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Analysing Anthropometric Influences on Electromyographical Patterns in Selected Upper and Lower Limb Muscles: A Correlational Study

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Abstract

Surface electromyography (EMG) is widely used to evaluate neuromuscular activation; however, its signal quality can be influenced by individual anthropometric factors such as body weight, body mass index (BMI), and subcutaneous fat thickness. Despite evidence linking body composition to EMG amplitude, limited research has explored these relationships in trained athletes, particularly comparing load-bearing lower-limb muscles with non-load-bearing upper-limb muscles. This study investigated the relationship between body weight, BMI, and EMG-derived muscle activation parameters-maximum amplitude, maximum root mean square (RMS), and average amplitude in competitive male footballers. Forty inter-university male footballers (age 23 ± 0.94 years) underwent anthropometric assessment (weight, BMI) followed by maximum voluntary contractions (10 s MVCs) of three muscles: biceps brachii, rectus femoris, and lateral gastrocnemius. EMG signals were recorded using an IWorx EMG system, and Pearson's correlation analysis was applied ($p < 0.05$). Body weight strongly correlated with BMI ($r = 0.743$, $p = 0.014$). Lower-limb muscles showed significant associations with BMI, including rectus femoris RMS amplitude ($r = 0.646$, $p = 0.044$) and gastrocnemius average amplitude ($r = 0.649$, $p = 0.042$). Upper-limb (biceps brachii) activation demonstrated weak, non-significant correlations. Lower-limb muscles exhibited stronger BMI-related neuromuscular responses than upper limbs, likely due to their load-bearing function. Body weight emerged as a more consistent predictor of muscle activation than BMI, emphasising the need for refined body composition assessments in sports science. These findings support the use of individualised EMG interpretation in athletic training, rehabilitation, and injury prevention.

Keywords: BMI, Footballer, Neuromuscular Activation, Surface Electromyography.

Introduction

Skeletal muscles, which are managed by complex neuromuscular processes, must contract simultaneously for human movement. Surface electromyography is a common non-invasive method for assessing motor unit recruitment, firing rate and neuromuscular synchronisation during voluntary muscle contractions (1, 2). In sports science, rehabilitation, and ergonomics, surface electromyographical (EMG) parameters such as maximum amplitude, root mean square (RMS), and average amplitude are used to assess muscle function (3). However, the reliability of this signal may depend on individual anthropometric characteristics. EMG reliably considers neuromuscular activation in individuals with different muscle compositions. In clinical and sports settings, BMI (Body Mass Index) is commonly used as an observational indicator of body composition, but it does not differentiate between overweight and obesity (4). Increased adiposity attenuates EMG amplitude due to greater skin-electrode distance and the low-pass filtering effect of fat tissue, while greater lean mass enhances signal amplitude through improved motor unit recruitment and force generation capacity (5, 6). Compared to upper-limb muscles like the biceps brachii, lower-limb muscles like the gastrocnemius and rectus femoris are more load-bearing and active muscles, and they may exhibit stronger correlations with body mass index (7, 8). The neurobehavioral adaptations of skilled athletes are still poorly understood, although numerous studies have shown similar effects in specific sites or clinical populations (9). The prior

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research frequently looked at individual muscles without evaluating the functional variations between the upper and lower limbs. This restricts our comprehension of how muscles react to variations in anthropometry. Furthermore, less obvious connections between body mass, muscle activation, and functional performance may be lost if body mass index is still used, as weight is a stronger predictor than BMI of body composition. Although BMI is partially derived from body weight, it represents a normalised ratio of weight to height and does not reflect the absolute mechanical load acting on the musculoskeletal system. Body weight directly influences joint loading, force requirements, and muscle activation during physical activity, whereas BMI does not distinguish between lean and fat mass. Consequently, BMI may obscure functionally meaningful relationships between body mass and neuromuscular responses, making body weight a more sensitive predictor than BMI in studies examining acute muscle activation (10, 11). Even though there is evidence that anthropometric parameters impact the quality of EMG signals, it is still unclear how much weight and BMI affect neuromuscular activation in competitive athletes, especially in both load-bearing lower limbs and non-load-bearing upper limbs. To improve EMG interpretation in sports performance monitoring, injury prevention, and rehabilitation, this gap must be filled.

Therefore, this study aims to determine how anthropometric parameters (body mass and BMI) and EMG parameters (maximum amplitude, RMS, and mean amplitude) relate to three functionally different muscles in inter-university-level football players. The researchers predicted a stronger correlation between body mass and EMG parameters, particularly in the weight-bearing muscles of the lower extremities, than between body mass and BMI. By clarifying these connections, this study offers methodological viewpoints for neuromuscular evaluation in sports populations and contributes to the creation of customised training and recovery plans.

Methodology

Participation

A total of forty male footballers [n = 40] were selected for this study using the convenience sampling method. The mean age of the selected subjects was 23 ± 0.94 years. All selected participants visited the exercise physiology laboratory at Jadavpur University's Department of Physical Education in Kolkata, West Bengal, India, on a designated day during the study period. Before beginning the EMG (surface electromyography) data collection process, the researchers measured the anthropometric variables.

"Inclusion criteria encompassed individuals who had participated in at least three inter-university football tournaments, ensuring that prior training experience would influence the comparison and analysis of the data (12). Exclusion criteria involved individuals with a history of any injury or surgical procedure occurring within the six months preceding this study (13).

Instrumentations

IWorx Surface EMG analysing software (IWorx System, Inc.) utilised here, It was set at a band-pass filter of 20–450 Hz and data was collected at a sampling rate of 2000 Hz (14). A human muscle EMG device (iwire-B3G) and foam solid gel disposal electrodes (A-GC-7165, 5×54 mm) were used to collect EMG amplitude data. Cotton and scrubbing gel were applied to clean the skin, and a razor was used to remove hair. A weighing machine, stadiometer, and measuring tape were utilised to measure anthropometric variables. BMI (Body Mass Index) was calculated using the formula Equation [1]:

$$\text{BMI} = \text{Body Weight in kg} / \text{Height in m}^2 \qquad [1]$$

Experimental Design

Forty inter-university male footballers were recruited using a convenience sampling method. Inclusion criteria required participants to have competitive playing experience and no history of musculoskeletal injury in the recent past. All participants first underwent anthropometric assessment, including measurements of body weight and body mass index (BMI), followed by a standardised warm-up protocol. Surface electromyography (EMG) recordings were then obtained during 10-second maximum voluntary contractions (MVC) of the biceps brachii, rectus femoris, and lateral gastrocnemius muscles (15).

These muscles were selected for their critical involvement in football-specific activities such as sprinting, kicking, jumping, rapid changes of direction, tackling, and upper-body stabilisation during match play. The rectus femoris plays a key role in knee extension and hip flexion and is highly activated during kicking, acceleration, and high-intensity running (16). The gastrocnemius contributes substantially to ankle plantarflexion and is heavily engaged during sprinting, jumping, and rapid directional changes, making it particularly relevant to football performance (17). The biceps brachii was included to represent upper-limb involvement, as it contributes to arm swing during running, balance control, and physical contests such as shielding and tackling (18). Furthermore, these muscles are commonly examined in football-related surface EMG studies due to their functional relevance, accessibility, and reliable signal quality, allowing meaningful interpretation of neuromuscular activation patterns in football players (19, 20).

EMG parameters analysed included maximum amplitude, maximum root mean square (RMS) amplitude, and average amplitude. Data were statistically evaluated using Pearson's correlation to explore the correlation between muscle activation and anthropometric variables. Ethical clearance, informed consent, and confidentiality protocols were strictly followed throughout the procedure, as shown in Figure 1.

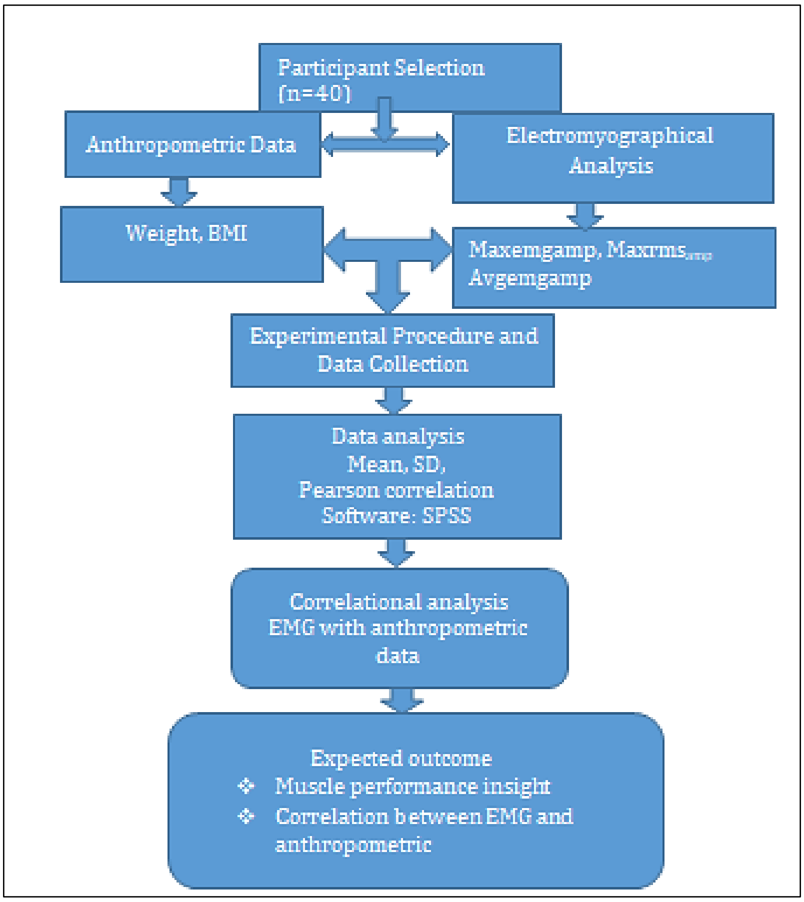

Figure 1: Experimental Design and Data Analysis Workflow

Figure 1 illustrates the experimental design of the study, including participant selection (n = 40), anthropometric measurements (weight and BMI), and electromyographical (EMG) signal acquisition. The workflow summarises EMG outcome variables (maximum amplitude, average amplitude and maximum RMS amplitude) and the statistical analysis performed using Pearson correlation in SPSS (Statistical Package for the Social Sciences) to evaluate relationships between anthropometric factors and muscle activation patterns.

Anthropometric Measurements

Height was measured using a fixed stadiometer (HM01, Ambala, India), and BMI was calculated from weight and height, followed by the measurement procedure of NIHR Southampton Biomedical Research Centre (21).

Surface Electromyography

Participants first underwent an orientation session that outlined the research objectives, equipment used, data collection procedures, and experimental task details. To ensure proper preparation, selected subjects completed a standardized three-minute warm-up protocol, incorporating running and dynamic stretches targeting the relevant joints and muscles (22). Following the warm-up, participants performed 10-second maximum voluntary contractions for the biceps brachii, rectus femoris, and lateral calf muscles (22), maintaining predefined positions. During these contractions, surface electromyography (EMG) data were recorded for selected muscles. Measurements included maximum EMG amplitude (maxEMGamp), maximum root mean square amplitude (maxRMSamp) and average EMG amplitude (avgEMGamp). Before the electrode placement, the skin over the target muscles was prepared in accordance with the recommendations of the Surface Electromyography for the Non-Invasive Assessment of Muscles (SENIAM) guidelines to ensure optimal signal quality and minimise skin electrode impedance. Hair at the electrode sites was removed using a disposable razor, if present. The skin was then gently abraded with fine abrasive material to remove dead skin cells, followed by cleansing with 70% isopropyl alcohol swabs to eliminate oils and sweat. The skin was allowed to dry completely before electrode placement (23). This standardised skin preparation procedure was performed consistently for all participants to reduce motion artefacts and enhance the reliability of the recorded EMG signals.

Figure 2: Represents the Electromyography Data Collection Procedure for the (A) Biceps Brachii Muscle, (B) Rectus Femoris Muscle, and (C) Calf Lateral Muscle

For the biceps brachii in Figure 2 (A), participants were seated with the shoulder in a neutral position, the elbow flexed at 90°, and the forearm supinated; the arm was stabilized against movement using straps across the distal humerus and torso, with the elbow supported on a padded surface (24). The electrodes were placed over the belly of the biceps brachii muscle, aligned parallel to the muscle fibres along the arm. The reference electrode was placed on the lateral epicondyle of the humerus to reduce signal noise (25).

The subjects were seated on a firm chair or testing bench with the hips and knees flexed at approximately 90 degrees. The trunk remained upright and stabilised using straps for fixed resistance. The subjects were instructed to perform a maximal isometric knee extension with a strap placed just above the ankle, without allowing actual movement in Figure 2(B). For the rectus femoris muscle. The electrodes were placed on the midline of the muscle at its midpoint, and the reference electrode was placed on the patella to minimise interference (23).

The subject should be in a seated position in Figure 2(C), with the knee fully extended and the ankle fixed at a 90° neutral position. A rigid mechanical setup was used to provide strong, immovable resistance. The subject is instructed to perform a unilateral isometric plantar flexion by pushing the forefoot downward against the resistance. The hip must be fixated to avoid compensatory movement (24). The electrodes were placed at one-third of the distance between the head of the fibula and the calcaneus on the lateral side of the calf, aligned parallel to the muscle fibres. The reference electrode was placed on the patella to reduce interference (25).

Data Processing

Participants were trained on each exercise before data collection to ensure correct performance. Clear instructions were given to them to perform maximum voluntary contractions. They were asked to exert their maximal force for 3 to 5 seconds, hold it for 3 seconds, and then gradually decrease the force over 3 seconds (25). Maximum surface electromyography amplitude (maxEMGamp), maximum root mean square amplitude ($maxRMS_{amp}$), and average surface electromyography amplitude (avgEMGamp) data were collected from 10 seconds of maximum voluntary contraction (MVC) (24). Surface electromyography (EMG) signals were recorded bilaterally from each target muscle. The mean of the left and right muscle activation values was subsequently calculated and used as the representative EMG amplitude for each selected muscle (25).

EMG Normalization

Peak EMG normalization methods were applied to normalize the raw EMG values (Equation [2]). Each participant performed three trials targeting muscles, and the average of the three trials was recorded as the actual value (3).

$$\text{Normalized EMG}=\frac{\textbf{Peak Trial1+Peak Trial2+Peak Trial3}}{\textbf{Total number of trails}} \qquad [2]$$

Statistical Analysis

Descriptive statistics were used to summarise the general characteristics of the participants, with all continuous variables presented as mean ± standard deviation (SD). Before inferential analysis, the normality of data distribution for each measured variable was examined using the Shapiro–Wilk test. Variables that satisfied the assumption of normality were subsequently included in parametric analyses. Pearson's product-moment correlation coefficient was employed to examine the strength and direction of the relationships between anthropometric variables (body weight and BMI) and surface electromyographical (EMG) activity of the selected muscles during maximum voluntary contractions. Correlation coefficients were interpreted using conventional thresholds to describe the magnitude of association. Statistical significance was set a priori at $p < 0.05$. All statistical analyses were conducted using IBM SPSS Statistics version 30.0 (IBM Corp., Armonk, NY, USA).

Results

Table 1: Pearson Correlation between Anthropometric Variables and Electromyographical Parameters of the Biceps Brachii Muscle

Selected Variables	Mean ± SD	Selected Variables	Mean ± SD	Number of Subjects	Pearson's Correlation Coefficient(r)	Sig.
Weight (kg)	63.93±7.28	BMI (kg/m^2)	22.56±2.43	n=40	0.743	0.014*
		max EMGamp	3.76 ± 1.48		0.311	0.382
		$maxRMS_{amp}$	0.56 ± 0.37		0.616	0.058
		avgEMGamp	0.80 ± 0.22		0.496	0.145
maxEMGamp (mV)	3.76 ± 1.48	BMI	22.56 ± 2.43		-0.113	0.756
		$maxRMS_{amp}$	0.56 ± 0.37		0.290	0.417
		avgEMGamp	0.80 ± 0.22		0.534	0.112
$maxRMS_{amp}$ (mV)	0.56 ± 0.37	BMI	22.56 ± 2.43		-0.355	0.17
		avgEMGamp	0.80 ± 0.22		0.191	0.597
avgEMGamp (mV)	0.80 ± 0.22	BMI	22.56 ± 2.43		0.176	0.47

Table 1 presents the Pearson correlation analysis between body composition variables (weight and BMI) and electromyographical parameters of the biceps brachii muscle, including maximum EMG amplitude, maximum RMS amplitude, and average EMG amplitude in 40 participants. Mean values, correlation coefficients (r), and significance levels are reported to assess the relationship between anthropometric factors and muscle activation. Pearson's correlation analysis calculated the value between weight and BMI, which indicates that higher body weight (63.93 ± 7.28 kg) and BMI (22.56 ± 2.43 kg/m^2) are indicating that higher body weight was associated with a higher BMI value. The calculated value also displayed that weight was not statistically significant in relation to maximum EMG amplitude, RMS amplitude and average EMG amplitude.

This finding suggests that weight is strongly correlated with BMI and it is also not strongly associated with neuromuscular activity parameters as measured by surface electromyography amplitude indicators. The correlation analysis between maximum EMG amplitude (3.76 ± 1.48 mV) and BMI (22.56 ± 2.43 kg/m^2) indicate no significant relationships (r = –0.113, p = 0.756). Maximum EMG amplitude and maximum RMS amplitude revealed a weak and non-significant positive correlation (r = 0.290, p = 0.417). Average EMG amplitude (r = 0.534, p = 0.112) also shows moderate and non-significant correlation with maximum EMG amplitudes. These findings suggested that maximal muscle activation levels, as measured by maximum EMG amplitude, were not significantly related to body composition (BMI) or to other amplitude parameters under the current experimental conditions. RMS amplitude (0.56 ± 0.37 mV) revealed a statistically non-significant and negative correlation with BMI (22.56 ± 2.43; r = –0.355, p = 0.170), suggesting that muscle activation intensity was not influenced by participants' body composition. Similarly, RMS amplitude indicates a weak and non-significant positive relationship with average EMG amplitude (r = 0.191, p = 0.597*). These values indicate that differences in RMS amplitude were independent of BMI and average neuromuscular activation patterns. A weak, positive, and non-significant correlation was found for the average EMG amplitude (0.80 ± 0.22 mV) with BMI (22.56 ± 2.43; r = 0.176, p = 0.470). These results specify that average muscle activation, as reflected by mean EMG amplitude, was not significantly related to BMI.

Table 2: Pearson Correlation between Anthropometric Variables and Electromyographical Parameters of the Rectus Femoris Muscle

Selected Variables	Mean	Selected Variables	Mean	Number of Subjects	Pearson's Correlation Coefficient (r)	Sig.
Weight (Kg)	63.93±7.28	BMI (kg/m^2)	22.56±2.43		0.743	0.014*
		MaxEMGamp	2.28 ± 0.61		0.366	0.298
		maxRMSamp	0.64 ± 0.24		0.646 *	0.044 *
		avgEMGamp	0.80 ± 0.16	n=40	0.300	0.399
$_{Max}EMG_{amp}$ (mV)	2.28 ± 0.61	BMI	22.56±2.43		0.051	0.889
		maxRMSamp	0.64 ± 0.24		0.010	0.978
		avgEMGamp	0.80 ± 0.16		0.036	0.921
$maxRMS_{amp}$(mV)	0.64 ± 0.24	BMI	22.56±2.43		-0.355	0.314
		avgEMGamp	0.80 ± 0.16		-0.018	0.961
avgEMGamp (mV)	0.80 ± 0.16	BMI	22.56±2.43		0.176	0.627

Table 2 summarises the Pearson correlation results examining the relationship between body composition indicators (weight and BMI) and electromyographical parameters of the rectus femoris muscle in 40 participants. Descriptive statistics, correlation coefficients (r), and significance values are provided for EMG amplitude and RMS measures.

Weight showed a positive and non-significant correlation with maximum EMG amplitude (2.28 ± 0.61 mV; r = 0.366, p = 0.298) and with average EMG amplitude (0.80 ± 0.16 mV; r = 0.300, p = 0.399) for the rectus femoris muscles' electromyographical activity. Although weight RMS amplitude (0.64 ± 0.24 mV; r = 0.646, p = 0.044) showed a significant positive correlation, suggesting that players with higher body weight can demonstrate greater overall neuromuscular activation. Maximum EMG amplitude (2.28 ± 0.61 mV) and BMI found no significant correlation (22.56 ± 2.43; r = 0.051, p = 0.889). Maximum RMS amplitude (0.64 ± 0.24 mV; r = 0.010, p = 0.978), average EMG amplitude (M = 0.80 ± 0.16 mV; r = 0.036, p = 0.921). and the maximum EMG amplitude were not significantly correlated. Analysis of RMS amplitude (0.64 ± 0.24 mV) found no statistically significant relationships with BMI (22.56 ± 2.43; r = –0.355, p = 0.314), indicating that overall muscle activation level was not influenced by body composition. RMS amplitude was not significantly correlated with average EMG amplitude (0.80 ± 0.16 mV; r = –0.018, p = 0.961). Average EMG amplitude (0.80 ± 0.16 mV) showed a weak, non-significant positive correlation with BMI (22.56 ± 2.43; r = 0.176, p = 0.627).

Table 3: Pearson Correlation between Anthropometric Variables and Electromyographical Parameters of the Calf Lateral Muscle

Selected Variables	Mean	Selected Variables	Mean	Number of Subjects	Pearson's Correlation Coefficient(r)	Sig.
Weight (Kg)		BMI (kg/m²)	22.56±2.43		0.743	0.014*
		max EMGamp	2.38 ± 0.92		0.444	0.199
	63.93±7.28	maxRMSamp	0.49 ± 0.18		0.139	0.701
		avgEMGamp	0.80 ± 0.11		0.122	0.736
$maxEMG_{amp}$ (mV)	2.38 ± 0.92	BMI	22.56±2.43	n=40	0.186	0.607
		maxRMSamp	0.49 ± 0.18		0.608	0.062
		avgEMGamp	0.80 ± 0.11		0.256	0.475
$maxRMS_{amp}$ mV)	0.49 ± 0.18	BMI	22.56±2.43		0.136	0.707
		avgEMGamp	0.80 ± 0.11		0.390	0.265
AvgEMGamp (mV)	0.80 ± 0.11	BMI	22.56±2.43		0.649 *	0.042 *

Table 3 indicates the relationship between anthropometric variables (weight and BMI) and EMG-derived activity of the lateral calf muscles in 40 participants. Electromyographical signal outcomes include maximum and average EMG amplitudes as well as RMS values. Statistical associations are quantified using Pearson's correlation coefficients with corresponding significance levels.

Body weight was not significantly correlated with electromyographical parameters. Specifically, maximum EMG amplitude (2.38 ± 0.92 mV; r = 0.444, p = 0.199) was not significantly associated with weight. Maximum RMS amplitude (0.49 ± 0.18 mV; r = 0.139, p = 0.701) and average EMG amplitude (0.80 ± 0.11 mV; r = 0.122, p = 0.736) also revealed no statistically significant correlation. The calculated maximum EMG amplitude was 2.38 ± 0.92 mV, which indicates no significant correlation with BMI (22.56 ± 2.43; r = 0.186, p = 0.607). RMS amplitude (0.49 ± 0.18 mV; r = 0.608, p = 0.062) and average EMG amplitude (M = 0.80 ± 0.11 mV; r = 0.256, p = 0.475) were not statistically significantly correlated with maximum EMG amplitude. Correlation analysis of RMS amplitude (0.49 ± 0.18 mV) showed non-significant correlation with BMI (22.56 ± 2.43; r = 0.136, p = 0.707), suggesting that the muscle activation intensity was not influenced by participants' body composition. And also, maximum RMS amplitude was not significantly associated with average EMG amplitude (0.80 ± 0.11 mV; r = 0.390, p = 0.265), indicating that variations in RMS measures were not reflected in electromyographical activity. Average EMG amplitude (0.80 ± 0.11 mV) was significantly positively correlated with BMI (22.56 ± 2.43; r = 0.649, p = 0.042), suggesting that participants with higher BMI lead to greater mean electromyographical activation. Pearson's correlation analysis was performed to investigate the relationships between body weight, BMI, and surface electromyographical (EMG) parameters for calf lateral muscles. Body weight was not significantly correlated with electromyographical parameters. Specifically, maximum EMG amplitude (2.38 ± 0.92 mV; r = 0.444, p = 0.199) was non-significantly associated with weight. Maximum RMS amplitude (0.49 ± 0.18 mV; r = 0.139, p = 0.701) and average EMG amplitude (0.80 ± 0.11 mV; r = 0.122, p = 0.736) also revealed no statistically significant correlation. The calculated maximum EMG amplitude was 2.38 ± 0.92 mV, which indicates a non-significant correlation with BMI (22.56 ± 2.43; r = 0.186, p = 0.607). Maximum RMS amplitude (0.49 ± 0.18 mV; r = 0.608, p = 0.062) and average EMG amplitude (M = 0.80 ± 0.11 mV; r = 0.256, p = 0.475) were not statistically significantly correlated with maximum EMG amplitude. Correlation analysis of maximum RMS amplitude (0.49 ± 0.18 mV) showed no significant correlation with BMI (22.56 ± 2.43; r = 0.136, p = 0.707), suggesting that the muscle activation intensity was not influenced by participants' body composition. And also, maximum RMS amplitude was not significantly associated with average EMG amplitude (0.80 ± 0.11 mV; r = 0.390, p = 0.265), indicating that variations in RMS measures were not reflected in electromyographical activity. Average EMG amplitude (0.80 ± 0.11 mV) was significantly positively correlated with BMI (22.56 ± 2.43; r = 0.649, p = 0.042), suggesting that participants with higher BMI have greater mean electromyographical activation.

Discussion

The present study aimed to explore the relationships between body composition, specifically body weight and Body Mass Index (BMI) and muscle activation characteristics as measured by surface electromyography (EMG) in three key skeletal muscles: the biceps brachii, rectus femoris, and lateral gastrocnemius (calf lateral muscle). Understanding these associations was critical because muscle activation profiles can offer insights into neuromuscular health, functional capacity, and the effects of body composition on muscle performance.

While statistically significant correlations were identified, such relationships do not establish direct causation or explain underlying physiological mechanisms. The findings, therefore, represent associative patterns rather than definitive cause–effect links. Interpretation of the physiological implications should be made within the limitations of the correlational design, and future controlled studies are warranted.

A consistent and statistically significant positive correlation was found between body weight and BMI, affirming that BMI was a valid, albeit limited, anthropometric index of body mass relative to height. However, the relationships between body composition and EMG-derived muscle activity were less straightforward and varied depending on the muscle group examined.

This variability across muscle groups was not unexpected, given that EMG signals are affected by a range of physiological and anatomical factors, including muscle fibres type distribution, subcutaneous fat thickness, muscle architecture, electrode placement, and motor unit recruitment patterns (2, 26). Additionally, the EMG signal was inherently sensitive to crosstalk and electrode-skin impedance, both of which can influence the amplitude and reliability of measurements (15).

In the biceps brachii, the correlations between EMG variables (maximum amplitude, RMS amplitude, and average EMG) and body composition were generally positive but not statistically significant. This suggests that higher body weight may contribute to slightly elevated muscle activity, likely due to increased muscle mass or neuromuscular efficiency, though these trends did not achieve statistical robustness.

Another research finding is that greater fat-free mass is associated with enhanced muscle strength and size, which, in turn, may influence EMG characteristics (6). However, the non-significance may reflect individual variability in muscle architecture or training history, as EMG amplitude is not only a function of force generation but also of motor unit synchronisation and firing rate (27).

Interestingly, BMI showed weaker and non-significant associations with all EMG parameters. This supports prior critiques that BMI may inadequately capture body composition, particularly in distinguishing between lean and fat mass (4, 26). In lean individuals or those with high muscle mass, BMI can be misleading and may not correspond to functional muscle properties (28).

In the rectus femoris muscle, a statistically significant relationship was observed between body weight and RMS amplitude. RMS is considered a reliable index of muscle activation level and reflects the number and synchronisation of active motor units (24). The observed positive association indicates that individuals with greater body weight tend to show higher quadriceps activation, potentially due to increased mechanical demand or muscle cross-sectional area (29).

Although BMI again showed weaker associations, it is worth noting that the quadriceps femoris group is a weight-bearing, locomotor muscle, more likely to respond to habitual physical activity and mechanical loading than upper limb muscles (30). Some studies suggest that increased muscle size in the lower limbs can enhance activation patterns, particularly in activities such as squatting or walking (31).

Nonetheless, the lack of significance for other EMG parameters may be attributed to the complexity of neuromuscular control in the lower limbs, where synergistic muscle activation and joint angle variability affect EMG readings (32). Subcutaneous fat in the thigh region may also act as a low-pass filter, diminishing EMG signal amplitude (33).

The lateral gastrocnemius showed one of the most intriguing findings: a significant positive correlation between average EMG amplitude and BMI. This result suggests that individuals with higher BMI may engage the calf muscle more intensely during tasks, possibly due to increased load-bearing demands on the lower limbs (8). This is consistent with previous studies indicating that overweight and obese individuals demonstrate altered muscle recruitment patterns and increased postural activity in the triceps muscles during walking and standing (34). It is notable that while RMS and maximum EMG amplitudes also trended positively, these did not reach significance. This pattern implies a consistent but sub-threshold relationship, which may become clearer in a larger sample. Moreover, gastrocnemius muscle function is highly responsive to both force output and balance control, making it an effective target for EMG-based functional assessments. Across the three muscles, a common theme is that body weight appears to influence EMG activity more consistently than BMI, especially in the lower limbs. This supports the notion that body weight may be a better predictor of absolute muscle load, while BMI lacks the specificity needed to explain functional muscle dynamics (35). Furthermore, EMG signal reliability can be compromised in individuals with greater adiposity, which introduces attenuation and distortion of the signal (2). The differences in correlation strength between upper and lower body muscles may also reflect functional and anatomical specialisations. Upper limb muscles like the biceps brachii are more involved in fine motor tasks and voluntary movements, whereas lower limb muscles such as the rectus femoris and gastrocnemius are specialised for load-bearing and postural control. These functional roles may influence baseline muscle tone and EMG responsiveness (29).

Conclusion

This study examined the associations between body composition metrics, specifically body weight and body mass index (BMI) and surface electromyographical (EMG) activity in the biceps brachii (BB), rectus femoris (RF), and lateral gastrocnemius (LG) muscles of trained football athletes. The analysis revealed that body weight demonstrated a consistent and significant positive correlation with EMG activity across all three muscles. Notably, higher body weight was associated with increased maximal and average EMG amplitudes in the lateral gastrocnemius, enhanced average EMG in the rectus femoris, and elevated maximal EMG in the biceps brachii. These findings suggest a pronounced influence of body weight on muscle activation, particularly in load-bearing musculature. In contrast, BMI exhibited weaker and more variable relationships. A marginal positive association was observed between BMI and maximal EMG in the rectus femoris, while non-significant correlations were found between BMI and EMG parameters in the biceps brachii muscle and lateral gastrocnemius muscles. Overall, the results underscore the superior predictive value of body weight over BMI in relation to neuromuscular activation patterns. This highlights the relevance of incorporating individualised anthropometric profiles, especially absolute body mass, when interpreting EMG signals for performance assessment and tailored athletic programming in sports science research.

Abbreviations

None.

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Author Contributions

Tajmed Khan: Investigation, experimentation, methodology, and manuscript writing, Papan Mondal, Sridip Chatterjee: provided overall supervision of the study, Sumanta Kumar Mondal: contributed to the experimentation and methodology, Najmun Nahar, Chandra Sankar Hazari: manuscript editing.

Conflict of Interest

All authors stated that they have conflicts of interest.

Declaration of Artificial Intelligence (AI) Assistance

No AI system was involved in data analysis, interpretation of results, or forming scientific conclusions.

Ethics Approval

The Jadavpur University Institutional Research Ethics Committee approved the study, reference number IEC/41/C/25.

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