Psychophysiological factors determining the success of elite Greco-Roman wrestlers using artificial intelligence methods

Factores psicofisiológicos que determinan el éxito de los luchadores grecorromanos de élite mediante métodos de inteligencia artificial

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Abstract

Introduction: The application of artificial intelligence methods to the analysis of psychophysiological indicators enables the identification of the most informative markers and the construction of profiles of preparedness in elite athletes within the framework of sports monitoring.
Objective: To identify the psychophysiological determinants that characterize the preparedness profile of elite Greco-Roman wrestlers using multivariate analysis methods and artificial intelligence tools.
Methodology: The study involved 44 Greco-Roman wrestlers: youth elite wrestlers (n = 21) and elite wrestlers (n = 23). A set of psychophysiological tests was used for the measurements. An algorithm for investigating psychophysiological indicators using artificial intelligence tools was applied, which included the stages of data collection, statistical processing of the results in the RStudio environment, and interpretation of the findings using the large language model GPT-5.2 (OpenAI).
Results: Psychophysiological determinants characterizing the wrestlers' preparedness profile were identified. No statistically significant differences were found between the Youth U-17 and Seniors groups across 10 key indicators. Latent components of wrestlers' psychophysiological functions and integral indices (LPI) were determined, making it possible to construct individual athlete profiles and to monitor psychophysiological functions during the training process.
Conclusions: The psychophysiological determinants identified in the study may be used as a basis for the individualization of monitoring, the identification of specific characteristics of psychophysiological functions, and the improvement of the monitoring system for wrestlers. The usefulness of a hybrid approach was confirmed, in which AI enhances the analytical process without compromising its scientific reproducibility.

Keywords

Elite athletes; Greco-Roman wrestling; psychophysiological indicators; multivariate analysis; artificial intelligence.

Resumen

Introducción: La aplicación de métodos de inteligencia artificial al análisis de indicadores psicofisiológicos permite identificar los marcadores más informativos y elaborar perfiles de preparación en atletas de élite, en el marco del seguimiento deportivo.
Objetivo: Identificar los determinantes psicofisiológicos que caracterizan el perfil de preparación de luchadores de élite de estilo grecorromano, utilizando métodos de análisis multivariante y herramientas de inteligencia artificial.
Metodología: El estudio contó con la participación de 44 luchadores de estilo grecorromano: luchadores de élite juveniles (n = 21) y luchadores de élite adultos (n = 23). Para las mediciones se utilizó un conjunto de pruebas psicofisiológicas. Se aplicó un algoritmo para analizar los indicadores psicofisiológicos mediante herramientas de inteligencia artificial, el cual incluyó las etapas de recopilación de datos, procesamiento estadístico de los resultados en el entorno RStudio e interpretación de los hallazgos utilizando el modelo de lenguaje de gran tamaño GPT-5.2 (OpenAI).
Resultados: Se identificaron los determinantes psicofisiológicos que caracterizan el perfil de preparación de los luchadores. No se hallaron diferencias estadísticamente significativas entre los grupos de juveniles (Sub-17) y adultos (Sénior) en 10 indicadores clave. Se determinaron los componentes latentes de las funciones psicofisiológicas de los luchadores y los índices integrales (LPI), lo que permitió elaborar perfiles individuales de los atletas y monitorear sus funciones psicofisiológicas durante el proceso de entrenamiento.
Conclusiones: Los determinantes psicofisiológicos identificados en el estudio pueden servir de base para individualizar el seguimiento, identificar características específicas de las funciones psicofisiológicas y perfeccionar el sistema de monitoreo de los luchadores. Se confirmó la utilidad de un enfoque híbrido, en el que la inteligencia artificial potencia el proceso analítico sin comprometer su reproducibilidad científica.

Palabras clave

Atletas de élite; lucha grecorromana; indicadores psicofisiológicos; análisis multivariante; inteligencia artificial.

Introduction

The modern development of combat sports is characterized by a high level of competition, which increases the demands for comprehensive management of training and competitive activities (Franchini et al., 2023; Latyshev et al., 2024). The continuous modification of competition rules, increasing bout intensity, and growing psychophysiological demands highlight the need for new approaches to assessing athletes' preparedness and competitive effectiveness (Curby et al., 2023; Junior et al., 2024). Traditional approaches, primarily based on the analysis of physical fitness and technical-tactical performance, do not always allow for the timely and accurate identification of an athlete's individual potential. In this context, particular importance is attached to the study of psychophysiological indicators that influence cognitive processes, reaction speed, stress resilience, and decision-making effectiveness during competition (Bunyatova et al., 2026; Romanenko et al., 2025a; Voigt et al., 2024).

The scientific literature indicates that characteristics such as short-term visuomotor memory, sensorimotor reaction speed, attention level, and the ability to switch between tasks are of considerable importance for success in combat sports (Podrigalo et al., 2025; Romanenko et al., 2025b). Research findings confirm that cognitive and psychophysiological factors may be as informative regarding sports performance as traditional anthropometric or physiological indicators (Korobeynikov et al., 2022; Podrihalo et al., 2021). At the same time, the integration of these parameters into athlete monitoring practice requires the use of modern analytical tools.

The application of advanced analytical approaches is particularly relevant in combat sports, where athletic performance is determined by the complex interaction of physical, technical-tactical, psychophysiological, and cognitive components. Unlike cyclic sports, combat athletes must operate under conditions of high uncertainty, limited decision-making time, and constantly changing competitive situations. Consequently, competitive success depends not only on the level of overall preparedness but also on the ability to rapidly perceive information, anticipate opponents' actions, and select optimal responses (Korobeynikov et al., 2023; Podrigalo et al., 2025). Modern athlete monitoring systems are characterized by the accumulation of large volumes of heterogeneous data. The analysis of such multidimensional datasets using traditional statistical methods is often complicated by the presence of numerous interrelationships among variables, which may limit the identification of hidden patterns. This necessitates the implementation of innovative approaches to data processing and interpretation capable of providing a deeper understanding of athletes' individual characteristics and the factors determining their performance (Cano et al., 2024; Dehbane et al., 2026).

In recent years, there has been growing interest in the application of artificial intelligence (AI) in sport, particularly as a tool for big data analysis, automated classification, and decision-support systems (Baca et al., 2022; Pang et al., 2025). The use of AI technologies creates opportunities for modeling complex nonlinear relationships between athletes' psychophysiological characteristics and the parameters of their competitive performance (Jianjun et al., 2025). Contemporary studies demonstrate that machine learning and computer vision algorithms can be effectively employed for the automated analysis of technical-tactical actions, performance prediction, and support of officiating decisions during competitions (Pang et al., 2025; Valero, 2018). Furthermore, machine learning algorithms are capable not only of identifying hidden patterns in multidimensional datasets but also of generating interpretable athlete profiles based on a combination of psychophysiological indicators (Zhu & Sun, 2019). This creates prerequisites for developing tools that assist coaches in assessing individual preparedness characteristics and making timely adjustments to training interventions. The integration of traditional sports diagnostics with AI-based technologies expands the possibilities of sports analytics and enhances the evidence-based nature of coaching decisions (Ahmadi et al., 2024; Pietraszewski et al., 2025). The further development of AI technologies in sport is associated with the personalization of training programs, automated analysis of technical-tactical actions, injury prevention, and monitoring of athletes' functional status (Sanabria Navarro et al., 2024; Manescu, 2025). In addition, modern computer vision systems and intelligent video analytics enable the automation of motor skill assessment, creating new opportunities for objective pedagogical control and the improvement of sports training processes (Al Ardha et al., 2025). In taekwondo, for example, AI-based systems are actively being developed for the automatic recognition of kicking techniques, evaluation of attack effectiveness, and enhancement of officiating objectivity, thereby contributing to greater fairness and transparency in the competitive process (Zhang et al., 2025).

Bibliometric analyses of research in sport indicate a rapid increase in the number of studies devoted to the application of artificial intelligence for talent identification, performance prediction, training program personalization, monitoring of athletes' functional states, and optimization of the training process (Hou, 2026; Mănescu & Mănescu, 2025; Tropin et al., 2023). These approaches are particularly relevant to combat sports, where competitive outcomes are determined by the complex interaction of physical, technical-tactical, and psychophysiological components.

Therefore, the application of artificial intelligence methods for the analysis of athletes' psychophysiological indicators represents a promising research direction that enables the identification of the most informative markers and the development of generalized preparedness profiles of qualified combat sports athletes within the framework of sports monitoring.

Objectives: To identify the psychophysiological determinants that characterize the profile of elite Greco-Roman wrestlers using multivariate analysis methods and artificial intelligence tools.

Method

Participants

The study involved 44 Greco-Roman wrestlers: youth elite wrestlers (U-17 National Team members), aged 15.9 years (SD = 0.81, n = 21), and senior elite wrestlers (Senior National Team members), aged 25.3 years (SD = 3.83, n = 23). All athletes were members of the Ukrainian National Team and participants in international competitions in their respective age categories. The wrestlers included in the study were medalists and champions of the European and World Championships in their respective age categories. The sample represents the available athletes within the chosen country and expertise level, and thus no a priori sample size estimations are applied.

The study was conducted in accordance with the fundamental principles of bioethics, including the Convention on Human Rights and Biomedicine of the Council of Europe (April 4, 1997), the World Medical Association Declaration of Helsinki on Ethical Principles for Medical Research Involving Human Subjects (1964-2008), and Order No. 690 of the Ministry of Health of Ukraine (September 23, 2009). Ethical review of the study was carried out by the Biomedical Ethics Committee of the National University of Ukraine on Physical Education and Sport (March 18, 2026, Protocol No. 3). All participants were informed about the aims of the study, testing procedures, and their right to withdraw from participation at any time and for any reason. For underage participants, parental consent was obtained, and the parents were present during testing. At the time of the study, all participants were healthy and reported no health complaints.

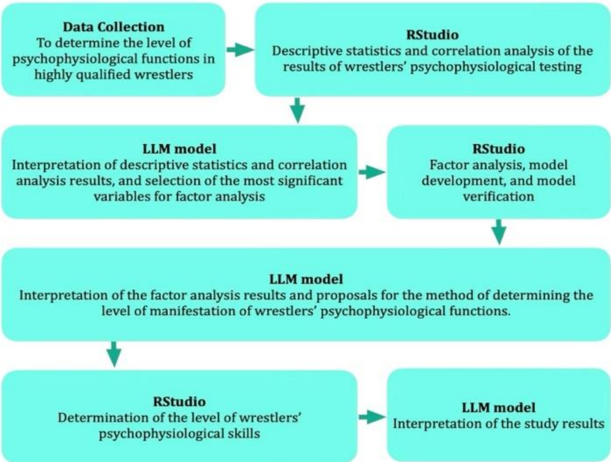
Procedure

Testing was carried out during a training camp in August. All assessments were performed on designated rest days between 8:00 and 10:00 a.m. over two consecutive days. For the testing procedure, seven tests designed to assess the level of psychophysiological function development were installed on three mobile devices (9th-generation iPads). All mobile devices had identical technical specifications. To increase motivation, the wrestlers were informed about the study's purpose and the practical value of the data obtained. A trial testing session was conducted to familiarize participants with the tasks in detail. Once an athlete was confident in performing the tasks, he proceeded to the actual test.

Figure 1 presents a generalized algorithm for studying psychophysiological indicators using artificial intelligence tools, including data collection, statistical processing in the RStudio environment, and AI-assisted interpretation of results using the large language model (LLM) GPT-5.2 (OpenAI). The selection of this model was motivated by its recency at the time of the study, robust performance in processing structured scientific data, and broad compatibility with standard analytical workflows, including integration with R-based statistical pipelines. The model is not used for comparative evaluation against alternative LLMs (e.g., Claude, Gemini) and is not intended to demonstrate superiority. Its role is strictly functional as a component of the AI-assisted data interpretation stage within the proposed analytical framework.

The information presented in Figure 1 reflects the use of AI (LLM, OpenAI) exclusively as an auxiliary technical tool. AI was not used to perform statistical calculations, automatic variable selection, or factor model construction; its application was limited to structuring the analytical process, formulating explanatory text blocks, and supporting the interpretation of already obtained statistical results.

Figure 1. Algorithm for the study of psychophysiological indicators using statistical methods and AI tools



Instrument

A battery of tests for tablet computers running iPadOS was used to perform the psychophysiological measurements:

- Choice reaction was assessed using the "Visuomotor Choice Reaction" test (Romanenko et al., 2022; Author's Certificate No. 125200). The main variables included: RT (reaction time, ms), SD (standard deviation, ms), and Errors (n), both for the test as a whole and separately for each stage (1-4);
- Response to a moving object was assessed using the "Reaction RMO Pro" test (Romanenko et al., 2024b; Author's Certificate No. 125201). The main variables were: RT (ms) and SD (ms), both for the test as a whole and separately for each stage (1-3);
- Inhibitory reaction was assessed using the "Reaction Go/No-Go" test (Romanenko et al., 2024a; Author's Certificate No. 127919). The main variables included: RT (ms), SD (ms), and Errors (%), recorded during performance of the test task with the left hand, right hand, and both hands;
- Short-term visual memory was assessed using the "Test ST Memory" test (Romanenko et al., 2020; Author's Certificate No. 127918). The main variables were: CSTM (percentage of accurate taps, %) and Duration (duration of the attempt at each test stage, s);
- Spatial perception was assessed using the "Spatial Perception" test (Romanenko et al., 2025a; Author's Certificate No. 134960). The main variables included: RT (ms), SD (ms), and Errors (%), both for the test as a whole and separately for each stage (1-4);
- Response to changes in object size was assessed using the "Size Test" (Author's Certificate No. 127912). The main variables were: RT (ms), SD (ms), and Errors (%);
- Functional asymmetry was assessed using the "Reaction SM Dual" test (Author's Certificate No. 127913). The main variables included: RT (ms), SD (ms), and Total taps (number of taps), both for the test as a whole and separately for each stage (1-6).

The tests are standard validated tests in performance settings in elite sports.

Data analysis

Mathematical and statistical analyses were performed in the RStudio environment (version 2026.01.0+392). Descriptive statistics are presented as mean and standard deviation (Mean ± SD). Between-group differences between wrestlers of different age categories were assessed using the Mann-

Whitney U test (Wilcoxon rank-sum test); for multiple comparisons, the Benjamini-Hochberg correction (FDR) was applied, and adjusted p-values of $p_{adj} < 0.05$ were considered statistically significant. To assess the strength and direction of relationships between variables, Spearman's rank correlation coefficient (ρ) with FDR correction was used. To identify latent components of psychophysiological functions, exploratory factor analysis (EFA) was performed using the principal axis factoring method (fm = "pa") with oblimin oblique rotation. The number of factors was determined based on the results of parallel analysis (Horn) and the criterion of model interpretability. The suitability of the data for factorization was assessed using the Kaiser-Meyer-Olkin index (KMO), individual measures of sampling adequacy (MSA), and Bartlett's test of sphericity. Factor scores (PA1, PA2) were calculated using the regression method for further athlete profiling.

The Level of Psychophysiological Functions Index (LPI) is an integral indicator proposed to summarize two latent domains of psychophysiological status. The integral LPI index was calculated as a weighted sum of the standardized factor scores PA1 and PA2. The factor scores obtained using the ten Berge method were first standardized into z-scores. Factor weights were determined based on the normalized proportion of variance explained by each factor in the final factor model: (LPI=zPA1×wPA1+zPA2×wPA2). The general logic of constructing such an index is consistent with approaches used in the development of integral indicators and multidimensional athlete profiling (Oleksy et al., 2022).

AI tools (LLM; OpenAI) were used only as an auxiliary means for structuring the textual description, systematizing intermediate conclusions, and supporting the interpretation of already calculated results. All numerical calculations, statistical tests, p-value correction, factor analysis, computation of factor scores, and LPI were performed exclusively in RStudio.

Results

Based on psychophysiological testing, aggregated indicators were obtained for the athletes. Descriptive statistics are presented for two groups of wrestlers (Youth U-17, n = 21; Seniors, n = 23) in a unified Mean ± SD format. For each test, the key integrated metrics (reaction time, variability, errors/accuracy, etc.) obtained for the test as a whole are presented. In most tests, the central tendencies of the indicators in the two groups are similar, indicating a comparable baseline level of psychophysiological functions within the studied sample (Table 1).

Table 1. Results of the assessment of psychophysiological indicators in elite wrestlers (U17 and senior)

Indicator	Youth U-17 (n=21), Mean±SD	Senior (n=23), Mean±SD
VCR: RT_mean (ms)	851.1±80.3	862.0±125.5
VCR: SD_mean (ms)	166.6±29.8	170.3±67.4
VCR: Errors_total (n)	10.5±10.2	14.8±17.2
RMO: RT_mean (ms)	30.1±8.7	29.4±7.5
RMO: SD_mean (ms)	20.6±5.9	20.3±5.0
RMO: Accurate (%)	8.7±4.8	13.3±12.2
RMO: Premature (%)	48.3±11.2	43.3±14.8
RMO: Delayed (%)	43.0±10.1	43.4±8.6
Go/No-go: RT_mean (ms)	366.2±33.8	368.0±29.5
Go/No-go: SD (ms)	48.2±10.8	47.9±11.6
Go/No-go: Errors (%)	13.8±12.1	12.0±8.1
STMemory: CSTM_mean (%)	89.7±5.5	89.8±5.0
STMemory: Duration (s)	1.62±0.25	1.60±0.20
Spatial: RT_mean (ms)	806.6±114.1	808.2±102.8
Spatial: SD_mean (ms)	137.1±47.7	144.8±41.8
Spatial: Errors_mean (%)	5.5±2.9	4.5±2.6
Size: RT_mean (ms)	961.7±98.5	892.1±111.8
Size: SD (ms)	191.1±81.2	159.8±42.9
Size: Errors (%)	4.4±4.0	4.6±5.8
SM Dual: LH taps (n)	200.3±15.9	201.3±15.4
SM Dual: RH taps (n)	202.5±15.8	203.3±15.5
SM Dual: LH RT_mean (ms)	586.2±49.4	593.6±41.8
SM Dual: RH RT_mean (ms)	580.1±48.7	587.5±41.1

Note: VCR - Visuomotor Choice Reaction; RT_mean/SD_mean - mean values across the test stages; Errors_total - total number of errors across the stages; ST Memory Duration - trial duration (5 stages). In Table 1, all results are presented in the Mean ± SD format.

The absence of pronounced between-group differences in the descriptive indicators may be explained by the similar level of preparedness of the participants, since both groups consisted of highly qualified athletes. For this reason, the subsequent analysis focused not only on comparing mean values, but also on examining the correlation structure and latent components of psychophysiological functions.

Correlation analysis was used as a preliminary step to assess the structure of relationships between the aggregated psychophysiological indicators. Tables 2 and 3 present only the strongest statistically significant correlations after FDR correction; therefore, these tables do not reflect the full list of variables considered for subsequent factor analysis.

In the Youth U-17 group, the strongest positive relationships were observed between the indicators of response to a moving object: RMO_RT_mean and RMO_SD_mean ($\rho = 0.974$; p_adj = 4.62e-12), as well as between indicators of bilateral motor control: ASYM_LH_RT_mean and ASYM_RH_RT_mean ($\rho = 0.962$; p_adj = 7.53e-11), and ASYM_LH_SD and ASYM_RH_SD ($\rho = 0.801$; p_adj = 1.90e-04). Among the inter-component relationships, a positive association was found between ASYM_LH_RT_mean and ASYM_RH_SD ($\rho = 0.601$; p_adj = 0.037), as well as the expected inverse relationship between speed in RMO and accuracy: RMO_RT_mean and RMO_Accurate ($\rho = -0.599$; p_adj = 0.037).

Table 2. Youth U-17 wrestlers: Top significant Spearman correlations (FA-variable set), ranked by |ρ|

Variable 1	Variable 2	ρ	FDR p_adj
RMO_RT_mean	RMO_SD_mean	0.974	4.62e-12
ASYM_LH_RT_mean	ASYM_RH_RT_mean	0.962	7.53e-11
ASYM_LH_SD	ASYM_RH_SD	0.801	0.00019
ASYM_LH_RT_mean	ASYM_RH_SD	0.601	0.0372
RMO_RT_mean	RMO_Accurate	-0.599	0.0372

Note. Positive ρ indicates that higher values of both variables tend to occur together; negative ρ indicates an inverse association. FDR-adjusted p-values are reported.

Table 3. Senior wrestlers: Top significant Spearman correlations (FA-variable set), ranked by |ρ|

Variable 1	Variable 2	ρ	FDR p_adj
ASYM_LH_RT_mean	ASYM_RH_RT_mean	0.993	3.28e-19
RMO_RT_mean	RMO_SD_mean	0.958	1.44e-11
ASYM_LH_SD	ASYM_RH_SD	0.771	0.000252
VCR_RT_mean	RMO_Accurate	-0.665	0.00605
RMO_RT_mean	RMO_Accurate	-0.619	0.0144
VCR_RT_mean	RMO_RT_mean	0.612	0.0144
VCR_RT_mean	RMO_SD_mean	0.559	0.0355

Note. Positive ρ indicates that higher values of both variables tend to occur together; negative ρ indicates an inverse association. FDR-adjusted p-values are reported.

In the Seniors group, very strong positive correlations also predominated between the left- and right-side indicators of the SM Dual test (ASYM_LH_RT_mean and ASYM_RH_RT_mean: $\rho = 0.993$; p_adj = 3.28e-19), between the RMO indicators (RMO_RT_mean and RMO_SD_mean: $\rho = 0.958$; p_adj = 1.44e-11), as well as in reaction variability between the hands (ASYM_LH_SD and ASYM_RH_SD: $\rho = 0.771$; p_adj = 2.52e-04). In addition, in this group, associations were identified between choice reaction and RMO characteristics: VCR_RT_mean was positively correlated with RMO_RT_mean ($\rho = 0.612$; p_adj = 0.014) and RMO_SD_mean ($\rho = 0.559$; p_adj = 0.036), and showed a negative association with RMO_Accurate ($\rho = -0.665$; p_adj = 0.006).

Comparison of the correlation structures in the Youth U-17 and Senior groups showed that strong relationships between within-test indicators were preserved in both samples; however, adult athletes more often demonstrated between-test associations, primarily between VCR and RMO. This could be explained by a stronger and integrated organization of sensorimotor control in more experienced wrestlers. The advantage of the Senior group is manifested not so much in a shift in mean values as in a more coordinated configuration of relationships between different psychophysiological indicators.

At the next stage, a final set of 10 variables for factor analysis was formed, taking into account the substantive relevance of the indicators, MSA values, and the interpretability of the factor model. The variable RMO_Delayed was included in the final set as an indicator of the response structure in the reaction to a moving object task. This variable is not presented in Tables 2 and 3 because it was not among the strongest significant correlation pairs, but it demonstrated acceptable individual adequacy for factor analysis. Factor analysis was used as a tool to identify the most significant psychophysiological indicators and to summarize them into latent components.

The suitability of the variables for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) index and individual measures of sampling adequacy (MSA) for each variable. All MSA values presented in Table 4 were calculated for the combined sample of all study participants (n = 44) rather than separately for each group. All selected aggregated indicators had MSA > 0.50 (range 0.618-0.878), which confirmed the appropriateness of including them in the factor analysis.

Table 4. Measures of sampling adequacy (MSA)

Diagnostic criterion	Value
KMO overall measure	0.68
Bartlett's test of sphericity	$\chi^2(45) = 372.79$
p-value	$p < 2\times10^{-16}$
Individual MSA range	
RMO_SD_mean	0.618
RMO_RT_mean	0.624
RMO_Accurate	0.634
ASYM_LH_SD	0.662
ASYM_RH_RT_mean	0.670
ASYM_LH_RT_mean	0.673
ASYM_RH_SD	0.727
GNG_RT_mean	0.756
VCR_RT_mean	0.808
RMO_Delayed	0.878

Note. Individual MSA values are presented for the pooled sample of all wrestlers (n = 44). Variables with MSA > 0.50 were considered suitable for factor analysis.

Between-group differences between Youth U-17 (n = 21) and Senior (n = 23) groups in the 10 most significant psychophysiological indicators were assessed using the Mann-Whitney U test. No statistically significant differences were found (p > 0.296; after Benjamini-Hochberg correction, p_fdr = 0.972). Effect sizes were predominantly trivial, while for several indicators (RMO_Accurate, ASYM_LH_SD, ASYM_LH_RT_mean, ASYM_RH_RT_mean) they corresponded to a small effect (r < 0.158), indicating an overall similar level of manifestation of the studied functions in the compared groups (Table 5).

Table 5. Differences in psychophysiological indicators between wrestlers in the Youth U-17 and Senior groups

Variable	W	p	Z	r	p_fdr
VCR_RT_mean	231.0	0.805	-0.247	0.037	0.972
RMO_RT_mean	243.0	0.972	0.035	0.005	0.972
RMO_SD_mean	240.0	0.972	-0.035	0.005	0.972
RMO_Accurate	198.0	0.305	-1.026	0.155	0.972
RMO_Delayed	247.0	0.897	0.13	0.02	0.972
GNG_RT_mean	238.5	0.944	-0.07	0.011	0.972
ASYM_LH_RT_mean	212.5	0.496	-0.681	0.103	0.972
ASYM_RH_RT_mean	204.0	0.378	-0.881	0.133	0.972
ASYM_LH_SD	197.0	0.296	-1.046	0.158	0.972
ASYM_RH_SD	225.0	0.698	-0.388	0.058	0.972

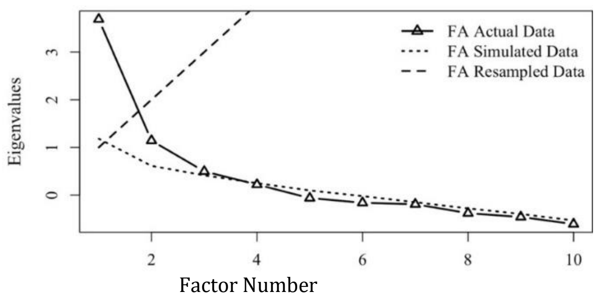
Note. VCR - Visuomotor Choice Reaction; RMO - Reaction to Moving Object; GNG - Go/No-go; ASYM - SM Dual (functional asymmetry). Effect size r computed as $|Z|/\sqrt{N}$ using standardized Z from asymptotic Wilcoxon test.

The absence of statistically significant differences between the study groups may be due to the similarity of the psychophysiological state of the participants, probably due to their elite athletic level and similar training.

The absence of statistically significant differences between the studied groups justified the use of factor analysis in order to identify latent variables across all study participants (n = 44). The analysis was performed on the final set of 10 aggregated psychophysiological variables (VCR_RT_mean, RMO_RT_mean, RMO_SD_mean, RMO_Accurate, RMO_Delayed, GNG_RT_mean, ASYM_LH_RT_mean, ASYM_RH_RT_mean, ASYM_LH_SD, ASYM_RH_SD) after listwise deletion. The obtained values indicated the relevance of the factor model: KMO = 0.68, and Bartlett's test was statistically significant ($\chi^2(45) = 372.79$, $p < 2 \times 10^{-16}$).

Parallel analysis confirmed the appropriateness of the two-factor model (Figure 2).

Figure 2. Parallel Analysis (Horn)



The first factor (PA1) was formed by indicators of bilateral motor organization and sensorimotor response stability (ASYM_LH_RT_mean = 0.868; ASYM_RH_RT_mean = 0.820; ASYM_LH_SD = 0.855; ASYM_RH_SD = 0.830). The second factor (PA2) was mainly determined by indicators of response to a moving object (RMO_RT_mean = 0.963; RMO_SD_mean = 0.967) and showed a moderate association with choice reaction (VCR_RT_mean = 0.324). Accuracy in RMO had a negative loading (RMO_Accurate = -0.324), which is consistent with the speed-accuracy trade-off (Table 6).

Table 6. Factor loadings (principal axis factoring, oblimin rotation)

Variable	PA1	PA2	h^2
VCR_RT_mean	0.265	0.324	0.233
RMO_RT_mean	0.022	0.963	0.942
RMO_SD_mean	-0.007	0.967	0.931
RMO_Accurate	-0.087	-0.324	0.132
RMO_Delayed	-0.174	-0.259	0.128
GNG_RT_mean	0.245	0.082	0.081
ASYM_LH_RT_mean	0.868	0.170	0.881
ASYM_RH_RT_mean	0.820	0.179	0.804
ASYM_LH_SD	0.855	-0.146	0.669
ASYM_RH_SD	0.830	-0.169	0.623

Note. VCR - Visuomotor Choice Reaction; RMO - Reaction to Moving Object; GNG - Go/No-go; ASYM - SM Dual (functional asymmetry)

Exploratory factor analysis (principal axis factoring, oblimin rotation) explained a total of 54.23% of the overall variance (PA1 = 30.90%; PA2 = 23.33%). Within the explained variance, the contribution of PA1 was 56.98%, whereas PA2 accounted for 43.02% (Table 7).

Table 7. Variance explained by extracted factors

Metric	PA1	PA2
SS loadings	3.0902	2.3328
Proportion Var	0.309017	0.233278
Cumulative Var	0.309017	0.542295
Proportion Explained	0.569832	0.430168
Cumulative Proportion	0.569832	1.000000

Note. Loadings with absolute values ≥ 0.30 were interpreted as meaningful. The variance explained indices were obtained directly from the exploratory factor analysis output in R.

Given the aim of the study, the integral LPI (Level of Psychophysiological Functions Index) was used for the generalized assessment of athletes' psychophysiological status. It was calculated as a composite indicator based on standardized key psychophysiological variables. This approach ensured a unified direction of scale interpretation, in which higher LPI values corresponded to a more favorable psychophysiological profile. The P25 and P75 percentiles were used for the interpretation and classification of LPI. LPI values were classified as low when LPI < P25, moderate when P25 ≤ LPI ≤ P75, and high when LPI > P75. In addition, the factor scores PA1 and PA2 provided supplementary information on athlete profiles based on the percentile approach, making it possible to interpret individual differences not only through the integral index, but also at the level of generalized psychophysiological characteristics.

The reference ranges for LPI interpretation are presented in Table 8. They may be used as benchmarks for further monitoring of wrestlers' psychophysiological status and for comparing individual indicators within the studied sample.

Table 8. Integral LPI (Level of Psychophysiological Functions Index)

Group	n	P25	P75	Low n (%)	Medium n (%)	High n (%)
All	44	-0.500	0.566	11 (25.0%)	22 (50.0%)	11 (25.0%)
Youth	21	-0.415	0.774	5 (23.8%)	11 (52.4%)	5 (23.8%)
Elite	23	-0.503	0.410	6 (26.1%)	11 (47.8%)	6 (26.1%)

Figure 3 presents the values of the integral indices of psychophysiological functions in wrestlers in the Youth U-17 group

From an applied perspective integral index should be considered as a tool for monitoring and segmentation of wrestlers, rather than as an independent selection criterion without taking into account the training and competitive context.

Figure 3. LPI values of wrestlers in the Youth U-17 group

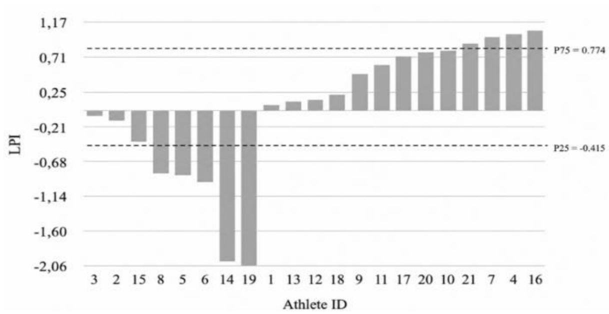
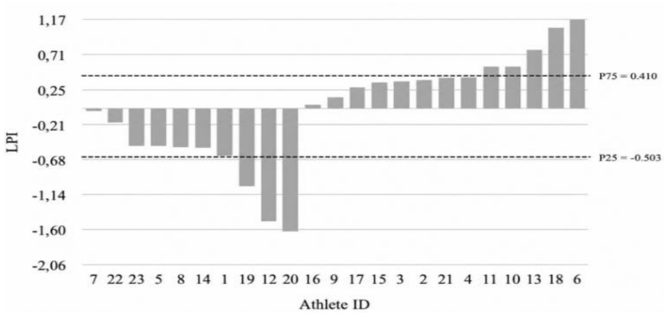


Figure 4 presents the values of the integral indices of psychophysiological functions in wrestlers in the Seniors group.

Figure 4. LPI values of wrestlers in the Seniors group



Within the framework of this study, AI tools were used only for the technical support of interpretation and for structuring the presentation of the obtained statistical results. Variable selection, hypothesis testing, correlation analysis, factorization, calculation of factor scores, and construction of the LPI were carried out entirely in RStudio without any automated computational intervention by AI.

Discussion

The present study evaluated the characteristics of psychophysiological functions in wrestlers of different age categories and further clarified the latent structure of relationships between the indicators of sensorimotor tests, followed by the construction of an integral profile. Similar studies have been conducted in athletes participating in team sports (Barrett et al., 2020) and individual sports (Volgemute et al., 2026). The obtained results demonstrated the absence of statistically significant differences between the Youth U-17 and Senior groups across most of the analyzed variables, which justified the application of factor analysis to identify hidden components of psychophysiological functions. This approach has also been used in the literature (Ervilha et al., 2020). Correlation analysis confirmed the presence of meaningful relationships between the indicators of individual tests, while exploratory factor analysis made it possible to identify a two-factor model reflecting the key domains of variability in psychomotor characteristics, as noted in previous research (Horn, 1965). On the basis of factor scores, individual profiles and an integral index (LPI) were constructed, creating a foundation for the practical use of the obtained data in monitoring athletes' preparedness and aligning with previous studies (Cano et al., 2024).

The absence of statistically significant differences between the Youth U-17 and Senior groups across most indicators should not be regarded as a "null" result, but rather as a meaningful signal that, within this sample, the basic psychophysiological characteristics may share a common foundation and reach a relatively high level in both groups. Studies involving highly qualified athletes have repeatedly emphasized that their advantages in general cognitive and sensorimotor tests are inconsistent and depend substantially on age, task specificity, and the speed-accuracy trade-off. Comparing mean values alone may therefore fail to reflect the key mechanisms underlying athletic mastery (Vona et al., 2024). A possible explanation is also that both groups consisted of combat athletes with a sufficiently high level of preparedness; therefore, between-group differences in aggregated metrics may have been "smoothed out." The sensorimotor advantage of more experienced athletes is sometimes manifested not in a simple acceleration of response, but in changes in performance structure or in other components of action control, which are not always captured by integral indicators. This is consistent with findings showing that, in elite vs. novice comparisons, differences may be fragmented and ambiguous (Vona et al., 2024; Ervilha et al., 2020; Barrett et al., 2020). Such an approach makes it possible to move to a higher level of analysis, where athletes' level is determined on the basis of a set of indicators that illustrate existing relationships, the contribution of individual criteria, and the integral qualities of the athletes.

That is precisely why, after the absence of clear between-group differences, the logical next step is to move from the analysis of mean values to the analysis of latent structure and profiles. Within groups of athletes who are homogeneous in terms of performance level, it may not be so much the absolute values that are informative, but rather the configurations of indicators and the relationships between them, including individual profiles of factor scores and the integral index. Such an approach makes it possible to identify hidden domains of variability and differences in the "types" of psychophysiological functions even when group means do not diverge (Vona et al., 2024).

Correlation analysis within each group showed that most variables formed meaningful clusters of interrelated indicators. The strongest relationships were observed between parameters describing the same domain (for example, mean reaction time and its variability, as well as related characteristics for the left and right hands). This pattern is an important prerequisite for factorization, since exploratory factor analysis is meaningful only when the correlation matrix differs from an identity matrix and contains a sufficient number of nontrivial relationships to identify common (latent) sources of variability. For this reason, preliminary examination of the correlation structure together with testing its suitability (in particular, by means of Bartlett's test of sphericity) is regarded as a methodologically appropriate step before factor extraction (Fabrigar et al., 1999; Lloret-Segura et al., 2014).

At the same time, comparison of the correlation matrices of wrestlers in the Youth U-17 and Senior groups indicates that qualitative differences may be manifested not in the mean values, but in the configuration of relationships. In elite-level athletes, along with within-test relationships, associations between indicators from different tests are more frequently observed, which may reflect a more integrated organization of sensorimotor control, or a transition of regulation to a higher level compared with novices. It is precisely such structural regularities that justify the shift from comparing mean values to searching for latent variables that summarize the shared variance of interrelated indicators and make it possible to construct individual profiles, which is consistent with the findings reported by Lloret-Segura et al. (2014).

The obtained diagnostic criteria confirmed that the data were suitable for factorization and that the two-factor model was justified. In particular, the KMO value of 0.68 indicated acceptable sampling adequacy for identifying common factors, while Bartlett's test of sphericity was statistically significant ($\chi^2(45) = 372.79$, $p < 2 \times 10^{-16}$), meaning that the correlation matrix differed substantially from the identity matrix and contained a sufficient number of systematic relationships for the search for latent variables. The number of factors was determined on the basis of parallel analysis (Horn, 1965) and an additional criterion of interpretability, which together supported the selection of two factors. As a result, the two-factor solution explained 54.23% of the total variance (PA1 = 30.90%; PA2 = 23.33%), which is a methodologically acceptable level for psychophysiological indicators and confirms the appropriateness of further using factor scores in athlete profiling, as supported by previous studies (Kaiser, 1974; Tobias & Carlson, 1969; Horn, 1965; Hayton et al., 2004; Fabrigar et al., 1999).

Factor PA1 is interpreted as a domain of bilateral motor stability and symmetry, since it is primarily formed by indicators reflecting asymmetry between the hands (ASYM) and its stability. Consistent changes in mean reaction time for the left and right hands, as well as in performance variability (SD), indicate that individual differences are determined not so much by the "speed of one hand," but rather by the degree of balance and reliability in the functioning of both limbs. Within this logic, higher PA1 values correspond to a profile in which the response is less shifted toward the dominant hand and is characterized by more stable and repeatable performance features, which is consistent with findings on the plasticity of lateralization. In high-level athletes, systematic training and competitive practice reduce unilateral advantage and decrease differences between the hands in the execution of motor actions (Stöckel & Weigelt, 2012; Badau et al., 2018). From an applied perspective in wrestling, PA1 may be interpreted as a marker reflecting the ability to perform technical and tactical actions effectively under conditions of rapid interaction with an opponent, without critical dependence on the dominant side. In combat sports, this is manifested in the capacity to respond and control actions equally reliably from both sides (changing stance, counteractions, work in grips), which increases the variability of tactical decisions and reduces predictability. Similar conclusions are supported by studies showing that prolonged specialized training is associated with reduced motor asymmetry and a more integrated organization of motor control (interhemispheric specialization and integration) (Witkowski et al., 2020; Serrien et al., 2006).

Factor PA2 can reasonably be interpreted as a domain of operational reactivity and performance stability with an accuracy component, since it is primarily formed by indicators of response to a moving object (RMO). The values of RMO_RT_mean and RMO_SD_mean indicate that this latent variable summarizes both reaction speed and reliability and repeatability in a task requiring rapid sensorimotor decisions. At the same time, the inverse loading of accuracy (RMO_Accurate) is consistent with the classical logic of the speed-accuracy trade-off. In some athletes, faster responding may be accompanied by a greater error cost, whereas in others a balance between speed and correctness is maintained. Thus, PA2 reflects an integral domain of sensorimotor control efficiency, which is consistent with previous studies (Cauraugh, 1990; Domingue et al., 2022; Lerche & Voss, 2018). From a practical perspective, PA2 may be interpreted as a marker of the ability to rapidly process a visual signal and execute a motor response without a substantial loss of accuracy, that is, as a characteristic of operational control under conditions of time pressure and uncertainty. This is especially relevant for combat sports, where the key is not only to "be faster," but also to maintain the quality of the response (minimize erroneous and premature responses) as speed demands increase, and to preserve response stability across repeated trials. For this reason, contemporary studies emphasize the importance of decomposing reaction into decision-making and execution components, as well as the fact that reactivity characteristics may vary depending on training conditions (Cano et al., 2024; Kurak et al., 2025). It should be noted that not all indicators were included in the two-factor structure, and this is important for the correct interpretation of the results. Variables of the Go/No-Go type may have low communalities or weak, ambiguous loadings if they reflect a different cognitive domain (inhibitory control, attention) that does not coincide with the structure of sensorimotor reactivity and bilateral stability. In addition, in the Go/No-Go test task, the results substantially depend on the speed-accuracy trade-off and response strategies. If the test is assessed only by reaction time (RT) without considering other components that influence the manifestation of this type of reaction, then the contribution of these variables to the overall variance decreases, and they may not be included in the extracted factors. From a methodological point of view, this means that the exclusion of some variables is not an error in itself, but rather indicates the need to refine the set of indicators, for example, by considering inhibition as a separate factor in future models. This interpretation is consistent with previous studies (Littman & Takács, 2017; Schulz et al., 2007; Seli et al., 2013).

The construction of individual profiles based on factor scores (PA1-PA2) has direct practical value for monitoring, as it transforms disparate test indicators into two generalized, interpretable axes through which a coach or researcher can quickly identify an athlete's strengths and weaknesses. This approach is consistent with the modern logic of athlete profiling, in which it is important not only to compare mean values, but also to identify configurations of characteristics associated with different training needs and different risks of functional breakdowns. In practical terms, this means the possibility of segmenting athletes into groups with similar profiles and selecting corrective interventions for their training process (Volgemute et al., 2026). The LPI is a convenient tool for presenting information, allowing for operational control and tracking the dynamics of athletic preparedness. Conceptually, this is consistent with approaches in which composite indices are created from standardized (z-) scores in order to compare athletes with one another and rapidly identify deviations from the group "norm." In this sense, the LPI can be used as an integral marker for decision-making in preparedness monitoring, where interpretation should rely on threshold zones and the training context (Fernández et al., 2021; Oleksy et al., 2022; Oliva-Lozano et al., 2024).

The obtained results are consistent with contemporary evidence showing that the advantage of older and more experienced athletes in psychophysiological tests is not universal and largely depends on the type of task and on control of the speed-accuracy trade-off (Scharfen & Memmert, 2019). In particular, a study of elite athletes demonstrated that, after accounting for age and the trade-off between speed and accuracy, differences in general cognitive indicators become less pronounced and do not always have practical significance, which conceptually supports the absence of group differences in some of the aggregated metrics (Vona et al., 2024). At the same time, meta-analytic evidence in combat sports shows that in tasks closer to the competitive context (perceptual anticipation, reaction to dynamic stimuli), more experienced athletes more often demonstrate an advantage in both speed and accuracy; that is, the "elite effect" is more strongly manifested when the stimulus and task demands are closer to real interaction with an opponent (Zhang et al., 2022). From the perspective of applied sports science, the conclusions of the present study correspond to work in wrestling emphasizing the importance of sensorimotor characteristics, although the effect may be manifested not only in mean values, but also through associations with performance outcomes or through the structure of indicators (Korobeynikov et al., 2022). It has been reported that in elite Greco-Roman wrestlers, reaction speed was associated with indicators of competitive effectiveness, which highlights the relevance of reactivity as a component of preparedness (Gierczuk et al., 2017). In this context, the transition to latent factors and subsequent profiling is logical. Factor structure and profiles may better reflect the organization of sensorimotor control.

Concerning the role of artificial intelligence, the obtained results confirm the appropriateness of its use in sports science only under the condition that methodological, statistical, and interpretative consistency is preserved. Contemporary reviews indicate that AI, including machine learning, deep learning, and computer vision methods, has considerable potential for the analysis of sports performance. However, its practical implementation is accompanied by several limitations, among which are particularly important the insufficient standardization of model evaluation, the limited transparency of algorithms, and the difficulty of transferring results from controlled conditions to the real sports environment. For this reason, the effectiveness of AI use is determined not by the mere presence of an algorithm, but by the quality of the research design, the correctness of variable selection, and the preservation of reproducible analytical procedures (Pietraszewski et al., 2025; Dehbane et al., 2026). In the present study, AI did not perform the function of a computational core and did not replace classical statistical procedures. All numerical stages of the analysis, including descriptive statistics, correlation analysis, factorization, and calculation of integral indicators, were carried out in the RStudio environment. The role of AI was limited to auxiliary support in structuring the analytical process, aligning the logic of result presentation, and interpreting the identified patterns (Siebert et al., 2025). Such an approach is consistent with the contemporary view of large language models as expert-support tools, rather than as independent substitutes for professional statistical or scientific judgment. In related fields, it has been shown that LLMs have their greatest value precisely as a "copilot" or assistive tool, whereas the final evaluation, verification of correctness, and decision-making should remain the responsibility of the researcher (Lai et al., 2025; Yang et al., 2025). From a methodological point of view, such a hybrid approach is justified, since it makes it possible to combine the strengths of multivariate statistics and AI-supported analysis without compromising scientific reproducibility. Classical statistical methods ensure the transparency of numerical procedures, control over model assumptions, and the possibility of direct verification of results, whereas AI can strengthen the analytical process at the stages of structuring complex multivariate data, formulating generalized interpretations, and preparing practically oriented conclusions. At the same time, requirements for interpretability and transparency are currently regarded as the key conditions for the responsible use of AI in the analysis of motor and psychophysiological data. Therefore, in the context of sports science, the most justified approach should be considered not the replacement of statistics by artificial intelligence, but their rational combination within a unified research protocol (Pietraszewski et al., 2025; Khan et al., 2025).

The limitations of the study include, first, the sample size and its specificity (n = 44), which may affect the stability of factor structure estimation and limit the generalizability of the findings. Second, the sample comprised only male athletes from a single discipline (Greco-Roman wrestling), which restricts the applicability of the results to other combat sports, female athletes, and different age or qualification groups. Third, the cross-sectional design does not allow causal inferences regarding the formation of the identified latent constructs, as the results reflect only associations at the time of measurement. In addition, it should be acknowledged that the experimental procedure, based on a tablet-based cognitive-motor task, represents a controlled and reductionist assessment of psychophysiological functions. Therefore, its ecological validity in relation to real competitive performance is limited, as actual competition involves complex contextual and stress-related factors (e.g., opponent interaction, emotional arousal, fatigue, sleep quality, injury status, and environmental influences) that are not fully reproduced in laboratory conditions. Finally, the use of aggregated indicators may reduce sensitivity to subtle intra-individual differences in performance strategies. Consequently, careful selection of task-specific variables (particularly in inhibition paradigms) and stricter control of participant characteristics (e.g., weight category, training experience, and functional status) are required to improve the robustness and interpretability of the results (Costello & Osborne, 2005; MacCallum et al., 1999, 2001; Fabrigar et al., 1999).

Future research should focus on expanding the battery of indicators and testing the reproducibility of the proposed model in independent samples. In particular, it would be advisable to supplement the sensorimotor metrics with more sensitive indicators for inhibition tasks, as well as to add indicators that better reflect speed-accuracy strategies and within-subject variability across series of trials. It is also important to verify the practical validity of profiling by establishing relationships between the factors and the LPI and real criteria of athletic performance (placements, rankings, technical-tactical indicators, effectiveness of actions during bouts) and to conduct stratification by weight category, age, and sex to improve the objectivity of the conclusions.

The results of the study emphasize the appropriateness of using artificial intelligence in sports science, provided that methodological and statistical rigor is preserved (Ahmadi et al., 2024; Pietraszewski et al., 2025). As in the work of other authors (Jianjun et al., 2025; Zhu & Sun, 2019), in the present study, AI performs the function of a tool for data integration and interpretation, rather than a replacement for classical quantitative methods of analysis, which strengthens the applied orientation of the results and expands the possibilities for monitoring and predicting athletes' preparedness.

Conclusions

Psychophysiological determinants characterizing the preparedness profile of elite Greco-Roman wrestlers were identified. No statistically significant differences were found between the Youth U-17 and Senior groups across 10 key indicators after FDR correction, indicating a similar baseline level of sensorimotor functions within the studied sample.

Correlation and factor analyses showed that the most informative latent components of wrestlers' psychophysiological functions were PA1, reflecting bilateral motor stability and symmetry, and PA2, characterizing operational reactivity in the task of responding to a moving object with an accuracy component. The two-factor model constructed on the combined sample (n = 44) explained 54.23% of the total variance in psychophysiological indicators. In the older group of athletes, between-test associations were more frequently identified, particularly between VCR and RMO indicators, which may reflect a more coordinated organization of sensorimotor control in more experienced wrestlers.

Based on standardized key indicators, the integral LPI (Level of Psychophysiological Functions Index) was calculated, which makes it possible to perform a generalized assessment of athletes' psychophysiological status. The use of LPI together with factor scores PA1 and PA2 expands the possibilities for individual profiling, comparison of athletes with one another, and monitoring of the dynamics of psychophysiological functions during the training process. The practical significance of the obtained results lies in the fact that the identified determinants can be used as a basis for the individualization of monitoring, identification of the specific features of psychophysiological functions, and improvement of the monitoring system for Greco-Roman wrestlers.

In this study, artificial intelligence was used as an auxiliary tool for structuring and interpreting the results, but not for performing statistical calculations. This confirms the promise of a hybrid approach, in which AI enhances the analytical process without compromising its scientific reproducibility.

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