THE RELATIONSHIP BETWEEN STRENGTH CAPACITY AND MOTOR PERFORMANCE IN THE GYMNASTIC HANDSTAND: A MACHINE LEARNING STUDY

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Original article *DOI: 10.52165/sgj.16.2.211-223*

Abstract

The present study investigated the relationship between strength capacity and motor performance in the gymnastic handstand. The hypothesis stipulated a positive relationship between motor performance and strength capacity levels. Thirty-two university students, 16 female and 16 male (24.03 ± 4.74 years of age,) participated in the study. The handstand was assessed using the absolute error of the three angles produced by the model (video) and the three angles produced by the performer. We conducted four strength tests: explosive force, maximum right-hand grip strength, maximum left-hand grip strength, and resistance force. The machine learning model was trained using 10 of the folds and cross-validated, and a linear regression test was performed using motor performance (absolute error) and strength tests (explosive force, maximum force right-hand, maximum force left-hand, and resistance force). The results showed that the machine learning model indicated a low relationship between strength capacity and motor performance. Additionally, motor performance was not found to be related to strength capacity. The results may indicate that specific capacities and the interaction of factors such as task specificity, environment, and individual characteristics influence motor performance.

Keywords: *sport, training, motor task, motor control, motor behavior.*

INTRODUCTION

The field of sports preparation is complex, involving the selection and assessment of athletes (Malina, 1974). In the development of these programs (Baker et al., 2012; Vaeyens et al., 2008; Mohamed et al., 2009), athletes are typically evaluated across a range of skills specific to their sport, as well as through general tests aimed at assessing capacities such as flexibility, endurance, and strength (Vaeyens et al., 2008; Mohamed et al., 2009). However, the relationship between these specific skills and capacities, particularly in the context of gymnastics handstands, remains an ongoing investigation.

Initial studies have adopted the perspective that capacities can predict sports success. They were grounded in a fundamental (general) capacity capable of elucidating performance across numerous skills, thus fostering success in sports (Brace, 1930; McCloy, 1934). It implies that capacity comprises attributes intricately linked to executing various movements (Rarick, 1937; Carpenter, 1942).

Although some studies have supported the perspective of a general capacity (Ibrahim et al., 2011; Liefeith et al., 2018; Hands, McIntyre, and Parker, 2018), other researchers have not revealed favorable results and have followed the perspective that performance may depend on the specificity of the task (Lage et al., 2017; Robin et al., 2005; Tremblay & Proteau, 1998), i.e., motor tasks can be influenced from a discrete set of capacities in a specific manner. Following this perspective, studies indicated that capacities such as coordination and agility, considered by some researchers as 'general capacities' transferable to a series of sports skills, are specific to certain motor tasks (Henry, 1968). The general capacity perspective has raised numerous questions and should have stimulated more research that supports this view (Ibrahim et al., 2011; Hands, McIntyre, and Parker, 2018).

Another perspective highlights the complex interaction among task demands, environment, and individuals in shaping motor performance (Newell, 1985;1986). In gymnastics, examples of task demand constraints include the routine's complexity and the timing and sequence of movement execution. Environmental constraints, for example, in gymnastics, encompass the temperature and humidity of the gymnasium. Individual constraints refer to inherent characteristics and attributes specific to the athlete, which can influence motor performance. In gymnastics, individual constraints may manifest through capacities such as flexibility, coordination, and strength. Therefore, the most crucial aspect is not an isolated element (such as individual characteristics like capabilities) but rather the interaction among these elements.

Currently, there is a lack of information about the studies that sought to relate specific skills to these propositions (Hands, McIntyre, and Parker 2018). In the context of gymnastics, tests evaluating athletes' capabilities serve as a method for athlete selection (Mkaouer et al., 2018). Among these capabilities, strength capacity stands out as a crucial component (Halin et al., 2002). For instance, Nassib et al. (2020) discovered that elite-level gymnasts demonstrate superior muscular strength in various forms, such as isometric, explosive, and resistance, surpassing the benchmarks established by the International Gymnastics Federation. Given the significance of capabilities in gymnastics, understanding their relationship with performance in specific tasks becomes paramount.

Therefore, the primary objective of this study was to delve into the relationship between strength capacity and motor performance in the context of gymnastics handstands. By employing machine learning models and linear regression, we aimed to uncover the intricate connection between strength, in its various forms, and motor performance. The anticipated outcome is a positive correlation between motor performance and strength capacity levels, a finding that could significantly impact the field of sports science and gymnastics.

METHODS

Thirty-two university students, 16 of whom were female, and 16 were male (24.03 ± 4.74 years of age) participated in the study. As criteria for participation in the experiment, the individuals had to be able to raise their legs. At the same time, both hands had to touch the ground, forming an angle of at least 90° between the Patella and Iliac crest (Rohleder & Vogt, 2018). Volunteers could not have a systematic experience with handstand skills and did not present any pathology that could directly interfere with movement performance. The selected volunteers were informed of the purpose of the study and provided their written informed consent to participate in this study. The experiment was reviewed and approved by the local Ethics Committee (BLIND INFORMATION) and was conducted in agreement with the 1964 Declaration of Helsinki.

We selected these tests to assess strength for two reasons. Firstly, their ease of application closely aligns with the training context in gymnastics. Secondly, the minimal similarity between the elements of motor task execution (handstand) and the tests was a decisive factor (Thorndike and Woodworth, 1901a,b,c)— this lack of similarity further challenges the study's hypothesis. If the elements of motor task execution (handstand skill) and the tests were more alike, the capacity to perform the handstand could influence the results.).

We collected data at the university laboratory, with standard lighting and windows covered adequately by curtains. To perform the kinematic analysis of handstand skills, we used a video camera (Nikon, D-750 Sigma - lens 17-50mm) with a 60 Hz frame rate and the Kinovea software (v.0.8.15) to analyze the data. We utilized a 2 kg medicine ball and measuring tape to administer the explosive force test on the upper limbs. The Maximum force test was conducted using a manual dynamometer (SGODDE, SKU), while a mat and a stopwatch (iPhone 5s cell phone) were employed for the Resistance force test. Additionally, two mattresses measuring 1.2 cm x 60 cm x 4 cm were positioned in front of the participant to mitigate the risk of potential frontal falls. Additionally, two researchers stood near the performers to ensure their safety.

Volunteers were marked on the right side of their bodies with red adhesive tape in the shape of the plus symbol (+) in the following locations: lateral condyle (knee), greater trochanter (hip), humeral head (shoulder), styloid process (hand) and the temporal bone (head). After placing landmarks, the volunteers received the following instructions: To perform the handstand skill, you must remove your feet off the ground while maintaining support with your hands and straighten your arms, legs, and spine as much as possible. You must touch the ground with the extended fingers and place the hands apart at shoulder width. The legs must remain together and upright, while the head must remain aligned with the body.

Furthermore, we showed each participant an image of the ideal task execution and subsequently played a video of an ideal execution pattern (performed by a professional) twice. Each individual was then required to make three attempts to familiarize themselves with the movement. Then, we instructed the participants to stay ready on the mattress and to initiate the movement only after the verbal command. Each participant performed three trials.

For the video analysis, we configured three angles using Kinovea. (Figure 1): (i)

Angle between the Patella and the Iliac crest; (ii) Angle between the Iliac crest and the Ulna; (iii) Angle between the Iliac crest and the Temporal bone. We selected the model based on a gymnast with over ten years of experience and participation in world artistic gymnastics (Rohleder & Vogt, 2018).

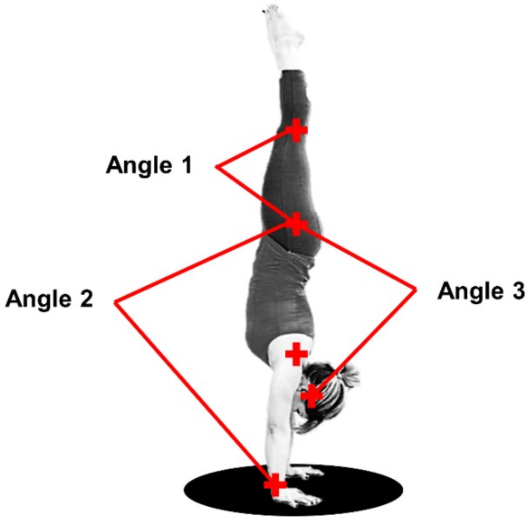

Figure 1. Angles analyzed.

Before the Explosive force test (Medicine-ball test), we demonstrated the participant's movement ("hold it close to the chest with the elbows flexed"). Then, the participants positioned themselves in the indicated location and threw the ball. After the familiarization procedure, the participants received the verbal command, "Throw the ball as far as possible, keeping their backs against the wall!". The distance reached was measured after identifying where the medicine ball touched the ground. Each participant performed three trials.

For the Maximum force test (Upper limb grip strength), participants were seated on a chair with their shoulders and hips aligned against the backrest. The hand holding the dynamometer remained with the palm facing the body, while the other hand rested over the leg opposite to the hand that held the dynamometer. Before conducting the test, we demonstrated the correct execution. At the verbal command of the experimenter, the volunteers held the dynamometer and performed the test while another experimenter registered the values obtained. The procedure was repeated by alternating the hands after 30-second intervals, involving three trials for each hand.

We used the Push-up test (Resistance force test) to measure the Resistance force. To conduct the test, the individual assumed a prone position with their hands placed slightly wider than shoulder-width apart and aligned with the chest. For males, the body formed a straight line from head to heels, with the feet together or slightly apart. Females positioned their knees on the ground and placed their hands 10 to 20 cm apart from the shoulder line. Upon a signal to begin, the individual lowered their body by bending their elbows until their chest touched the ground, ensuring the body remained straight throughout the movement. Then, they pushed their body back up to the starting position by extending their arms, completing one full repetition. We instructed them to perform as many correct executions as possible within 30 seconds.

We analyzed the explosive force test of the upper limbs by using the mean score of the three trials, while we analyzed the maximum force test by considering the maximum value attained with each hand on the manual dynamometry. For the Resistance force test, we computed only the correct executions.

Motor performance was measured by the absolute error: the difference in the three angles produced by the model and the three angles produced by the performer (Rohleder & Vogt, 2018). The angle error was obtained using the following equation:

absolute error = $|a1_{goal} - a1_{real}| + |a2_{goal} - a2_{real}| + |a2_{goal} - a2_{real}|$

where a_{1goal}, a_{2goal}, and a_{3goal} represent the model's values, and a_{1real}, a_{2real}, and a_{3real} denote the values obtained by the performer during the attempt.

The four predictor variables (explosive force, maximum force right-hand, maximum force left-hand, and resistance force) entered into the logistic regression were used to train the machine learning model (Naive Bayes classifier) (Webb et al., 2005). These machine-learning approaches determine the most probable outcome associated with a given set of predictor variables (Kononenko, 2001; Bunker & Thabtah, 2019). The value related to the performance in the task (absolute error) does not indicate class, just the absolute value of error. So, firstly, we determine the outcomes in classes and classify the absolute error into two classes: above average or below average [(value > 74.5: above average), (value < 74.5: below average)] (Figure 2).

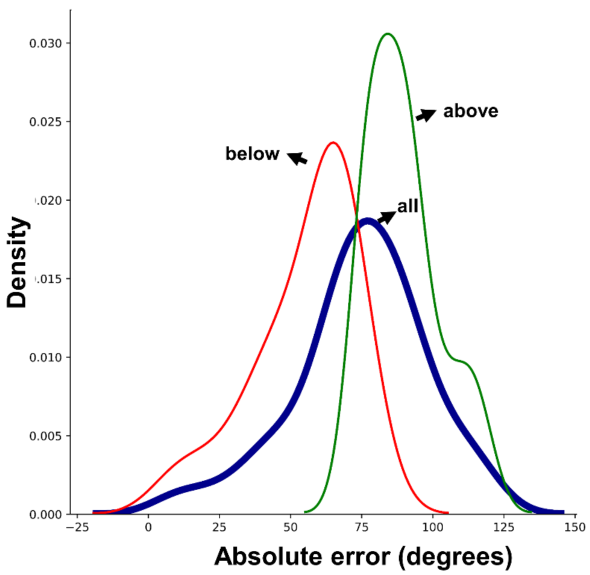

Figure 2. Histogram of the density of class above average, below average, and all interval

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After classifying the data, we trained the machine learning model using ten folds and cross-validated it (Stratified K-Fold and Shuffled). The machine learning data was analyzed through the mean of accuracy in all folds, with values closer to 1 indicating that predictor variables explain well. Finally, we used the parameters of the train machine learning model to compare the absolute error actual (y_actual) and the predicted absolute error (y_predicted) and indicated the coefficient of determination (R^2) of comparison.

A linear regression test used motor performance (absolute error) and strength tests (explosive force, maximum right-hand, maximum left-hand, and resistance force). We chose an alpha level of .05 for all inferential statistics. We calculated the effect sizes using Cohen's (*f2*). In this study, we adopted 0.02 as indicating a small effect size, 0.15 as a medium effect size, and 0.35 as a large effect size.

RESULTS

Figures 3 display the correlation matrix (A) and confusion matrix (B). All regression coefficients (Pearson) showed positive values, indicating that all relationships between predictor variables (explosive force, maximum force right-hand, maximum force left-hand, and resistance force) and absolute error are proportional (Figure 3A). The confusion matrix exhibited a high error rate in classifying the absolute error into two classes, above average and below average (Figure 3B). The mean accuracy of the machine-learning model was 0.44.

When we compared the data simulations of 32 subjects (using the parameters of the model trained) to the actual data, the R^2 was 0.22 (Figure 4).

Figure 5 displays the results regarding motor performance and the Explosive force test of the upper limbs. The regression test did not detect significant differences [$F(1,30) = 3.36$, $p = 0.07$, $R^2 = 0.10$, $f2 = 0.11$].

Regarding motor performance and the Maximum force test (right-hand), the regression test did also not detect significant differences[$F(1.30) = 1.70$, $p = 0.20$, $R^2 = 0.05$, $f2 = 0.25$] (Figures 6).

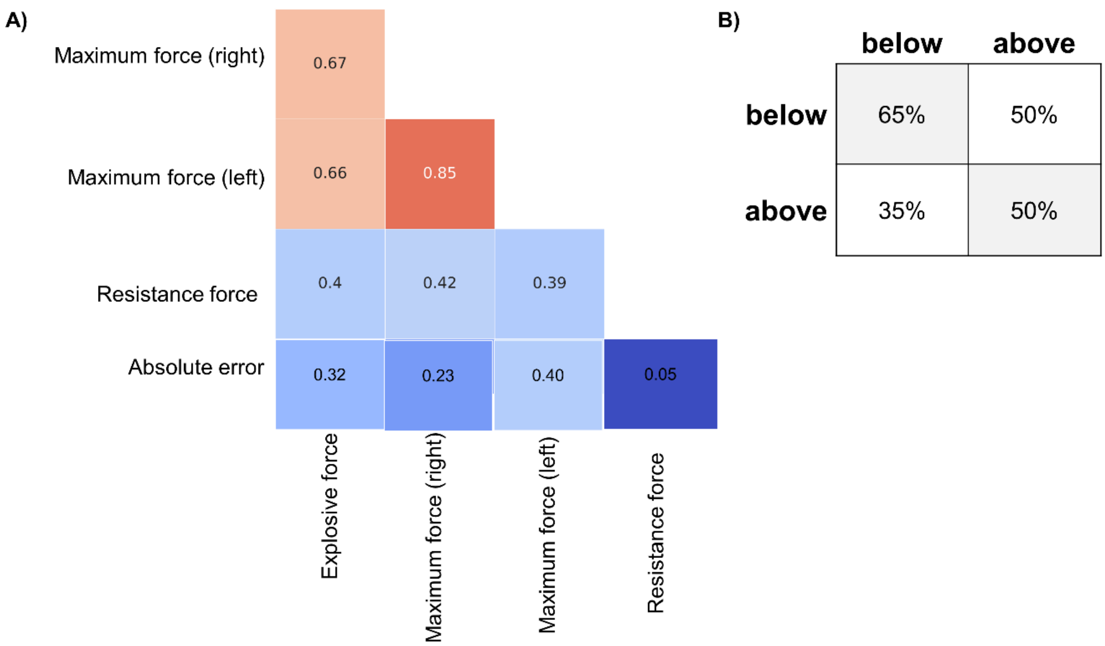

Figure 3. Correlation matrix (A) and confusion matrix (B).

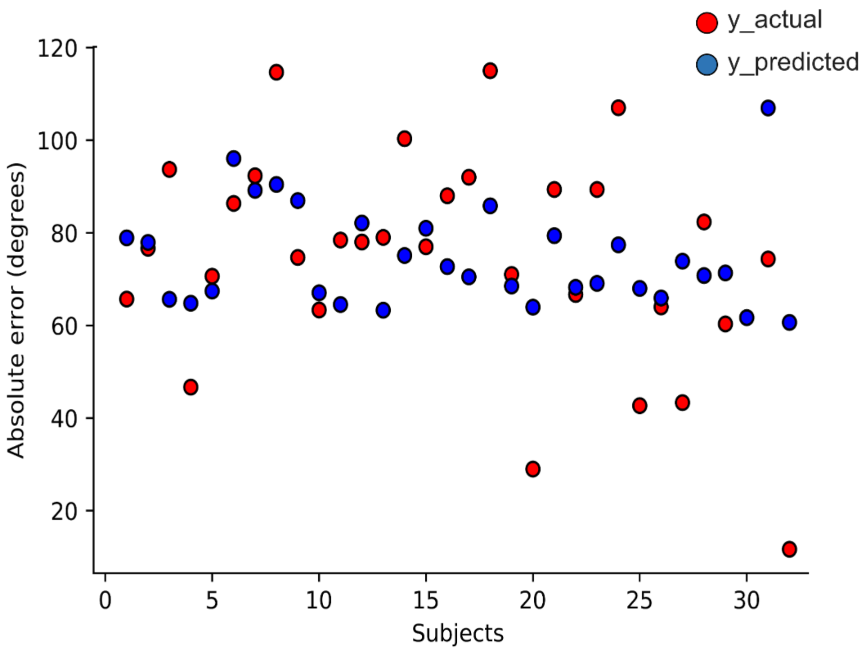

Figure 4. Data simulates of 32 subjects and the actual data.

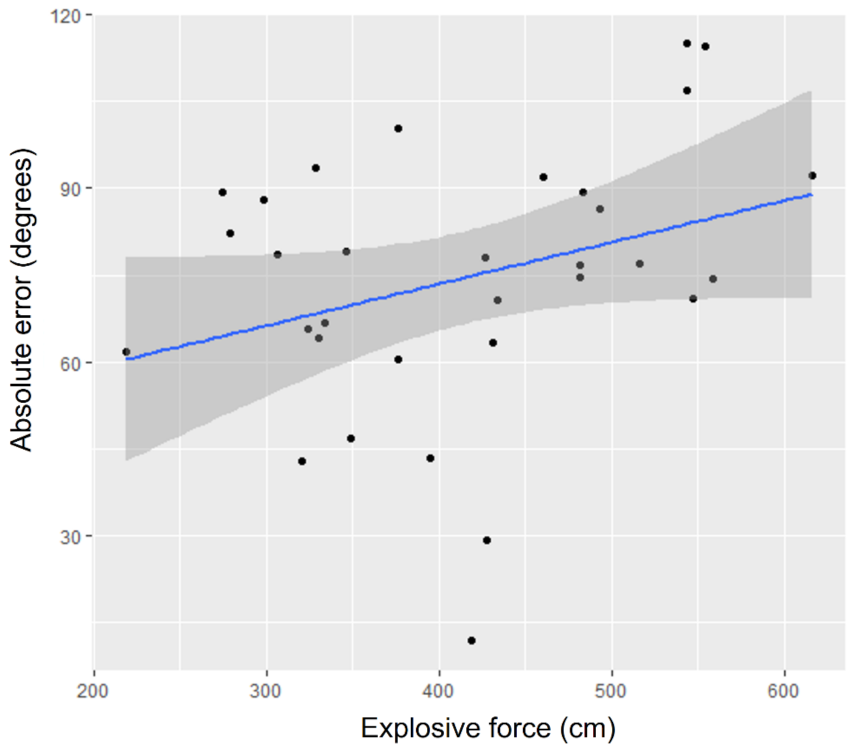

Figure 5. Linear regression: absolute error and explosive force.

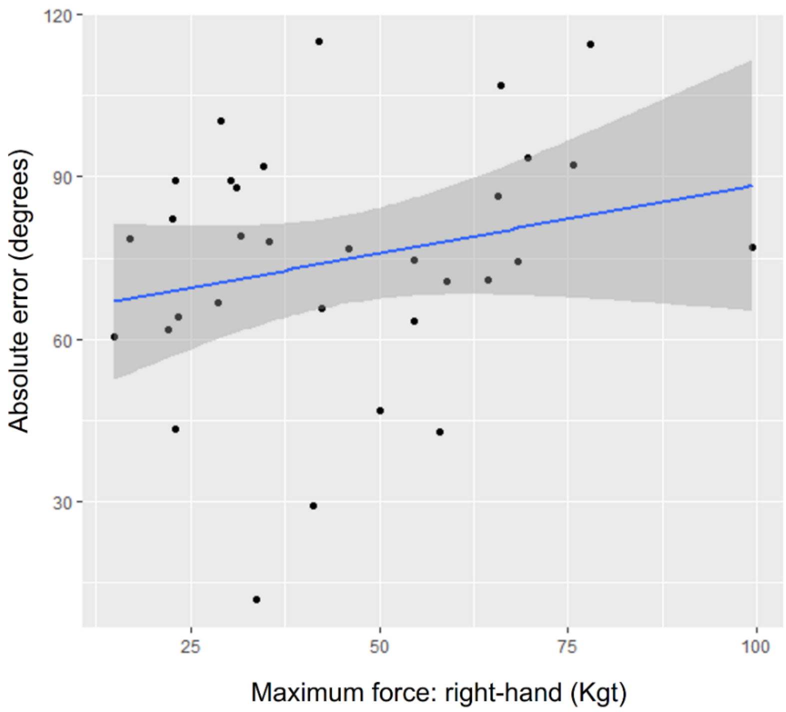

Figure 6. Linear regression: absolute error and maximum force (right-hand).

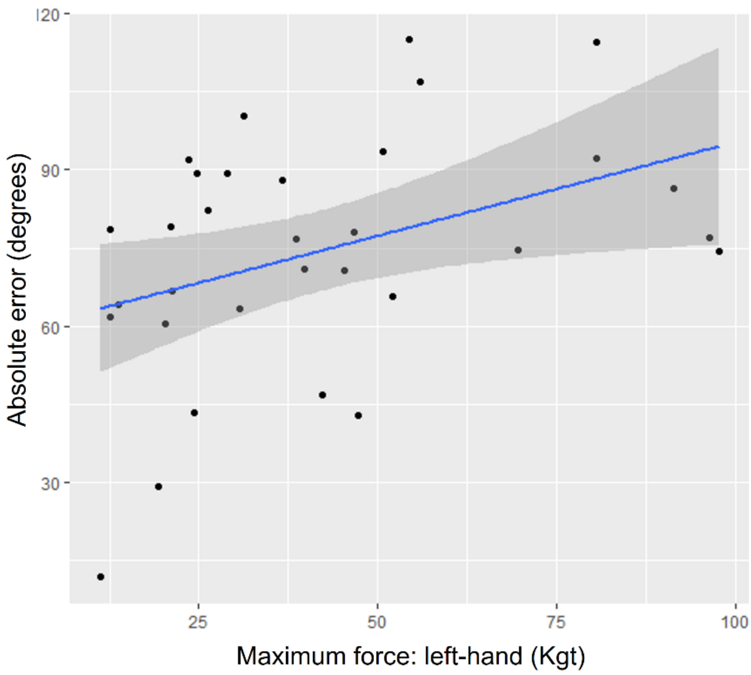

Figure 7. Linear regression: absolute error and maximum force (left-hand).

However, the regression analysis revealed significant differences in motor performance and Maximum force test (left-hand) [$F(1,30) = 5.59$, $p = 0.02$, $R^2 = 0.15$, $f2 = 0.17$], suggesting that error values in the motor task can be positively predicted based on the level of strength achieved in the handheld dynamometry (Figures 7).

Additionally, the regression test did not detect significant differences between motor performance and the Resistance force test [$F(1,30) = 0.08$, $p = 0.76$, $R^2 = 0.00$, $f2 = 0.00$] (Figures 8).

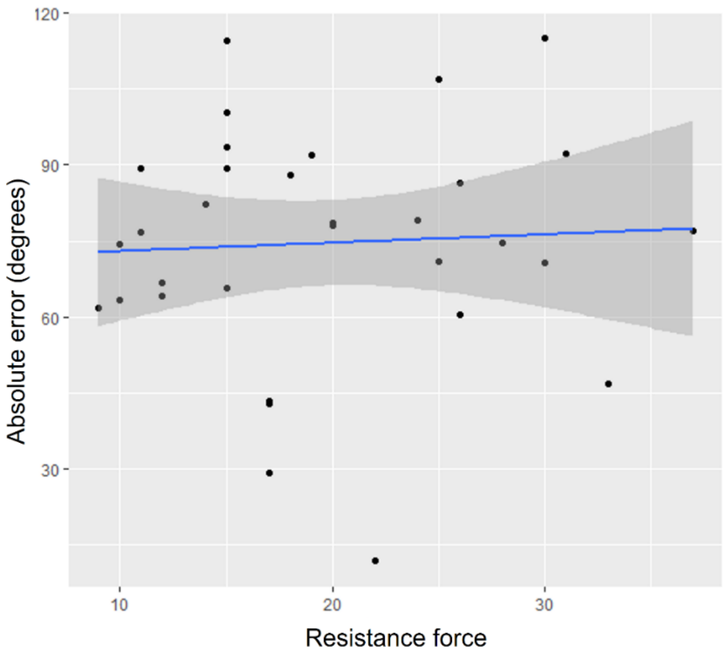

Figure 8. Linear regression: absolute error and Resistance force.

DISCUSSION

The aim of the present study was to explore the connection between strength capacity and motor performance in the gymnastic handstand, utilizing machine learning models and linear regression. It was anticipated that levels of strength capacity would predict the attained level of motor performance in the gymnastic handstand skill. However, our results did not corroborate the proposed hypothesis. The machine learning model revealed a weak relationship between strength capacity and motor performance. Furthermore, upon analyzing various forms of force manifestation (explosive, maximum, and resistance) alongside motor performance, we did not find evidence to support the hypothesis regarding the relationship between strength capacity and motor performance.

As previously mentioned, three distinct perspectives in the literature have been proposed to elucidate the relationship between motor performance and capacity. The first perspective suggests the existence of a general capacity that could underlie success in any motor task (McCloy, 1934; Hands, McIntyre, & Parker, 2018). The second perspective posits that performance may be contingent upon the specificity of the task (Lage et al., 2017; Robin et al., 2005; Tremblay & Proteau, 1998). The third perspective underscores the intricate interplay among task demands, environment, and individual factors (Newell, 1985; 1986).

Our results indicate a lack of a linear relationship between strength capacity and gymnastic handstand skill, implying that individuals with greater strength do not necessarily demonstrate superior performance in the skill. Contrary to the notion of a general capacity, motor responses within the environment do not appear to rely solely on a single motor capacity but rather on specific motor capacities or the dynamic interaction between task, environment, and individual characteristics.

Studies involving postural control (Kiss et al., 2018) and strength analysis (Berger, 1962) have reported similar findings. Even skills often considered "generic," such as coordination and agility, have been demonstrated to be specific to certain motor tasks (Henry, 1968). Moreover, other research has emphasized the crucial role of the interaction between various components, including cognitive aspects, in the successful execution of motor skills (Robertson et al., 2004; Roca et al., 2011). The capacities examined in this study represent one of these components, suggesting that possessing a high level in only one capacity may not suffice to ensure favorable outcomes across different motor tasks. Therefore, elevated levels of strength may not guarantee overall success in tasks that involve different components.

An intriguing finding in our study was the relationship between maximum left-hand grip strength and motor performance. Our results indicated that increased maximum left-hand grip strength is associated with poorer performance. Conversely, the right hand exhibited no significant relationship between maximum grip strength and motor performance. This disparity between hands and its correlation with motor performance can be elucidated by the inherent asymmetry between the upper limbs (Fernandes et al., 2018). In certain skills, particularly those involving bimanual coordination like the handstand skill, upper limb asymmetry may indicate inferior performance (Santos et al., 2017; Sanders et al., 2011). In the realm of gymnastics specifically, there are indications that asymmetry negatively impacts motor performance (Batista et al., 2019). However, this assertion warrants further investigation with a more targeted research design.

A potential limitation of the study was the omission of strength values normalized by participant mass or height. Future studies are advised to incorporate parameters for result normalization. Another potential limitation was the degree of fit of the regression model (R^2) and the effect size, both of which were low. Two primary factors may account for these results. Firstly, the number of participants could be a limiting factor. The sample size affects measures such as regression model fit and effect size (Nakagawa and Cuthill, 2007), thus increasing the sample size is recommended for future studies. Secondly, there may be more complex and nonlinear dynamics among the study variables and other elements influencing motor response. These results suggest that even when significant relationships exist, the magnitude of the relationships between variables may be low. It is possible that more complex dynamics among other elements, besides strength capacity, contribute to motor response in the environment (motor output). In a sense, these results challenge our hypothesis but support the study's main finding.

CONCLUSIONS

Our study aimed to investigate the relationship between strength capacity and motor performance in gymnastic handstands using machine learning models and linear regression. Contrary to our initial hypothesis, our results did not provide support for a linear relationship between strength capacity and motor performance. This challenges the idea of a generalized capacity influencing success in motor tasks. Rather, our findings imply that motor performance is contingent upon specific capacities or the interplay of various factors, including task specificity, environmental factors, and individual characteristics.

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Article received: 15.11.2023
Article accepted: 2.4.2024