The Effects of Wearable-Based Real-Time Feedback on Muscle Activation During Kettlebell Compound Exercises

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Abstract

Purpose: This study aimed to investigate the effects of wearable-based real-time feedback on muscle activation during kettlebell compound exercises and to compare the results with supervised and self-directed training conditions.
Methods: Eighteen healthy adults were randomly assigned to three groups: wearable feedback group (WG, n = 6), supervised group (SG, n = 6), and self-directed group (SDG, n = 6). All participants performed a standardized kettlebell training program consisting of six compound exercises once per week for four weeks. Electromyography (EMG) was recorded from the Biceps brachii, Triceps brachii, Rectus femoris, and Gastrocnemius according to ENIAM guidelines. Muscle activity was normalized to maximal voluntary isometric contraction (%MVIC). Statistical analyses were conducted using one-way ANOVA and paired t-tests ($\alpha = 0.05$).
Results: The wearable feedback group showed significantly greater increases in %MVIC for the Biceps brachii ($p = .014$), Triceps brachii ($p = .042$), and Rectus femoris ($p = .017$) compared with other groups. Within-group analysis also revealed pre–post improvements across multiple muscles in WG, whereas SG and SDG showed limited or nonsignificant changes. Gastrocnemius activation increased post-intervention in WG but did not differ significantly between groups.
Conclusions: **:** Wearable-based real-time feedback effectively enhanced muscle activation and self-regulation during kettlebell compound exercises compared with supervised or self-directed conditions. These findings highlight the potential of wearable feedback systems as practical tools to optimize training quality, improve exercise adherence, and support individualized programs in fitness and rehabilitation settings.

Keywords: Wearable feedback, Real-time monitoring, Kettlebell compound exercise, Resistance training, Muscle activation, Electromyography

I. Introduction

The rapid development of wearable technology has brought revolutionary changes to sports science and exercise physiology research. In particular, wearable devices such as smartwatches can monitor various physiological parameters in real time, including heart rate, oxygen saturation, and calorie expenditure, thereby greatly contributing to the improvement of training effectiveness and safety (1). The biosensors embedded in smartwatches continuously measure the wearer's physiological signals in a non-invasive manner and transmit the data in real time via wireless communication technologies such as Bluetooth, allowing immediate assessment of exercise intensity and recovery status (2,3). Such advances in wearable technology enable scientific training approaches in both daily life and exercise settings, and allow more precise physiological analyses across different modes of exercise.

With the recent popularization of functional training for health promotion and performance enhancement, kettlebell training has attracted attention as an efficient resistance exercise that simultaneously improves whole-body coordination and explosive strength. According to the study by Meigh et al. (2022), kettlebell compound exercises also have positive effects on muscular endurance and cardiorespiratory fitness. As they are based on multi-joint compound movements such as swings, squats, cleans, and presses, kettlebell exercises stimulate both cardiovascular endurance and muscular endurance, making them an effective strategy for improving functional movement. Previous studies have shown that electromyography (EMG) during exercise is a valid method for quantitatively evaluating muscle activation patterns, intermuscular coordination, and exercise intensity changes associated with specific movements (4). Among EMG measures, %MVIC analysis is considered an essential tool for reliably verifying the physiological responses to exercise programs (5).
Kettlebells are a traditional yet effective resistance training tool, and when combined with wearable technology—especially smartwatches—they now allow more accurate measurement and optimization of training effects. Wearable technology serves as a promising tool for real-time monitoring of resistance exercise, playing an important role in scientifically analyzing and improving the effects of kettlebell resistance training programs (KRTG) (6). When heart rate is monitored through smartwatches during kettlebell exercise, autoregulated training methods can be applied, whereby rest is taken until heart rate recovers below a certain

threshold (7). Real-time feedback via wearable devices enables individuals to make informed decisions regarding their physical activity, thereby enhancing self-regulation (8). According to Soro et al. (2023), wearable technology provides detailed physiological and biomechanical information—such as heart rate, caloric expenditure, and positional changes over time—during resistance training. This information allows real-time adjustments and optimization of programs such as kettlebell training, offers opportunities to evaluate and refine training effectiveness, and enables personalized exercise prescriptions (9).
On the other hand, exercise programs that rely on IoT-based wearable devices may be less effective than those involving direct human supervision or feedback. In fact, some studies have pointed out the limitations of wearable data reliability and user experience (12). Furthermore, the health indicators provided by wearable devices are not always sufficiently specialized or contextualized to deliver accurate personalized health coaching programs (10). Additionally, due to limitations of machine learning models applied to wearable data, such devices may not accurately analyze complex exercise patterns like kettlebell movements (11).

Therefore, to date, there is still a scarcity of research comprehensively evaluating the scientific validity, safety, and reliability of combining kettlebell training with wearable devices. In particular, there is a lack of objective verification regarding the impact of wearable feedback on qualitative improvements in exercise performance and increased muscle activation, especially in non-professional or self-directed exercise settings. Consequently, concerns have been raised that wearable-device–based programs may have limited effectiveness in promoting health improvements due to issues of data accuracy, reliability, and user experience. Inaccurate or incomplete data may lead users to misjudge exercise intensity or even risk their health. Thus, systematic and empirical studies are urgently needed to examine the effectiveness and data reliability of wearable-device–assisted training programs (12).
In this study, participants were divided into three groups: those who performed kettlebell exercises with wearable-based feedback, those who exercised under verbal instruction from an experienced supervisor, and those who exercised independently without assistance. By comparing muscle activation (%MVIC) across the three groups through EMG analysis, this study aimed to provide scientific evidence to enhance the safety, reliability, and effectiveness of wearable-device–assisted exercise programs.

II. Materials and Methods

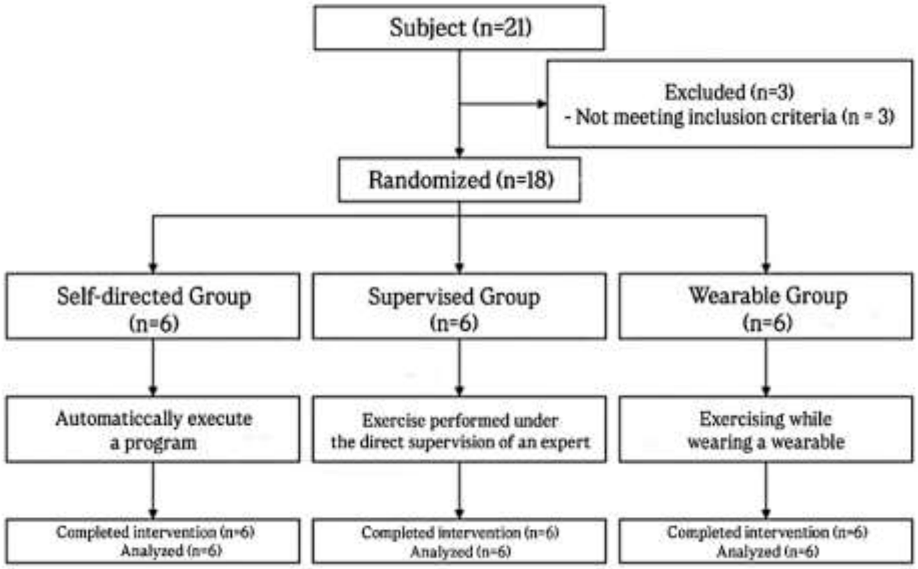
2.1. Participants

A total of 18 healthy adults voluntarily participated in this study. All participants had at least six months of resistance training experience and maintained a consistent training routine for at least two weeks prior to the start of the study.(13,14) The inclusion criteria were as follows 1) men and women aged 20–35 years, 2) no history of musculoskeletal disorders or pain in the upper or lower extremities, 3) ability to perform kettlebell exercises without difficulty during familiarization, 4) agreement to wear and use the wearable device, 5) body composition within a BMI range of 18.5–28 as measured by Inbody analysis, and 6) no record of injury within the past three months. Exclusion criteria were 1) history of musculoskeletal or neurological disorders or current pain, 2) history of orthopedic surgery or rehabilitation within the past three months, 3) adverse responses such as dizziness, pain, or vertigo during kettlebell intervention, (4) dermatological or allergic conditions, tattoos, or other factors interfering with EMG electrode attachment, and 5) body fat percentage ≥ 35% or BMI ≥ 30, which could attenuate EMG signals. Body composition was assessed prior to the intervention using the Inbody 770 analyzer, which included height, weight, and body mass index (BMI).

2.2. Experimental Procedures.

This study was therefore designed as a three-group randomized controlled experiment including pre- and post-intervention comparisons. In this study, a randomized controlled trial design was adopted to investigate the effect of wearable-based real-time feedback on muscle activation during kettlebell compound exercises. Participants were randomly assigned into three groups: a self-directed group (SDG, n = 6), a supervised group (SG, n = 6), and a wearable feedback group (WG, n = 6) [Figure 1]. The intervention was conducted once per week for four weeks (a total of four sessions), and all groups participated in an identical exercise program based on the same exercise components. The appropriate sample size for this study was calculated using G*Power 3.1. The analysis type was set as F-test – ANOVA: A prior: compute required sample size. Independent variables included group (3 levels) and time (2 levels: pre- and post-intervention). The effect size was determined as medium (f = 0.25), with a significance level (α) of 0.05, statistical power (1–β) of 0.80, and a correlation among repeated measures of 0.5. The results indicated that a minimum of 6 participants per group (total n = 18) was required.

Figure 1. Research Procedure



2.2.1 Kettlebell Exercise Program Items

Participants were randomly assigned to three groups, and each group performed the same exercise program under different intervention conditions. The applied kettlebell exercise program was designed around functional compound movements and consisted of six full-body kettlebell training exercises. Each session consisted of a 3-minute warm-up including dynamic stretching and joint mobility exercises, followed by six kettlebell compound movements performed for three sets of 10 repetitions each(15). [Figure 2]. Exercise intensity was set at 60–70% of the individual's estimated 1RM, with 30 seconds of rest between sets and 60 seconds of rest between exercises, and the session concluded with a 2-minute cool-down consisting of static stretching.

Figure 2. Kettlebell Exercise Program a-b: Kettlebell Swing, c-d: Goblet Squat, e-f: Clean and Press, g-h: Lunge with Pass Through, i-j: High Pull, k-l-m: Turkish Get-up

2.3. Measurement Tools and Methods

2.3.1. Smart Watch

In addition to electromyographic analysis, real-time heart rate (HR) monitoring was implemented in the wearable feedback group using a commercially available smartwatch health application [Fig 3]. HR was continuously recorded throughout all kettlebell compound exercise sessions. To maintain appropriate exercise intensity, the health application was programmed with a target

HR zone of 146–156 beats per minute (BPM), corresponding to approximately 65–75% of the estimated maximum HR for the study population.(19) When a participant's HR dropped below 146 BPM, the smartwatch delivered immediate auditory, vibratory, and visual alerts prompting the participant to increase intensity. Conversely, when HR exceeded 156 BPM, a notification instructed the participant to reduce intensity or take a brief rest(20). This individualized HR feedback system ensured that participants maintained the desired cardiovascular load throughout kettlebell training, thereby optimizing both exercise efficiency and safety. HR data were exported for subsequent statistical analysis, and mean, minimum, and maximum HR values were compared across pre- and post-intervention sessions.(21,22)

[Fig 3] Smartwatch interface displaying real-time heart rate monitoring during kettlebell exercise

2.3.2. EMG (Electromyography)

In this study, eight muscles of the upper and lower limbs were selected as target muscles for electromyographic (EMG) analysis during kettlebell exercises. Electrode placement followed the ENIAM guidelines to ensure signal accuracy and reproducibility. A 4-channel wireless EMG system (FREEEMG 300, BTS Bioengineering, USA) with high temporal resolution was used to record muscle activity. The system sampled signals at 1,000 Hz with a band-pass filter of 20–450 Hz and a common mode rejection ratio (CMRR) greater than 100 dB. Signal processing and analysis were conducted using BTS EMG Analyzer software. Raw EMG signals were smoothed with a 50 ms moving root mean square (RMS) window(23). For each muscle, mean %MVIC values were calculated at baseline and after the 4-week intervention. EMG signals were continuously recorded in real time during three sets of 10 repetitions for each kettlebell exercise. For analysis, RMS values from the 3rd to 7th repetitions of each set (approximately 10–15 seconds) were extracted to minimize distortion caused by warm-up effects and end-stage fatigue accumulation. This mid-repetition extraction method has been recommended in previous studies as a reliable approach for obtaining representative values during dynamic resistance exercise(24) Prior to electrode attachment, the skin was shaved, degreased, and disinfected with alcohol, and electrodes were placed parallel to the muscle fiber orientation at the anatomical center of each target muscle. This configuration minimized motion artifacts during exercise and ensured reproducibility of signals, consistent with previous studies that have employed these muscles as standard sites for surface EMG recording.(25)

2.3.3. Anatomic positions of electrodes

In this study, muscle selection was based on those reported to be commonly activated during the six compound kettlebell exercises included in the intervention [Fig 4]. For the upper limbs, two muscles were selected: the Biceps brachii and the Triceps brachii**.** The Biceps brachii is highly activated during movements such as the clean and high pull, where it functions in elbow flexion, as well as during the Turkish get-up, where it plays a role in supporting the kettlebell. Electrodes were placed at the midpoint of the anterior upper arm between the shoulder and the elbow. The Triceps brachii acts as the primary agonist of elbow extension during pressing movements. Electrodes were positioned on the lateral head, midway between the acromion and the elbow(26). For the lower limbs, the Rectus femoris and Gastrocnemius were selected. The Rectus femoris contributes to knee extension and hip flexion, playing a key role in generating propulsion for the lower extremities. Electrodes were attached at the midpoint between the anterior superior iliac spine (ASIS) and the patella(27). The Gastrocnemius is continuously activated in exercises requiring lower-limb support and balance, such as lunges and the Turkish get-up. Electrodes were placed on the most prominent portion of the medial muscle belly of the calf. This site was chosen based on prior research identifying the gastrocnemius as a major muscle activated during kettlebell swing, squat, and press movements(28).

Figure 4. Location of electrodes
a: biceps brachii, b: triceps brachii, c: rectus femoris, d: gastrocnemius

2.3.4. Maximal voluntary Isometric contraction measurements

To normalize the electromyography (EMG) data, maximum voluntary isometric contraction (MVIC) tests were conducted for each target muscle in accordance with the ENIAM guidelines for non-invasive assessment of muscles. Participants performed two MVIC trials for each muscle, with each contraction maintained for 5 seconds and separated by a 1-minute rest period to minimize fatigue. The highest root mean square (RMS) value was used as the reference for normalization(28). EMG signals obtained during MVIC were used to normalize dynamic exercise data, expressed as a percentage of MVIC (%MVIC) (29). This procedure ensured reliable comparisons of muscle activation both within and between groups. For the Biceps brachii, participants sat with the elbow flexed at 90° and the forearm supported in a supinated position. Manual resistance was applied against elbow flexion at the distal forearm. For the Triceps brachii, participants lay supine with the shoulder flexed at 90° and the elbow flexed at 90°. Manual resistance was applied against elbow extension (30). For the Rectus femoris, participants sat with both the hip and knee flexed at 90°. Manual resistance was applied against knee extension at the distal tibia. For the Gastrocnemius, participants stood with the knee fully extended. Manual resistance was applied against ankle plantar flexion at the distal metatarsals while the participant attempted to raise the heel(31). [Fig 5]

Figure 5. Maximal voluntary Isometric contraction measurements
a: biceps brachii, b: triceps brachii c: rectus femoris d: gastrocnemius

2.3.5. MVIC Measurement and Normalization (%MVIC)

To quantify muscle activity data and allow comparisons across participants, EMG signals were normalized to %MVIC based on maximal voluntary isometric contraction (MVIC). Each participant performed three 5-second isometric contractions for each target muscle, and the highest value was adopted as the MVIC. 1-minute rest was provided between measurements to prevent fatigue accumulation(32). The mean RMS values recorded during exercise were converted according to the following formula: Normalization. to %MVIC is a standardized method widely used in resistance exercise research, offering effective comparisons of fatigue accumulation, activation intensity, and inter-individual variability.(33,34) %MVIC = mean EMG value during exercise / MVIC value × 100 (35).

2.4. Statistical analysis

The statistical analyses were performed using IBM SPSS Statistics version 26.0 (IBM Corp., Armonk, NY, USA). To compare differences in muscle activity (%MVIC) before and after the intervention among the three groups—wearable feedback group, non-wearable self-directed exercise group, and non-wearable supervised exercise group—a one-way ANOVA was conducted. When significant differences were identified between groups, post-hoc analyses using the Least Significant Difference (LSD) test were applied to further examine intergroup differences(36). Paired t-tests were employed to compare pre- and post-intervention values within each group, allowing the evaluation of whether muscle activation (%MVIC) significantly changed after the 4-week intervention. Prior to the analyses, the normality of all variables was confirmed using the Kolmogorov–Smirnov test, and the statistical significance level was set at $\alpha = 0.05$

III. Results

This study measured and compared muscle activation (%MVIC) before and after the 4-week intervention across three groups: the wearable feedback group, the supervised group, and the self-directed group. Muscle activation was assessed using surface electromyography (EMG) to calculate the mean and peak %MVIC of the biceps brachii, triceps brachii, rectus femoris, and gastrocnemius.

3.1. General Characteristics of Participants

The general characteristics of the participants are presented in [Table 1]. No statistically significant differences were observed among the three groups in terms of age, height, weight, and body mass index (BMI) ($p > 0.05$). Therefore, the groups were considered homogeneous and appropriate for analysis

Table 1. Comparison of DMD, MAC, Lung capacity according to intervention

Groups	Age(year)	Height(m)	weight(kg)	Body mass index(kg/m^2)
SDG(n=6)	22.00±2.45	168.00±11.78	63.07±15.47	21.99±2.59
SG(n=6)	23.33±3.93	173.17±6.99	67.02±10.76	27.24±12.09
WG(n=6)	23.67±1.63	174.33±7.12	68.300±10.92	22.35±2.67
p value	23.00±2.77	171.83±8.84	66.13±12.03	23.86±7.29

***Mean ± standard deviation**

3.2. Within-group pre-post changes in muscle activation (%MVIC)

This study analyzed the effects of wearable-based real-time feedback on muscle activation (%MVIC) during kettlebell compound exercises. The results showed that the wearable group demonstrated statistically significant changes in muscle activation in the Triceps brachii, Rectus femoris, and Gastrocnemius [Table 2]. In particular, the Biceps brachii and Triceps brachii exhibited clear differences when compared with the other groups. These findings suggest that wearable feedback is effective in enhancing self-regulation and muscle recruitment efficiency during exercise performance. In group comparisons, the wearable group displayed significantly higher activation differences in the Biceps brachii and Triceps brachii than the other groups, and intergroup significance was also confirmed for the Rectus femoris. In contrast, the Gastrocnemius showed significant pre-post changes only within the wearable group, but no significant differences were observed in intergroup comparisons. Overall, the wearable group proved to be more effective in eliciting changes in the activation of specific muscle groups compared to supervised or self-directed exercise.

Table 2. Differences in post-intervention changes between interventions

Variable (%MVIC)	Self-directed Group	Supervise Group	Wearable Group	f	p

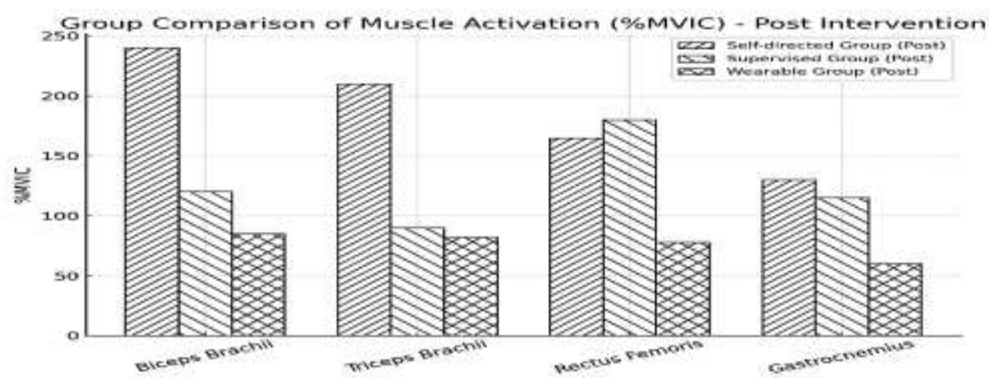
Biceps Brachii	Pre	152.17±70.25	119.57±70.81	111.87±71.95	0.545	0.591
%MVIC	Post	244.08±132.92[a]	117.83±52.65[b]	84.13±44.99[ab]	5.697	0.014*
	t	-2.352	0.059	1.333		
	p	0.065*	0.955	0.240		
Triceps Brachii	Pre	190.58±120.09	135.67±56.99	115.20±78.34	1.150	0.343
%MVIC	Post	209.15±117.73	92.55±73.53[b]	82.25±58.03[b]	3.950	0.042*
	t	-0.553	2.009	2.653		
	p	0.604	0.101	0.045*		
Rectus Femoris	Pre	126.52±40.65	234.27±125.19[c]	107.47±25.05[c]	5.420	0.017*
%MVIC	Post	161.10±81.89	179.08±77.15	78.37±16.06[b]	4.021	0.040*
	t	-1.811	3.098	4.102		
	p	0.130	0.027*	0.009*		
Gastrocnemius	Pre	95.18±46.37	146.17±69.28	84.15±33.87	2.433	0.122
%MVIC	Post	129.77±88.77	115.60±61.52	59.10±25.89	2.040	0.165
	t	-1.382	0.827	3.214		
	p	0.226	0.446	0.024*		

*p<.05, **p<.01, ***p<.001, Mean±SD, a: the difference between Self-directed Group and Wearable Group, b: the difference between Supervise Group and Wearable Group, c: the difference between Supervise Group and Self-directed Group

3.2. Post-intervention group comparison of muscle activation (%MVIC)

The results of the post-intervention comparison of muscle activation (%MVIC) among groups are presented in [Figure 6] In the Biceps brachii, a statistically significant difference was observed among the three groups (F = 5.697, p = .014), and post-hoc analysis revealed that the wearable group showed significant differences compared with the other groups [figure 6]. In the Triceps brachii, intergroup differences were also significant (F = 3.950, p = .042), with the wearable group exhibiting statistically significant changes in activation compared with the supervised group. For the Rectus femoris, significant differences among groups were confirmed (F = 5.420, p = .017), with the wearable group demonstrating a distinct reduction pattern compared to the other groups. In contrast, while the Gastrocnemius showed pre-post changes within the wearable group, no statistically significant differences were observed among groups at the post-test (p > 0.05). Overall, the wearable-based real-time feedback group demonstrated statistically significant differences in the Biceps brachii, Triceps brachii, and Rectus femoris compared to the other groups, indicating that wearable feedback is effective in regulating the activation of specific muscle groups.

Figure 2. Post-intervention group differences in muscle activation (%MVIC) across selected muscles



IV. Discussion

This study was conducted to investigate the effects of wearable-based real-time feedback on muscle activation during kettlebell compound exercises over a four-week intervention. The results indicated that, when comparing changes in muscle activation (%MVIC) across the three groups—self-directed, supervised, and wearable feedback—the wearable feedback group demonstrated the most statistically significant increases in key muscle groups, including the Biceps brachii, Triceps brachii, and Rectus femoris. This suggests that wearable feedback effectively enhances self-regulation and improves the efficiency of muscle recruitment. Similarly, Cinarli and Kafkas (2025) reported that wearable real-time feedback significantly increased neuromuscular

activation during dynamic core training.
In particular, the wearable group consistently showed greater improvements in muscle activation both in pre-post comparisons and in intergroup analyses, whereas the supervised and self-directed groups exhibited only limited or non-significant changes. Additionally, compared to the other groups, wearable feedback appeared to increase participants' exercise focus and facilitated immediate recovery of exercise intensity when performance declined, thereby helping to prevent fatigue accumulation (37). This demonstrates that the advantage of real-time monitoring of exercise intensity and physiological parameters through wearable devices is valid even in complex training tasks (38). Conversely, the self-directed group showed some difficulty in self-regulating exercise intensity due to the absence of feedback, highlighting the limitations of training without structured guidance. These findings reinforce that wearable-based real-time feedback induces greater motivation and muscle activation than external supervision or self-directed methods, This result aligns with previous studies on wearable-based real-time feedback (39), suggesting that it represents an effective approach for improving self-regulation, especially in non-professional or unsupervised exercise environments. Within-group analysis also confirmed significant pre-post increases in muscle activation in the wearable group. The supervised group showed some improvements, though with less statistical significance compared to the wearable group, while the self-directed group exhibited mostly limited or non-significant changes. Collectively, these results demonstrate that wearable feedback is more effective for enhancing exercise performance compared to exercise without real-time feedback.
However, further analysis regarding the accuracy of heart rate measurement and the diversity of feedback delivery methods in wearable devices is necessary. Xu et al. (2024) also suggested that IoT-based wearable feedback is effective in improving exercise concentration and performance accuracy through self-monitoring. Wearable real-time feedback provides an environment that enables both self-monitoring and self-regulation while minimizing participant burden. This feature is delivered in a repetitive and non-coercive manner, increasing user acceptance and ultimately enhancing training adherence and continuity. Hernando, D. (2021) reported that wearable feedback, unlike human-centered feedback, reduces the psychological burden on exercisers and fosters a more focused environment. In line with this, the present study also demonstrated improvements not only in muscle activation but also in exercise concentration in the wearable group. Additionally, the real-time heart rate monitoring function of wearable devices played a critical role in maintaining exercise intensity and managing fatigue. Jamieson et al. (2024) emphasized that providing such physiological data strengthens exercise adherence and self-regulation behaviors.
Future studies should evaluate the effectiveness and user experience of wearable feedback systems across a variety of exercise modalities, age groups, and fitness levels. Wearable-based feedback has been reported to positively influence exercise quality, self-regulation, and concentration while reducing the burden of supervised feedback, thereby increasing user satisfaction and accessibility (43). The strength of wearable feedback is evident in quantitative %MVIC evaluation via electromyography. Beyond improvements in muscular endurance and functional strength through kettlebell training, wearable feedback systems were shown to broadly facilitate exercise quality and the regulation of muscle activation. Compared with traditional coaching or self-directed exercise, device-based feedback improves self-monitoring, satisfaction, exercise intensity, and muscle activation (44). Surface EMG-based %MVIC analysis revealed significantly higher muscle activation in the wearable group compared with both the self-directed and supervised groups. This indicates that EMG monitoring of muscle activation effectively reflects the impact of feedback systems, particularly in compound, full-body exercises such as kettlebell training. Furthermore, wearable devices provide qualitative improvements in exercise focus and muscle recruitment efficiency by delivering real-time feedback, not merely measurement data (45).
Muscle-specific results further support these conclusions. In the Biceps brachii, significant increases in muscle activation were observed both within and between groups in the wearable feedback condition. This can be explained by the repetitive elbow flexion and forearm supination demands of kettlebell compound exercises. These results are consistent who reported that kettlebell swing exercises enhance biceps function, and EMG-based %MVIC analyses in the with Saeterbakken et al.(2020), is study clearly confirmed these findings. This suggests that wearable feedback strengthens upper limb involvement, thereby improving upper body stability and lifting efficiency. The Triceps brachii plays a key role in elbow extension and shoulder stabilization, especially in high-intensity exercises where it contributes to fatigue reduction and force maintenance. The wearable group exhibited significant increases in %MVIC for the Triceps brachii, indicating that real-time feedback facilitated efficient activation of the extensors during movement execution. Lyons et al., (2017) similarly reported increased triceps activation during kettlebell press exercises, and the EMG analyses in this study (showing increases in both RMS and %MVIC) confirmed that wearable feedback contributed to maintaining stable performance even under fatigue.
The Rectus femoris, a primary muscle of the quadriceps, is critical for knee extension and hip flexion. Significant pre-post changes were observed in the wearable group, aligning with findings by Schwartz et al., (2020), who reported that various feedback modalities improved quadriceps activation. EMG analyses confirmed that the Rectus femoris served as a primary mover during kettlebell squats and lunges, with increases in both RMS and %MVIC under feedback conditions, suggesting improved propulsion and stability in lower limb movements. The Gastrocnemius contributes to ankle plantarflexion and lower limb stability, particularly

during movements requiring balance(49). such as lunges and Turkish get-ups. In this study, significant changes in activation were observed in the wearable group, consistent with Santana and Vera-Garcia (2022), who highlighted the role of the gastrocnemius and soleus in lower limb support and balance. EMG-based %MVIC analysis showed higher activation at post-test compared to baseline, indicating that wearable feedback promoted sustained intensity and endurance capacity. Notably, the integration of real-time heart rate monitoring further enabled immediate intensity recovery under fatigue, allowing continuous gastrocnemius activation.

In summary, the observed increases in muscle activation across individual muscle groups in the wearable feedback group were validated through EMG-based %MVIC quantification. These findings suggest that wearable real-time feedback not only improves performance but also contributes to more efficient muscle recruitment(51). and enhanced movement stability across both upper and lower limbs. Consequently, wearable-based feedback offers significant potential for optimizing muscle activation patterns in complex exercise environments, and holds promising applications in rehabilitation and individualized training prescriptions. Ultimately, this study demonstrated that wearable-based real-time feedback can enhance muscle activation during kettlebell compound exercises, providing both qualitative and quantitative improvements in exercise performance. These findings highlight the practical value of wearable technologies in smart fitness, personalized training, and future rehabilitation programs.

The limitations of this study include a small sample size and a short intervention period. In addition, because the participants were limited in age and fitness level, caution should be taken when generalizing the findings. Future studies should incorporate long-term follow-up, larger samples including a wider range of ages and fitness levels, and analyses of the differential effects of feedback delivery methods(52). Furthermore, it is necessary to comprehensively evaluate the accuracy of wearable devices and the user experience. in order to clarify how continuous use influences exercise adherence and motivation.

V. Conclusions

In conclusion, this study examined the effects of wearable-based real-time feedback on muscle activation during kettlebell compound exercises by comparing electromyographic (%MVIC) changes across a wearable feedback group, a supervised group, and a self-directed group. The results showed that the wearable feedback group demonstrated significant increases in Biceps brachii, Triceps brachii, and Rectus femoris activation, with statistically more pronounced improvements compared to the supervised and self-directed groups. Furthermore, pre–post changes were also observed in the Gastrocnemius, confirming that wearable feedback effectively enhances both upper- and lower-limb muscle activation and overall exercise efficiency. These findings align with previous studies indicating that real-time heart rate monitoring and exercise intensity feedback from wearable devices improve muscle recruitment efficiency, exercise focus, and self-regulation capacity. Notably, wearable-based feedback demonstrated practical potential beyond simple performance enhancement by contributing to exercise adherence, prevention of cumulative muscle fatigue, and optimization of individualized training. Therefore, wearable-based real-time feedback can be applied as an efficient and scientific training strategy for complex exercises such as kettlebell training, and it holds promising clinical and practical applications in fields such as personalized fitness, smart training, and remote rehabilitation.

References

1.de Beukelaar, T. T., & Mantini, D. (2023). Monitoring resistance training in real time with wearable technology: Current applications and future directions. Journal of Functional Morphology and Kinesiology, 8(3), 118.

2. Weakley, J. J., Banyard, H. G., & Morrison, M. A. (2023). The effect of feedback on resistance training performance and adaptations: A systematic review and meta-analysis. Sports Medicine, 53(6), 1239–1262.

3. Vancini, R. L., Gentil, P., Andrade, M. S., de Lira, C. A. B., & Nikolaidis, P. T. (2019). Kettlebell exercise as an alternative to improve aerobic capacity. Sports, 7(3), 61.

4. Meigh, N. J., Gill, N. D., Batt, M. E., & Beaven, C. M. (2022). Effects of supervised high-intensity hardstyle kettlebell training on grip strength and health-related physical fitness in insufficiently active older adults: The BELL pragmatic controlled trial. BMC Geriatrics, 22(1), 353.

5. Hermens, H. J., Freriks, B., Disselhorst-Klug, C., & Rau, G. (2000). Development of recommendations for SEMG sensors and sensor placement procedures. Journal of Electromyography and Kinesiology, 10(5), 361–374.

6. Burden, A. (2010). How should we normalize electromyograms obtained from healthy participants? What we have learned from over 25 years of research. Journal of Electromyography and Kinesiology, 20(6), 1023–1035.

7. Mann, T., Lamberts, R. P., & Lambert, M. I. (2013). Methods of prescribing relative exercise intensity: Physiological and practical considerations. Sports Medicine, 43(7), 613–625.

8. Staunton, C., Wundersitz, D., Gordon, B., Kingsley, M., & Gordon, S. (2019). Autoregulation of training using subjective indicators of recovery status in male soccer players. International Journal of Sports Physiology and Performance, 14(8), 1069–1076.

9. Soro, A., Fahey, M., & Bianchi, F. (2023). Wearable technology in resistance training: Applications, challenges, and opportunities. Frontiers in Sports and Active Living, 5, 1182732.
10. Piwek, L., Ellis, D. A., Andrews, S., & Joinson, A. (2016). The rise of consumer health wearables: Promises and barriers. PLoS Medicine, 13(2), e1001953.
11. Hossain, M. S., Muhammad, G., Rahman, M. A., & Amin, S. U. (2020). Applying deep learning for IoT-based personalized healthcare: A distributed edge computing framework. IEEE Access, 8, 16836–16846.
12. Sperlich, B., Holmberg, H. C., & Zinner, C. (2022). Wearables for athletes: Limitations and opportunities. Sensors, 22(8), 2957.
13. Meigh, N. J., Gill, N. D., Batt, M. E., & Beaven, C. M. (2022). Effects of supervised high-intensity hardstyle kettlebell training on grip strength and health-related physical fitness in insufficiently active older adults: The BELL pragmatic controlled trial. BMC Geriatrics, 22(1), 353.
14. Vancini, R. L., Gentil, P., Andrade, M. S., de Lira, C. A. B., & Nikolaidis, P. T. (2019). Kettlebell exercise as an alternative to improve aerobic capacity. Sports, 7(3), 61.
15. Lake, J. P., & Lauder, M. A. (2012). Kettlebell swing training improves maximal and explosive strength. Journal of Strength and Conditioning Research, 26(8), 2228–2233
16. Lyons, B. C., Mayo, J. J., Tucker, W. S., Wax, B., & Hendrix, R. C. (2017). Electromyographical comparison of muscle activation patterns across three commonly performed kettlebell exercises. Journal of Strength and Conditioning Research, 31(9), 2363–2370.
17. Van Gelder, L. H., Hoogenboom, B. J., Alonzo, B., Briggs, D., & Hatzel, B. (2015). EMG analysis and sagittal plane kinematics of the two-handed and single-handed kettlebell swing: A descriptive study. International Journal of Sports Physical Therapy, 10(6), 811–826.
18. Andersen, V., Fimland, M. S., Gunnarskog, A., Jungård, G., Slåttland, R.-A., Vraalsen, Ø. F., & Saeterbakken, A. H. (2016). Core muscle activation in one-armed and two-armed kettlebell swing. Journal of Strength and Conditioning Research, 30(5), 1196–1204.
19. Ludwig, C. J. H., Edwards, L., & Murdoch, R. (2018). Measurement, prediction, and control of individual heart rate responses during exercise: A review. Frontiers in Physiology, 9, 778.
20. Eston, R., Faulkner, J., & Mason, S. (2019). Revisiting heart rate target zones through the lens of wearable technology. European Journal of Sport Science, 19(7), 1024–1032
21. Doherty, A., Jackson, D., Hammerla, N., Ploetz, T., Olivier, P., Granat, M. H., White, T., van Hees, V. T., Trenell, M. I., Owen, C. G., & Brage, S. (2024). Keeping pace with wearables: A living umbrella review of the accuracy of wearable devices for measuring heart rate and energy xpenditure. Sports Medicine, 54(2), 215–229.
22. Reddy, R. K., Pooni, R., Zaharieva, D. P., Senf, B., El Youssef, J., Dassau, E., & Doyle, F. J. (2018). Accuracy of wrist-worn activity monitors during common daily physical activities and types of structured exercise: Evaluation study. JMIR mHealth and uHealth, 6(12), e10338.
23. Konrad, P. (2006). The ABC of EMG: A practical introduction to kinesiological electromyography. Scottsdale, AZ: Noraxon USA.
24. Hug, F. (2011). Can muscle coordination be precisely studied by surface electromyography Journal of Electromyography and Kinesiology, 21(1), 1–12.
25. Hermens, H. J., Freriks, B., Disselhorst-Klug, C., & Rau, G. (2000). Development of recommendations for SEMG sensors and sensor placement procedures. Journal of Electromyography and Kinesiology, 10(5), 361–374.
26. Andersson, E. A., Nilsson, J., & Thorstensson, A. (1997). Intramuscular EMG from the gastrocnemius muscle during human walking and running. Acta Physiologica Scandinavica, 161(4), 361–370
27. Schwartz, C., Wang, F.-C., Forthomme, B., Brüls, O., Croisier, J.-L., & Denoël, V. (2020). Normalizing gastrocnemius muscle EMG signal: An optimal set of maximum voluntary isometric contraction tests for young adults considering reproducibility. Gait & Posture, 82, 196–202.
28. Medical Journals. (2009). Quantified electromyography of lower-limb muscles. Journal of Rehabilitation Medicine, 41(8), 610–617.
29. Quittmann, O. J., Abel, T., Wirth, K., & Hortobágyi, T. (2020). Assessment of maximal voluntary isometric contractions: Manual resistance versus sport-specific testing procedures. European Journal of Applied Physiology, 120(3), 643–653.
30. Hur, S., Jung, H., & Lee, D. (2024). Reliability of surface electromyography from the lower extremity: Comparison of maximal and submaximal voluntary isometric contractions. Journal of Electromyography and Kinesiology, 75, 102787.
31. Ball, N., & Scurr, J. (2013). Electromyography normalization methods for high-velocity muscle actions: Review and recommendations. Journal of Applied Biomechanics, 29(5), 600–608.
32. Skalski, D. T., Nowak, A. M., & Juras, G. (2025). Electromyography normalization and assessment methods. Baltic Journal of Health and Physical Activity, 17(1), 1–13.
33. Edwards, P. K., Ebert, J. R., Littlewood, C., & Ackland, T. (2017). A systematic review of electromyography studies in sport and exercise. Journal of Orthopaedic & Sports Physical Therapy, 47(8), 559–576.

34. Juarros-Basterretxea, J., Espinosa-Fernández, L., & González-González, C. S. (2024). Post-hoc tests in one-way ANOVA: The case for normal distribution. International Journal of Research and Method in Education, 47(3), 289–305.
35. Cinarli, F. S., & Kafkas, M. E. (2025). Neuromuscular activation following anti-movement and dynamic core training: A randomized controlled comparative study. European Journal of Applied Physiology, 125(9), 2449–2459.
36. Weakley, J. J., Banyard, H. G., & Morrison, M. A. (2023). The effect of feedback on resistance training performance and adaptations: A systematic review and meta-analysis. Sports Medicine, 53(6), 1239–1262.
37. Pacholek, M., Suchomel, T. J., & Taborsky, F. (2024). The influence of real-time quantitative feedback and verbal encouragement on bench press performance, motivation, competitiveness, and mood. Frontiers in Physiology, 15, 1329432.
38. Simić, D., Đorđević, O., Marković, M., Đorđević, V., & Mitić, P. (2024). Wearable device for personalized EMG feedback-based treatments. Journal of Biomedical Informatics, 152, 104727.
39. Xu, Y., Peng, J., Jing, F., & Ren, H. (2024). From wearables to performance: How acceptance of IoT devices influences physical education results in college students. Scientific Reports, 14, 23776.
40. Bayoumy, K., Gaber, M., Elshafeey, A., Mhaimeed, O., Dineen, E. H., Marvel, F. A., Martin, S. S., Muse, E. D., Turakhia, M. P., & Tarakji, K. G. (2021). Smart wearable devices in cardiovascular care: Clinical update and future directions. Nature Reviews Cardiology, 18(8), 581–599.
41. Del-Valle-Soto, C., López-Buenrostro, J. A., Escobar-Martínez, J., García-Magariño, I., & Torres-Rodríguez, A. (2024). A comprehensive review of behavior change techniques in wearables and IoT: Implications for health and well-being. Frontiers in Digital Health, 6, 1448712.
42. Jamieson, M., Rawstorn, J. C., & Maddison, R. (2024). A guide to consumer-grade wearables in cardiovascular research. npj Digital Medicine, 7(1), 49.
43. Jamieson, M., et al. (2024). Evaluation of wearable devices for monitoring physiological data to support exercise adherence and self-regulation: A scoping review. Journal of Medical Internet Research, 26(1), e55925.
44. Del-Valle-Soto, C., López-Buenrostro, J. A., Escobar-Martínez, J., García-Magariño, I., & Torres-Rodríguez, A. (2024). A comprehensive review of behavior change techniques in wearables and IoT: Implications for health and well-being. Sensors, 24(8), 2429.
45. Keats, M. R., Culos-Reed, S. N., & Courneya, K. S. (2023). Use of wearable activity-monitoring technologies to improve self-awareness, motivation, and behavior change. International Journal of Environmental Research and Public Health, 20(6), 4784.
46. Chukwuemeka, U. M., Ibrahim, A., Yusuf, A., & Rahman, M. S. (2025). Mobile-application-based performance feedback improves performance and maintains motivation via wearable sensors. BMC Digital Health, 5, 206.
47. Saeterbakken, A. H., Mo, D.-A., Scott, S., & Andersen, V. (2020). Muscle activation with swinging loads in bench press. PLOS ONE, 15(9), e0239202.
48. Lyons, B. C., Mayo, J. J., Tucker, W. S., Wax, B., & Hendrix, R. C. (2017). Electromyographical comparison of muscle activation patterns across three commonly performed kettlebell exercises. Journal of Strength and Conditioning Research, 31(9), 2363–2370.
49. Schwartz, C., Wang, F.-C., Forthomme, B., Brüls, O., & Croisier, J.-L. (2020). Normalizing gastrocnemius muscle EMG signal: An optimal set of maximum voluntary isometric contraction tests for young adults considering reproducibility. Gait & Posture, 82, 196–202.
50. Ferri-Caruana, A., Cejudo, A., Gijon-Nogueron, G., & Chicharro, J. L. (2024). Gastrocnemius activation and balance performance during functional lower-limb exercises: An electromyographic study. Frontiers in Sports and Active Living, 6, 1445129.
51. Santana, J. C., & Vera-Garcia, F. J. (2007). Resistance exercise and core muscle activation: A review of EMG studies on trunk and lower-limb support. Journal of Strength and Conditioning Research, 21(4), 1100–1106.
52. Thompson, W. R. (2022). Worldwide survey of fitness trends for 2022. ACSM's Health & Fitness Journal, 26(1), 11–20.