Multivariate analysis of anthropometric determinants of training load in youth badminton

Análisis multivariante de los determinantes antropométricos de la carga de entrenamiento en el bádminton juvenil

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How to cite in APA

Afzal, S., Bhaskar Raj, N., Muazu Musa, R., Rahim, M., & Ishfaq Khan, M. (2025). Multivariate analysis of anthropometric determinants of training load in youth badminton. *Retos, 71*, 988-997. https://doi.org/10.47197/retos.v71.117465

Abstract

Background: Monitoring training load in youth athletes is essential for optimizing performance and reducing injury risk, yet limited research has examined how anthropometric characteristics influence load tolerance in badminton. This study investigated the association between training load measures and anthropometric profiles in competitive youth players.
Methods: Fifty male and female athletes participated, with external workload captured via *accelerometer* sensors and anthropometric assessments conducted following standardized protocols. Louvain clustering was applied to classify players into different load groups, while multinomial logistic regression (MLR) identified key predictors of load classification.
Results: Louvain clustering revealed three distinct load groups i.e., High Load (HL), Moderate Load (ML), and Low Load (LL) groups, reflecting natural patterns in external workload distribution. The MLR analysis demonstrated that height, weight, and leg length were significant predictors of load classification. Taller and heavier players were more likely to belong to the HL group, while longer leg length was positively associated with ML classification, potentially linked to stride mechanics and movement economy. Other circumferential measures (waist, hip, MUAC) showed minimal impact, and years of playing experience did not significantly predict load tolerance.
Conclusion**:** These findings emphasize the value of combining network-based clustering with multivariate modeling to capture complex athlete load interactions. Practically, the results suggest that specific anthropometric traits particularly stature, body mass, and limb length, play an important role in shaping athletes' ability to sustain training loads. Integrating individualized anthropometric assessment into load monitoring can support evidence-based coaching strategies that enhance performance and mitigate injury risk in developing badminton players.

Keywords

Training load, anthropometry, youth athletes, badminton performance, clustering analysis.

Resumen

Antecedentes: El monitoreo de la carga de entrenamiento en atletas juveniles es esencial para optimizar el rendimiento y reducir el riesgo de lesiones; sin embargo, existe investigación limitada sobre cómo las características antropométricas influyen en la tolerancia a la carga en el bádminton. Este estudio investigó la asociación entre las medidas de carga de entrenamiento y los perfiles antropométricos en jugadores juveniles competitivos.Métodos: Participaron cincuenta atletas, hombres y mujeres, con la carga externa registrada mediante sensores acelerométricos y evaluaciones antropométricas realizadas bajo protocolos estandarizados. Se aplicó el algoritmo de clustering Louvain para clasificar a los jugadores en diferentes grupos de carga, mientras que la regresión logística multinomial (RLM) identificó los predictores clave de la clasificación de carga.Resultados: El clustering Louvain reveló tres grupos de carga distintos: Alta (HL), Moderada (ML) y Baja (LL), reflejando patrones naturales en la distribución de la carga externa. El análisis de RLM mostró que la estatura, el peso corporal y la longitud de pierna fueron predictores significativos de la clasificación. Los jugadores más altos y pesados tendieron a pertenecer al grupo HL, mientras que una mayor longitud de pierna se asoció positivamente con la clasificación ML, posiblemente vinculada a la mecánica de zancada y la economía del movimiento. Otras medidas circunferenciales (cintura, cadera, perímetro braquial medio) tuvieron un impacto mínimo, y los años de experiencia no predijeron significativamente la tolerancia a la carga.Conclusión: Estos hallazgos subrayan el valor de combinar técnicas de clustering basadas en redes con modelos multivariados para capturar interacciones complejas en la carga del atleta. En la práctica, los resultados sugieren que ciertos rasgos antropométricos, particularmente la estatura, la masa corporal y la longitud de las extremidades, desempeñan un papel importante en la capacidad de los atletas para sostener cargas de entrenamiento. La integración de evaluaciones antropométricas individualizadas en el monitoreo de carga puede respaldar estrategias de entrenamiento basadas en evidencia que potencien el rendimiento y reduzcan el riesgo de lesiones en jugadores juveniles de bádminton.

Palabras clave

Carga de entrenamiento; antropometría; atletas juveniles; rendimiento en bádminton; análisis de conglomerados.

Introduction

Badminton is a physically demanding racquet sport characterized by frequent high-intensity actions, including repeated accelerations, decelerations, rapid changes of direction, and explosive jumps (Phomsoupha & Laffaye, 2015). Success in this sport requires a unique combination of speed, agility, power, and balance. The ability to maintain stability and generate force efficiently during dynamic movements is fundamental to performance and injury prevention (Kibler et al., 2006). Previous work has emphasized the importance of physical and anthropometric characteristics such as body composition, stature, and limb length in shaping badminton-specific performance profiles (Cabello & González-Badillo, 2003; Bisht et al., 2019; Dong et al., 2023). Comparisons across playing levels also highlight that elite and sub-elite players differ in physiological and anthropometric characteristics (Ooi et al., 2009), and junior players show distinctive development-related features compared to adults (Angga, 2019). More recent syntheses confirm that anthropometrics remain central to the demands of high-level badminton (Phomsoupha & Laffaye, 2020).

In parallel, advances in sports monitoring have accentuated the importance of quantifying training load, broadly defined as the cumulative stress an athlete experiences through training and competition (Impellizzeri et al., 2019; Halson, 2014). Training load is typically divided into internal load, reflecting the physiological responses to exercise (e.g., heart rate, rating of perceived exertion) (Foster et al., 2017), and external load, which quantifies the mechanical and movement demands of activity (e.g., accelerations, decelerations, (Soligard et al., 2016). Effective monitoring of these loads is essential for optimizing performance while minimizing injury risk, particularly given the strong evidence linking sudden spikes in training load with overuse injuries across sports (Gabbett, 2016). This concern is heightened in youth athletes, where inadequate load management can negatively affect both performance trajectories and long-term health (Murray, 2017).

Although workload assessment has been widely studied in team and endurance sports periods (Bartlett et al., 2017; Taylor et al., 2020), research specific to racquet sports, and badminton in particular, remains limited. Existing studies have largely focused on match play or selected training sessions (Simpson et al., 2020), with less attention given to the interaction between athletes' anthropometric profiles and their load responses. This relationship is important because anthropometric factors such as stature, body mass, and body composition can influence both mechanical demands during play and the physiological cost of training (Alcock & Cable, 2009; Sasaki et al., 2022). Understanding these associations in youth athletes is crucial for designing individualized training programs that support development while reducing injury risk (Gaurav et al., 2010; Musa et al., 2025; Phomsoupha et al., 2018)

Therefore, the present study aims to examine the associations between different internal and external load measures and the anthropometric profiles of competitive youth badminton players. By classifying players into high- and low-load groups according to their anthropometric characteristics, this work provides practical insights for coaches and practitioners. Such information may support the alignment of training demands with athletes' physical readiness, thereby optimizing performance development and safeguarding long-term athletic health.

Method

Participants

Fifty competitive youth badminton players (22 females, 28 males; mean ± SD age: 15.0 ± 1.8 years; playing experience: 6.3 ± 2.3 years) were recruited from established badminton academy programs in Malaysia through purposive sampling. Players were selected based on their competitive participation level and training experience, ensuring that the sample represented athletes actively engaged in structured performance pathways. All participants were free from musculoskeletal injuries at the time of data collection.

Prior to participation, the study procedures and potential risks were explained to all players and their guardians. Written informed consent was obtained from participants aged 18 years and above, while parental or guardian consent was secured for those under 18. Ethical approval for this study was granted by the Universiti Sultan Zainal Abidin Human Research Ethics Committee (UHREC; Approval No: UniSZA.800-1/1/4 Jld.3 (27).

A priori sample size estimation was conducted using G*Power software(Faul et al., 2017), based on anticipated effect sizes, an alpha level of 0.05, and the planned statistical analyses. This ensured that the study was sufficiently powered to detect meaningful differences in the variables of interest.

Anthropometrics Assessment

Basic anthropometric measurements were obtained following standardized procedures to ensure accuracy and reliability. Height was measured to the nearest 0.1 cm using a wall-mounted stadiometer (Seca Bodymeter 206, Hamburg, Germany), while body mass was recorded to the nearest 0.1 kg using a calibrated digital scale (Omron Karada Scan HBF-375, Kyoto, Japan) placed on a firm, level surface (Steels et al., 2020). Leg length was assessed with a non-elastic tape as the distance from the anterior superior iliac spine (ASIS) to the medial malleolus, following the protocol previously described (Taha et al., 2018). Mid-upper arm circumference (MUAC) was measured at the midpoint between the acromion and the olecranon process of the right arm using a flexible, non-elastic tape measure (Maliki et al., 2018). All measurements were taken twice by trained assessors, and the average of the two values was used for analysis.

External player load tracking

External load was monitored during competitive play using wearable inertial sensors (Xsens Dot, Movella, Enschede, The Netherlands), which provide high-resolution kinematic data. Each player wore a single sensor securely positioned on the lumbar region of the spine using an elastic strap to minimize movement artefacts as shown in Figure 1. The devices were paired with the Movella Dot mobile application via Bluetooth and calibrated prior to data collection to ensure alignment with the body's axes. The Xsens Dot records tri-axial accelerations (X, Y, Z) with a dynamic range of ±16 g and angular velocity, with data sampled at 30 Hz to balance accuracy and recording efficiency (Vanrenterhgem et al., 2017) (Biró et al., 2024). The collected inertial data were subsequently exported in raw format for further processing and analysis, expressed as acceleration (m/s^2) and angular velocity (°/s), following established protocols (Vartak et al., 2016).

Figure 1. Sensor attachment for tracking external workload

Player's external load calculation

The player's external load was calculated using triaxle accelerometer data, which measured acceleration in three dimensions (ax, ay, az). The player load was computed based on the rate of change in acceleration across these axes, using the following formula:

$$\text{Players load:} = \frac{\sqrt{(\Delta ax)^2 + (\Delta ay)^2 + (\Delta az)^2}}{100}$$

Where Δax, Δay, and Δaz reflect the differences in acceleration between consecutive samples in the x, y, and z directions, respectively. The square root of the sum of squared differences in accelerations is divided by 100 to normalize the load (Martín-Martín et al., 2022).

Data analysis procedure

Descriptive statistics (mean ± standard deviation) were first computed for the players' anthropometric and fitness characteristics to provide an overview of the dataset and identify potential outliers or distributional patterns. Subsequently, a cluster analysis was performed to group players based on shared characteristics. Inferential analyses included multinomial logistic regression, which was used to examine the association between cluster membership and relevant predictor variables. All collected data were analyzed using Jamovi Statistical Software version 2.4 for Windows. Detailed procedures for each analytical step are presented in the subsequent sub-sections.

Clustering

In this study, the Louvain clustering algorithm was employed to classify players based on their external load measures. Louvain clustering is a community detection method originally developed for network analysis, where the goal is to maximize modularity, a measure of the density of connections within clusters compared to between them (Blondel et al., 2008). By iteratively optimizing modularity, the algorithm partitions the dataset into internally cohesive groups. For the present analysis, external player load served as the primary feature for cluster formation, and players were categorized into three distinct groups: high load (HL), medium load (ML), and low load (LL). The number of clusters was fixed at three (k = 3) to capture the main variations in load distribution among participants. Although, conventional methods such as k-means or hierarchical clustering are common for continuous data, the Louvain algorithm was preferred because it does not assume spherical clusters or rely on centroid initialization. Instead, it optimizes modularity to detect more complex community structures, making it better suited to capture the non-uniform and interdependent patterns often seen in external load data.

Development of multinomial logistic regression model

A multinomial logistic regression (MLR) model was applied to examine the associations between external load classifications and the anthropometric profiles of competitive youth badminton players. The categorical dependent variable was derived from the Louvain clustering results, which grouped players into three categories: high load (HL), medium load (ML), and low load (LL). Independent variables included a range of fitness components and anthropometric measures. MLR was selected because it is well-suited for modeling nominal outcome variables with more than two classes, allowing the estimation of the probability of group membership based on predictor profiles.

To evaluate model performance, the dataset was stratified into training (70%, n = 35) and testing (30%, n = 15) subsets, ensuring proportional representation of all categories and thereby preserving class balance. The model generated regression coefficient estimates, standard errors, z-values, p-values, odds ratios (OR), and 95% confidence intervals, enabling assessment of both the direction and magnitude of associations (Mohamed et al., 2025). This approach allowed for interpretable, statistically rigorous insights into how specific fitness and anthropometric characteristics influence the likelihood of belonging to each external load category. The findings provide an evidence-based foundation for tailoring individualized training strategies in youth badminton.

Results

Figure 2 illustrates the distinct classes identified through Louvain clustering analysis of players' external load levels. Three well-defined categories emerged: High Load (HL, n = 10), Moderate Load (ML, n = 28), and Low Load (LL, n = 12). The HL group recorded the highest external load, averaging a score of approximately 9, while the ML group demonstrated a moderate load with mean values around 4. The LL group exhibited the lowest external load, with a mean slightly above 1. The relatively small error bars across all groups suggest low within-group variability. Overall, the figure demonstrates a clear descending trend in external load from HL to LL, highlighting distinct differences between the clusters.

Figure 2. Classification of players into High Load, Moderate Load, and Low Load groups based on Louvain clustering.

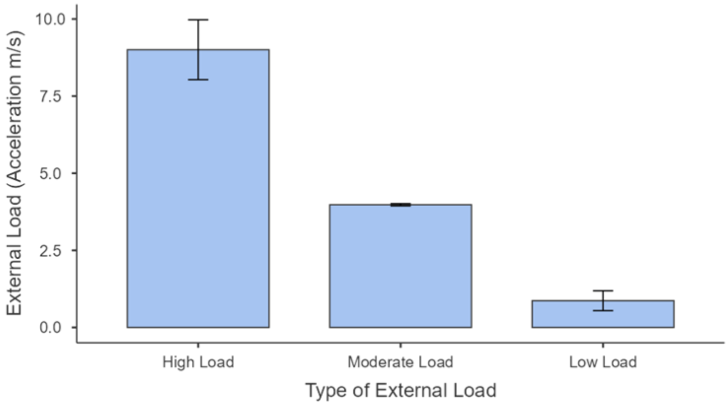

Table 1 presents the anthropometric and physical characteristics of players across the high-, moderate-, and low-load groups. Group comparisons were performed using one-way ANOVA, with Duncan's post-hoc test applied to determine the reliability of differences between High Load (HL), Moderate Load (ML), and Low Load (LL) groups. Statistical significance was set at $p < 0.05$. Notable differences were observed in playing experience, height, and weight, with the high-load group generally showing statistically greater values relative to the moderate- and low-load groups. In contrast, abdominal, waist, hip, and mid-upper arm circumference (MUAC) showed only minor variations between groups, while leg length was slightly greater in the low-load group. These findings suggest that specific physical attributes, particularly overall body size and playing experience, may contribute to differences in external load distribution among players.

Table 1. Group comparisons across measured variables

Variables	External load group		
	High load (n=10)	Moderate load (n=28)	Low load (n=12)
Experience (years)	7.50±1.84	5.65±2.09	6.83±2.66*
Height (cm)	166.90±9.53	158.71±12.39	163.08±13.15*
Weight (kg)	54.08±8.00	47.80±10.00	54.19±12.38*
Abdominal CC (cm)	69.40±4.60	70.36±10.22	69.33±5.18
Leg length (cm)	89.10±2.99	90.02±6.59	91.50±8.42
Waist CC (cm)	73.00±5.46	71.00±8.02	71.67±6.96
Hip CC (cm)	82.20±7.73	82.82±5.56	83.33±6.84
MUAC (cm)	23.70±1.77	23.29±2.71	23.67±2.64

Values are presented as mean ± Standard Deviation
CC = Circumference; MUAC = Medial Upper Arm Circumference
*Significance difference among the three load categories (p<0.05).

Table 2 presents the fit statistics for the multinomial logistic regression model predicting external load classification among youth badminton players. It is worth noting that all the variables, notably the experience and anthropometric-related predictors, were used as revealed by the table. The model demonstrated a moderate fit, with a Nagelkerke R^2 of 0.389, indicating that 38.9% of the variance in load group membership was explained by anthropometric and experience-based predictors. The likelihood ratio test was significant ($\chi^2 = 31.2$, df = 16, p = 0.013), confirming that the full model provided a better fit than the null model. Information criteria values (AIC = 104; BIC = 138) supported model parsimony, while the deviance statistic (67.7) suggested an acceptable level of unexplained variation. Collectively, these findings highlight the relevance of anthropometric profiling in differentiating external load groups and underscore its potential value in guiding individualized training strategies for youth badminton players.

Table 2. Multinomial logistic regression analysis of anthropometric predictors of external load classification (High Load = reference group).

				Overall Model Test		
Deviance	AIC	BIC	R^2N	χ^2	df	p
67.7	104	138	0.389	31.2	16	0.013

The multinomial logistic regression analysis (Table 3) evaluated the influence of anthropometric and experience-related factors on the likelihood of players being classified into Low Load (LL), Moderate Load (ML), or High Load (HL) groups, with HL serving as the reference category. Height, weight, and leg length emerged as significant predictors ($p < 0.05$). Each 1 cm increase in height reduced the odds of LL and ML classification by 24.4% and 21.5%, respectively, indicating that taller players were more likely to sustain higher external loads, potentially due to biomechanical advantages. Similarly, weight negatively predicted ML membership, with each additional kilogram lowering the odds by 23.4%, suggesting that heavier players may be better conditioned to tolerate higher loads. In contrast, leg length positively predicted ML classification, where each 1 cm increase raised the odds by 48.4%, possibly reflecting movement efficiency associated with moderate loading. Other measures, including abdominal, waist, hip, and mid-upper arm circumferences, along with playing experience, were not statistically significant, though hip circumference showed a near-significant trend. Overall, these results emphasize the role of specific morphological traits in shaping external load profiles and support their integration into individualized training and load management strategies for youth badminton players.

Table 3. Multinomial Logistic Regression Model of External Load Classification

							95% Cl	
External Load Group	Predictor	Estimate	SE	Z	P	OR	Lower	Upper
LL - HL	Intercept	5.72	7.02	0.81	0.42	303.55	3.20	2880.00
	Experience (years)	-0.26	0.32	-0.81	0.42	0.77	0.41	1.45
	Height (cm)	-0.28	0.12	-2.34	0.02*	0.76	0.60	0.96
	Weight (kg)	0.06	0.13	0.44	0.66	1.06	0.82	1.36
	Abdominal CC (cm)	0.04	0.22	0.20	0.84	1.04	0.68	1.60
	Leg Length (cm)	0.27	0.16	1.66	0.10	1.31	0.95	1.80
	Waist CC (cm)	-0.14	0.19	-0.72	0.47	0.87	0.60	1.27
	Hip CC (cm)	0.29	0.18	1.61	0.11	1.34	0.94	1.92
	MUAC (cm)	-0.09	0.29	-0.31	0.75	0.91	0.52	1.60
ML - HL	Intercept	-15.77	6.27	-2.52	0.01*	0.00	0.00	0.03
	Experience (years)	-0.22	0.31	-0.73	0.47	0.80	0.44	1.46
	Height (cm)	-0.24	0.12	-2.05	0.04*	0.79	0.62	0.99
	Weight (kg)	-0.27	0.13	-2.05	0.04*	0.77	0.59	0.99
	Abdominal CC (cm)	0.39	0.21	1.81	0.07*	1.47	0.97	2.24
	Leg Length (cm)	0.39	0.16	2.51	0.01*	1.48	1.09	2.02
	Waist CC (cm)	-0.13	0.19	-0.68	0.50*	0.88	0.61	1.28
	Hip CC (cm)	0.32	0.18	1.75	0.08*	1.38	0.96	1.96
	MUAC (cm)	-0.32	0.30	-1.06	0.29	0.73	0.41	1.31

Note: *p<0.05; SE=Standard Error; OR = Odd Ratio, LL =Low Load; ML = Moderate Load; HL = High Load
CC = Circumference; MUAC = Medial Upper Arm Circumference

Discussion

This current study examined the relationship between anthropometric profiles and training load classifications among competitive youth badminton players. Using Louvain clustering, players were grouped into High Load (HL), Moderate Load (ML), and Low Load (LL) categories, while multinomial logistic regression identified the anthropometric factors most predictive of load group membership as demonstrated in Table 1. Height and weight emerged as significant predictors, with taller and heavier players more likely to sustain higher external loads. Leg length was also influential, being positively associated with ML classification, likely due to its role in stride mechanics and movement efficiency. These findings align with previous work linking favorable body proportions to enhanced sport-specific performance (Buchheit & Laursen, 2013; Nikolaidis et al., 2019).

Interestingly, other circumferential measures such as abdominal, waist, hip, and MUAC showed minimal variation across load groups, and were not significant predictors in the regression model. This suggests that while overall size and limb length are important, regional body composition may have a limited direct effect on external load tolerance in this context. Moreover, experience was not found to be a statistically significant predictor, although descriptive analysis showed a trend where players in the HL group had slightly more playing experience. This indicates that technical skill and exposure alone may not determine load tolerance without the necessary physical support (Buchheit & Laursen, 2013b).

The multinomial logistic regression model demonstrated acceptable predictive performance, with moderate explanatory power (Nagelkerke $R^2 = 0.389$) and a statistically significant overall model fit ($\chi^2 = 31.2$, df = 16, p = 0.013). This confirms its effectiveness in classifying players into High Load (HL), Moderate Load (ML), and Low Load (LL) groups based on anthropometric characteristics (Bewick et al., 2005).

Height consistently emerged as a significant predictor in both the LL–HL (OR = 0.76, p = 0.02) and ML, HL (OR = 0.79, p = 0.04) comparisons, indicating that taller athletes were more likely to be classified in the HL group. Weight was also a meaningful factor in the ML, HL comparison (OR = 0.77, p = 0.04), suggesting that heavier players had an increased likelihood of experiencing high external workloads (Mohamed et al., 2025). Additionally, leg length showed a significant positive association in the ML, HL comparison (OR = 1.48, p = 0.01), indicating that athletes with longer legs were more likely to belong to the ML group relative to HL, potentially due to differences in stride mechanics and movement efficiency (Musa et al., 2025). These results underscore the impact of certain anthropometric characteristics especially height, body mass, and limb length on an athlete's capacity to sustain varying training loads in competitive youth badminton. This aligns with previous research showing that advantageous body proportions can enhance sport-specific performance by improving reach, movement efficiency, and power output (Buchheit & Laursen, 2013a; Nikolaidis et al., 2019).

The finding that taller and relatively leaner athletes were more likely to be classified in the high-load group may reflect underlying biomechanical and maturational mechanisms. Taller players benefit from greater limb length and reach, which enhance stride mechanics and reduce relative energy cost for repeated movements, facilitating sustained workloads despite lower muscle bulk (Phomsoupha & Laffaye, 2015). In youth populations, leaner profiles may also signal advanced biological maturation relative to peers, as shown by Malina et al., (2004), thereby conferring advantages in workload tolerance independent of chronological age. This may explain why the anthropometric traits observed in our sample differ from those of elite adult badminton players, whose higher muscle mass is necessary to support the anaerobic-glycolytic demands of the sport. Our findings, therefore highlight the importance of considering growth and maturation factors when interpreting workload responses in youth athletes.

Overall, the findings accentuate the importance of integrating load monitoring with individualized anthropometric assessments in youth badminton. As highlighted by Malina et al., (2004), adolescent athletes exhibit substantial variability in growth, maturation, and training response, which necessitates tailored approaches for performance optimization and injury prevention. The combination of Louvain clustering and multinomial regression provided robust insights into how player characteristics relate to training demands, supporting the development of data-driven, athlete-centred coaching strategies.

Conclusions

In conclusion, this study highlights training load measures based on anthropometric profiles of competitive youth badminton players using advanced analytical techniques, including Louvain clustering and multinomial logistic regression. The results emphasize that specific physical characteristics, especially height, weight, and leg length, are important factors influencing an athlete's ability to handle external load. By applying Louvain clustering and multinomial logistic regression, athletes were successfully categorized into high, moderate, and low load groups. The analysis showed that taller and heavier players were more likely to endure higher workloads, whereas leg length was linked to classification within the moderate load group. The weak association between internal and external loads underscores the complex, multifaceted nature of training responses and highlights the importance of personalized monitoring and load management strategies. These results advocate for combining anthropometric profiling with training load analysis to guide athlete-centred coaching methods that improve performance while minimizing the risk of overtraining or injury.

Conflict interest

The authors have no conflict of interest to declare.

Acknowledgements

The authors wish to thank Badminton World Federation (BWF 2023) for their support in carrying out this study. The authors also thank all the participants for their commitment throughout the data collection process.

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