figure 2, Table 3), the selected predictors of sports performance were: recovery time (GTI 114), number of training sessions (GTI 111), and load time (GTI 113).

Third branch: The predicted average sports performance of 626 points (for n= 52 performances) is determined by recovery time greater than 1 hour per week (GTI 114, F= 15.570; p< 0.01; 690 points; n= 9) and training load time less than or equal to 10 hours (GTI 113, F= 23.478; p= 0.004; 729 points; n= 4).

Second and first branches predict lower sports performance.

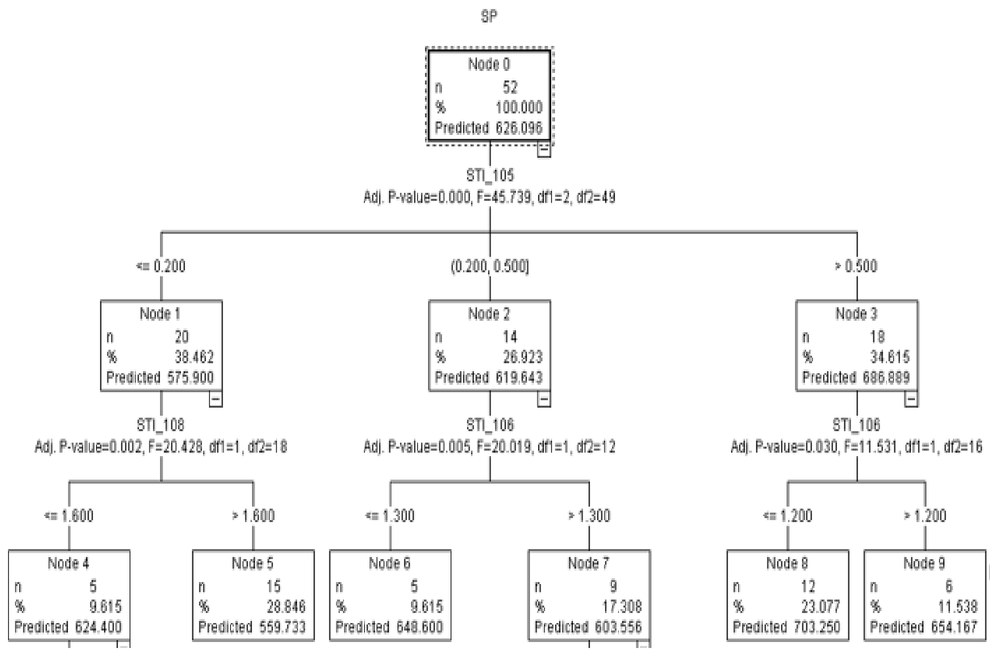

Figure 3. Regression tree of selected special training indicators STI 101–108 in relation to sports performance using the CHAID method
(R: 0.939; SD: 20.376; MAE: 14.258; ME 0.0; MAXE 42.267, MINE -63.25)

Table 4. Predictive model of special training indicators for sports performance in swimming selected using the CHAID method

Node		Criterium	Prediction	Effect	N	%
1		STI 105 <= 0.2	575.9	-50.196	20	38.462
	4	STI 108 <= 1.6	624.4	48.5	6	9.615
	5	STI 108 > 1.6	559.733	-16.167	15	28.846
2		STI 105 > 0.2 and STI 105 <= 0.5	619.643	-6.453	14	26.923
	6	STI 106 <= 1.3	648.6	28.957	5	9.615
	7	STI 106 > 1.3	603.556	-16.087	9	17.308
3		STI 105 > 0.5	686.889	60.793	18	34.615
	8	STI 106 <= 1.2	703.25	16.361	12	23.077
	9	STI 106 >1.2	654.167	-32.722	6	11.538

Discusion

Proper timing of peak athletic form for major events requires thorough planning, which should take into account a multi-year period. Naturally, such a broad task must be broken down into smaller, manageable units (Maglischo, 2003). The swimmer's training load structure followed a model for a double-peak season. The first peak occurred in the second mesocycle (Figure 1), when the swimmer competed at the World Championships in Doha. The second peak was in the sixth mesocycle, directed toward the European Championships in Belgrade.
In the literature, Hermosilla et al. (2021) recommend the commonly used pyramid model of training load periodization, where volume decreases as the main event approaches.

Thanks to the analysis of the annual training cycle, we were able to highlight the intra-individual periodization of training load. The selected periodization includes adapting the training load to the swimmer's specific needs and goals. According to Bompa and Haff (2009), it may involve a combination of several periodization types adjusted to the swimmer's progress or needs. Among the general training indicators, the swimmer completed 415 water-based training sessions and 71 dryland training sessions during the 2024 RTC, with a total training time of 734 hours and a cumulative swimming distance of 1,795 km. Vaňkova (2010) reported 423 training sessions for elite Czech swimmers, with a volume of 2,511.7 km and a total training time of 780 hours. Krčková (2013) analyzed an Olympic swimmer who completed 518 training sessions with a total volume of 2,873 km in one training year. Mitrenga (2006) described an Olympic swimmer's annual cycle consisting of 295 days of training, 696 total hours, and 1,829.8 km swum.

On a weekly microcycle level, the swimmer performed a minimum of 3 and a maximum of 10 water sessions, and up to 2 dryland sessions. Regarding training frequency, Finney (2003) recommends 10–11 sessions per week. Meeusen et al. (2013) describe an intentional reduction to 9 sessions per week among British swimmers to avoid overtraining. Total weekly training time ranged from a minimum of 6 to a maximum of 20 hours. Finney (2003) recommends a maximum weekly training load of 23 hours.

The impact of training load on sports performance has been discussed by Chatard & Stewart (2011); Hellard et al. (2019); Solonenco et al. (2021); Maria Gonzalez Rave et al. (2021); Hermosilla et al. (2021); and Ravé et al. (2022). Based on training volume, we were able to compare our findings with the recommendations in the literature. Chatard and Stewart (2011) reported weekly microcycle loads ranging from 45 to 60 km. Bonifazi et al. (2000) and Mujika et al. (2002) described weekly loads of 50–60 km, which were applied to the Italian national team and the Australian Olympic team. Meeusen et al. (2013) reported lower weekly volumes of 43–53 km for British swimmers to reduce overtraining risk. Maria Gonzalez Rave et al. (2021) recommended 25–90 km of total weekly load for swimmers performing at 850–900 FINA points.

After several months of high-volume training, a period of gradual volume reduction should follow. Decreasing training load leads to significant improvements in performance, with the main goal being to reach peak form at the right moment (Chatard & Stewart, 2011). This statement fully corresponds with our findings. In mesocycles containing peak events, the training volume was reduced, and the swimmer achieved their highest performance scores (mesocycles 2 and 6) (Figure 1).

Solonenco et al. (2021) described the general preparation phase in the macrocycle as focusing on improving aerobic endurance, strength, flexibility, technique, starts, turns, and coping with psychological stress. Training sessions in this phase mainly consisted of arm drills, leg drills, technical exercises, and low-intensity resistance training. In the competition phase, the focus shifts to major events, and the training content significantly changes—high-intensity resistance and sprint training are introduced for all swimmers, regardless of specialization, but with varying volumes for sprinters, middle-distance swimmers, and distance swimmers.

The total volume of warm-up and cool-down during the annual cycle was 229.45 km. Aerobic endurance volume was 1,145 km, and anaerobic endurance volume was 59.40 km. In comparison, Mitrenga (2006) reported 748.80 km for warm-up and cool-down, 574.40 km for aerobic endurance, and 87 km for anaerobic endurance in an Olympic swimmer. This swimmer's warm-up and cool-down volume was more than double ours, aerobic endurance was over 50% lower, and anaerobic endurance was at a similar level.

The annual volume for arm drills was 75.70 km, and for leg drills, 150.80 km. Tavačová (2020) reported 24.3 km for arm drills and 112.6 km for leg drills in a Slovak national team swimmer—significantly lower volumes than ours. In contrast, Mitrenga (2006) noted 169.7 km for arm drills and 203.8 km for leg drills, with arm drills more than doubling our results.

Technical drills are an essential part of training and reached a total of 117.85 km over the year. Tavačová (2020) reported a higher volume of technical drills—162.50 km.

Figure 1 shows that the swimmer's highest race-pace volume occurred in the 6th mesocycle. Table 1 shows a maximum weekly race-pace volume of 1.1 km. Pollock et al. (2019) reported an average of 1.3 km per week, which is higher than our findings, while Maglischo (1994) recommended up to 3 km. Over the annual cycle, the swimmer completed a total of 18.80 km at race pace. Krčková (2013) reported a swimmer completing 70 km annually at race pace—considerably more than our swimmer. Mitrenga (2006) reported 47.90 km.

This study is an example of highly individualized periodization of training load in relation to the monitored swimmer. Our findings correspond with recommendations from swimming and sports science literature. Regarding race-pace volume, we found higher recommendations for maximum values in weekly training load (Maglischo, 1994) compared to ours.

Conclusions

This paper highlights the intra-individual periodization of training load in a Slovak national swimmer (T.P.) during the 2024 annual training cycle (RTC 2024). Using regression trees via the CHAID method, we identified training indicators that showed a strong correlation with the swimmer's year-round sports performance. Optimal load was subsequently characterized in terms of volume and intensity, as well as the variability of predicted performance.

A significant influence of race-pace volume (STI 105) on performance changes was demonstrated. Arm technique drills (STI 106) and technical drills (STI 108) played a key role in preparation.

We believe that for swimmers specializing in the 400m freestyle, the volume of race-pace training is crucial for simulating race conditions during training. Arm-only swimming is especially important, as it builds strong and stable strokes, allowing swimmers to conserve their legs for the final part of the race. Technical drills are vital for ensuring correct technique and stroke efficiency.

Among the general training indicators, the influence of recovery time (GTI 114), number of training sessions (GTI 111), and total load time (GTI 113) was confirmed.

The retrospective analysis classified the training methods that contributed most to improving the swimmer's performance. Accurately identifying these elements allows for a more rational approach to periodizing the training process, aligning the conceptual basis of sports preparation, and improving the tapering and peaking strategies for major competitions.

References

Bompa, O. T. (1999). Periodization: Theory and methodology of training. Human Kinetics.

Bompa, O. T., & Haff, G. G. (2009). Periodization: Theory and methodology of training (5th ed.). Human Kinetics.

Bonifazi, M., Sardella, F., & Lupo, C. (2000). Preparatory versus main competitions: Differences in performances, lactate responses and pre-competition plasma cortisol concentrations in elite male swimmers. European Journal of Applied Physiology, 82(5–6), 368–373. https://doi.org/10.1007/s004210000230

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). Classification and regression trees. Wadsworth.

Camp, N. J., & Slattery, M. L. (2002). Classification tree analysis: A statistical tool to investigate risk factor interactions with an example for colon cancer (United States). Cancer Causes & Control, 13, 813–823. https://doi.org/10.1023/A:1020611416907

Chatard, C. J., & Stewart, M. A. (2011). Training load and performance in swimming. In World book of swimming: From science to performance. Meyer & Meyer Sport.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.

Finney, J. (2003). How they train: Four days of workouts with Grant Hackett and Michael Phelps. Swim News, 276.

González-Ravé, J. M., Pyne, D. B., Del Castillo, J. A., González-Mohíno, F., & Stone, M. E. (2021). Training periodization for a world-class 400 meters individual medley swimmer. Biology of Sport, 39(4), 883–888. https://doi.org/10.5114/biolsport.2022.109954

Hellard, P., Avalos-Fernandes, M., Lefort, G., Pla, R., Mujika, I., Toussaint, J., & Pyne, D. B. (2019). Elite swimmers' training patterns in the 25 weeks prior to their season's best performances: Insights into periodization from a 20-years cohort. Frontiers in Physiology, 10, Article 363. https://doi.org/10.3389/fphys.2019.00363

Hermosilla, F., González-Ravé, J. M., Del Castillo, J. A., & Pyne, D. B. (2021). Periodization and programming for individual 400 m medley swimmers. International Journal of Environmental Research and Public Health, 18(12), 6474. https://doi.org/10.3390/ijerph18126474

Krčková, R. (2013). Training and performance of swimmers of international level in the category of juniors, seniors and masters [Bachelor's thesis, Charles University]. DSpace. https://dspace.cuni.cz/handle/20.500.11956/55611

Lehmann, E. L. (1975). Nonparametrics: Statistical methods based on ranks. Holden-Day.

Maglischo, E. W. (1994). Swimming even faster. Mayfield Publishing Company.

Maglischo, E. W. (2003). Swimming fastest: The essential reference on technique, training, and program design. Human Kinetics.

Meeusen, R., Duclos, M., Foster, C., Fry, A. C., Gleeson, M., Nieman, D. C., Raglin, J. S., Rietjens, G., Steinacker, J. M., & Urhausen, A. (2013). Prevention, diagnosis, and treatment of the overtraining syndrome. Medicine & Science in Sports & Exercise, 45(1), 186–205. https://doi.org/10.1249/MSS.0b013e318279a10a

Mitrenga, P. (2006). Štvorročný olympijsky cyklus vrcholového plavca [Diploma thesis, Charles University].

Mujika, I., Padilla, S., & Pyne, D. B. (2002). Swimming performance changes during the final 3 weeks of training leading to the Sydney 2000 Olympic Games. International Journal of Sports Medicine, 23(8), 582–587. https://doi.org/10.1055/s-2002-35526

Pla, R., Le Meur, Y., Aubry, A., Toussaint, J., & Hellard, P. (2019). Effects of a 6-week period of polarized or threshold training on performance and fatigue in elite swimmers. International Journal of Sports Physiology and Performance, 14(2), 183–189. https://doi.org/10.1123/ijspp.2018-0179

Platonov, V. (2019). Theory of periodization of elite athlete preparation during a year: Prerequisites, formation, criticism. Science in Olympic Sport, 118–137.

Pollock, S., Gaoua, N., Johnston, M. J., Cooke, K., Girard, O., & Mileva, K. N. (2019). Training regimes and recovery monitoring practices of elite British swimmers. Journal of Sports Science & Medicine, 18(3), 577–585.

Ravé, J. M. G., González-Mohíno, F., Rodrigo-Carranza, V., & Pyne, D. B. (2022). Reverse periodization for improving sports performance: A systematic review. Sports Medicine - Open, 8(1), Article 45. https://doi.org/10.1186/s40798-022-00445-8

Solonenco, G., Stepanova, N., Onoi, M., & Viorel, D. (2021). Analysis of training programs of the performance swimmers within the basic macrocycle of the annual training cycle. Ştiinţa Culturii Fizice, 35(1). https://doi.org/10.52449/1857-4114.2020.35-1.09

Tavačová, B. (2020). Športová príprava slovenskej plaveckej juniorskej reprezentantky v disciplínach 200 P a 400 PP [Diploma thesis, Palacký University in Olomouc].

Vaňková, K. (2010). Analysis of the training diary of an elite swimmer [Bachelor's thesis, Palacký University in Olomouc]. https://theses.cz/id/lx0koq/128406-233451294.pdf