Applied Ergonomics 132 (2026) 104699

Contents lists available at ScienceDirect

Applied Ergonomics

journal homepage: www.elsevier.com/locate/apergo

Assessing forearm exertion in manual tasks with surface EMG: A comparative analysis of through-forearm vs. muscle-specific EMG placements

Xuelong Fan [a,*], Johan Rydgård [a,b], Liyun Yang [c], Peter J. Johansson [a,b]

[a] Occupational and Environmental Medicine, Department of Medical Science, Uppsala University, Uppsala, Sweden
[b] Occupational and Environmental Medicine, Uppsala University Hospital, Uppsala, Sweden
[c] Institute of Environmental Medicine, Karolinska Institutet, Stockholm, Sweden

A R T I C L E I N F O

Keywords:
Force
Perceived exertion
OMNI-Resistance exercise scale
Electromyography
Polynomial mixed-effects models
Through-forearm

A B S T R A C T

Background: Hand-intensive work is associated with musculoskeletal disorders (MSDs), highlighting the need to estimate external forearm loads. Surface electromyography (sEMG) with muscle-specific placements enables continuous load monitoring but has notable limitations. This study evaluated a novel through-forearm sEMG placement against traditional extensor and flexor placements for estimating force and perceived exertion during hand-intensive tasks.
Methods: Sixteen participants performed four tasks at five exertion levels. sEMG signals, self-rated exertion, and exerted force were recorded. Polynomial mixed-effects models estimated self-rated exertion and exerted force, while correlations between sEMG placements were analyzed.
Results: All sEMG placements predicted exertion and force with strong fit ($R^2 > 0.95$) and high precision. Through-forearm sEMG slightly outperformed extensor and flexor placements and was closely correlated with their signals.
Conclusion: Through-forearm sEMG offers marginally better performance for exertion estimation in manual tasks. Further research should explore individual calibration and task-specific methods for broader applications.

1. Introduction

Musculoskeletal disorders (MSDs) of the hand and arm are a prevalent issue (Govaerts et al., 2021), negatively impacting life expectancy and expected years without activity limitation(Ritsuno et al., 2021), and productivity (Epstein et al., 2018), while also incurring great economic costs (Power et al., 2022). Workers involved in hand-intensive tasks are particularly susceptible to developing MSDs, such as carpal tunnel syndrome, tendinitis, and nerve entrapments (Arvidsson et al., 2003, 2021; Mathew and John, 2021; Palmer et al., 2006; Van Rijn et al., 2008).

To mitigate the risk of musculoskeletal disorders (MSDs), regular risk assessments are essential for identifying and addressing hazardous work activities, as mandated by health and safety regulations (Council of the European Union, 1989). Accurate assessment of physical workload plays a critical role in MSD prevention (Zhang et al., 2024). Traditionally, risk assessment tools (Bonfiglioli et al., 2013; Jorgensen et al., 2024; Steven Moore and Garg, 1995) rely on visual observations or self-rating tools to estimate force exposure and task duration. Recent advancements in risk assessment frameworks have recognized the multifactorial nature of MSDs, incorporating elements beyond physical exposures such as psychological and organizational factors (Das et al., 2024; Zhang et al., 2024). This shift underscores the need for flexible, reliable, scalable, and efficient tools to evaluate each contributing factor in a large study population. While these tools that are based on self-ratings and visual observation provide valuable insights and are cost-effective and easy to deploy, they often require inputs from subjects during work, which disrupts their normal work activities, or the observers need to watch lengthy videos, making the protocol hard to scale for longer working hours, more dynamic work tasks, and multiple subjects with distinct individual functions. Additionally, these methods are often susceptible to inter-observer biases, sex biases, and long-term scalability issues (Dahlgren et al., 2022; Graben et al., 2022; Nyman et al., 2023), making it less reliable for long-term individual monitoring in various

* Corresponding author.
E-mail address: xuelong.fan@uu.se (X. Fan).

https://doi.org/10.1016/j.apergo.2025.104699
Received 15 January 2025; Received in revised form 25 November 2025; Accepted 30 November 2025
Available online 2 December 2025

occupational scenarios in daily clinical practices.

To address these limitations, sensor-based assessment tools, such as inertial measurement units (IMUs) and surface electromyography (sEMG), have emerged as promising alternatives. These technologies reduce observer bias, enable continuous monitoring, and decrease the burden on workers and analysts. For decades, kinematic and muscle activity data obtained from IMUs and sEMG have been linked to the prevalence of work-related MSDs (Balogh et al., 2009; Hansson et al., 2006; Nordander et al., 2004). Threshold values derived from such data are commonly used to assess risk in specific body regions (Arvidsson et al., 2021). Furthermore, traditional ergonomic assessment tools, such as the Rapid Upper Limb Assessment (RULA) (McAtamney and Nigel Corlett, 1993), have been enhanced by replacing self-reported or observed data with sensor-based measurements (Baklouti et al., 2024; Singh et al., 2024). Machine learning approaches have also been applied to multi-channel IMU data to automatically identify risky postures and quantify time spent in such positions (Zhao and Obonyo, 2021), facilitating integration with existing risk models.

However, while kinematic data provide valuable insights into posture and movement, they do not capture external loads or exerted forces. This limits their ability to distinguish between forceful and non-forceful tasks, reducing their applicability in scenarios where high external loads are common and repetitive. Directly measuring external loads in the forearm and hand during everyday work activities remains technically challenging. Alternative approaches, such as estimating muscle bulging via elastic tension, are difficult to scale and unsuitable for fine motor assessment (Tahir et al., 2023). As a result, subjective ratings are still frequently used as proxies for actual external loads, highlighting the continued need for convenient, efficient, reliable, and unobtrusive monitoring tools.

Surface electromyography (sEMG) offers a viable solution by enabling continuous estimation of muscular effort with minimal interference in work tasks (Fan et al., 2022; Hansson et al., 2009, 2010). sEMG signals have been shown to correlate with exerted hand force (Barański et al., 2024; Bardizbanian et al., 2020; Mao et al., 2023a), filling a critical gap in current risk assessments. Nonetheless, several factors—such as inter-subject variability, electrode placement differences, forearm posture, wrist posture, and muscle contraction velocity—can affect signal quality and interpretation (Forman et al., 2021; Takala and Toivonen, 2013; Wu et al., 2023). While combining multiple muscle signals may improve prediction accuracy (Martinez et al., 2020; Tepe and Demir, 2022), it increases system complexity. The limited surface area of the forearm also constrains electrode placement. Although multi-channel sEMG systems (e.g., ring arrays) have demonstrated high accuracy in gesture recognition (Tepe and Demir, 2022), their high cost and limited availability hinder widespread adoption in occupational settings.

Takala and Toivonen (2013) proposed a pragmatic alternative by measuring surface sEMG through the forearm (through-forearm) using a single bipolar channel, with one electrode on the extensor and one on the flexor muscle groups. This approach demonstrated more consistent exertion load estimations across various wrist and forearm postures compared to muscle-specific placements, such as those targeting only the extensor or flexor. The through-forearm approach appears to offer a viable alternative for assessing the general physical load on the forearm and hand in occupational environments.

However, research on through-forearm sEMG placement is limited. The existing study by Takala and Toivonen (2013) did not examine the performance of the through-forearm placement during other common work-related tasks, such as twisting and pinching, nor did it evaluate the ability of through-forearm sEMG to predict exerted force. Therefore, further investigation is necessary to examine the performance of through-forearm sEMG for assessing the exerted force in a wider range of hand-intensive tasks.

Overall, the study intended to explore whether the through-forearm can be a viable or better sEMG placement in predicting the external exertion in the forearm than the commonly-used, muscle-specific sEMG placement. With this purpose, the study focused on two specific aims.

1) To investigate whether the through-forearm sEMG placement provides better and more consistent estimates of external exertion across different tasks compared to the muscle-specific sEMG placements on the extensor and flexor muscles. The measures of exertion include:
   a. Self-reported perceived exertion
   b. External exerted force
2) To explore the correlations between the through-forearm sEMG placement and the extensor and flexor placements to understand the muscle activity captured by the through-forearm sEMG.

The two-fold aims are also illustrated in Fig. 1.

2. Methods and materials

2.1. Participants

Sixteen healthy, female (56 %) and male (44 %) participants (mean ± SD: age, 41 ± 10 years; height, 173 ± 9 cm; BMI, 24 ± 3 kg/m^2; wrist circumference, 166 ± 13 mm), either right- (75 %) or left-handed (25 %), from a Swedish research institute participated the study voluntarily (Table 1). All participants were informed of the studies and have given their consent. The study was approved under ethical approval by The Ethical Review Board in Gothenburg (Ref. no. 2022-02531-01) and funded by AFA Insurance Ref.no. 200070.

2.2. Experiment settings

The study included four predefined simulated manual tasks: gripping, thumb-pressing, screwing, and key-pinching. The experiment consisted of two phases: calibration and task.

The **calibration phase** included one resting period and four maximal voluntary contraction (MVC) periods (one for each task). The **resting period** took place at the beginning of the experiment. During the resting period, participants first stood upright with their eyes facing forward and arms hanging naturally at their sides for 15 s. They were then seated in a chair with back support, with the dominant arm placed on an armrest at a 90° elbow angle for 15 s. The height of the armrest was adjusted to ensure that the shoulder remained relaxed. This resting period was used to determine the noise level for the sEMG measurements, which could be obtained from either the standing or sitting position (See Section 2.5). The four **MVC periods** were conducted at the start of each task to acquire the maximal voluntary contraction (MVC) of the forearm for the task. During each period, participants were instructed to 1) hold or rest their hand on the tool for the corresponding task in a standardized posture, 2) rest in the posture and position for 10 s, 3) gradually increase their exertion to the maximum, under verbal encouragement from a researcher, 4) hold this maximal voluntary contraction for 3 s, and release the tool and relax their hands. The relaxing part last at least 30 s. The four MVC periods were used to normalize the exerted force for the four tasks. Noticeably, the MVC period for gripping was also used to normalize EMG signals (See 2.5 Signal processing below).

In the **task phase**, participants performed the four predefined tasks. The order of tasks was fixed to minimize the number of participant groups required, and at least 2 min of rest was provided between the tasks. Before each task, participants positioned their dominant hand on a corresponding exertion meter in the appropriate posture and practiced the task until they felt ready. They then rested their hand in position without exerting force for 10 s to prepare for the task session. Following the MVC period for each task and a resting period of at least 30 s, participants were asked to increase their force to three predetermined perceived exertion levels, corresponding to the scores of 2, 4, and 8 on an OMNI-RES scale that was modified to better illustrate hand exertion

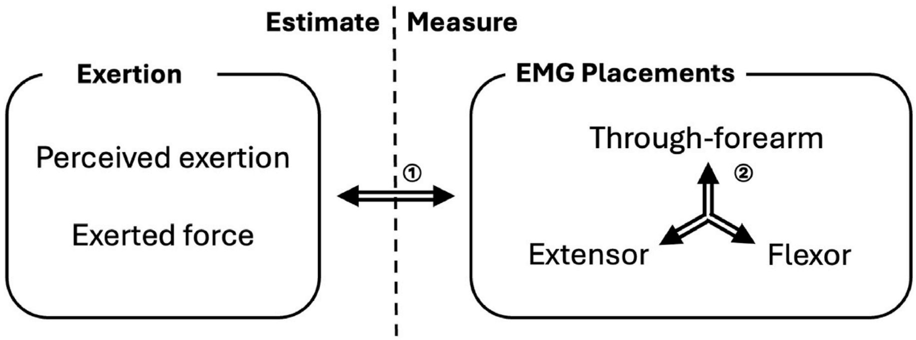

Fig. 1. The scheme of the study. Each multidirectional arrow corresponds to one aim of the study.

Table 1
Description of the participants (N = 16).

Characteristics	Value
Age, mean (SD), years	41 (10)
Female, N (%)	9 (56)
Height, mean (SD), cm	173 (9)
Weight, mean (SD), kg	73 (11)
BMI, mean (SD), kg/m^2	24 (3)
Wrist circumference, mean (SD), mm	166 (13)
Right-handed, N (%)	12 (75)

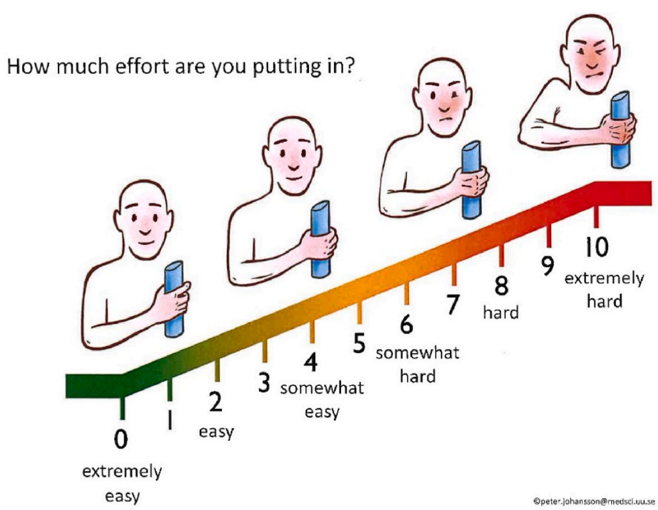

Fig. 2. The modified OMNI-RES scale with the question, anchor words, and figures.

(Fig. 2). A 10 on the modified OMNI-RES is defined as the maximal exerted force and a zero is defined as 5 % of the maximal exerted force or below. The rest numbers, e.g., 1, 2, 3, etc., represent 10 %, 20 %, 30 % of the maximal exerted force and so on. The participants were holding the level for 5 s before relaxing. A minimum resting period of 20 s was provided between each exertion.

To reduce the number of required participant, the exertion levels were presented in a hierarchically randomized order, with each participant assigned to one of four sequences: 2-4-8, 4-2-8, 8-2-4, or 8-4-2. Eventually, the number of participants was determined using convenience sampling, taking into account randomization balance (with at least 3 repetitions per order group) and power analysis based on findings from a previous study (Takala and Toivonen, 2013).

The detailed instructions for the standardized posture of each task were described as follows.

1) For the **gripping task**, participants were seated in a chair, holding the dynamometer in their dominant hand, with their wrist in a neutral position, their arm resting on the armrest, and their elbow positioned at a 90-degree angle. The grip size of the dynamometer was adjusted to individual preferences for comfort.
2) For the **thumb-pinching task**, participants stood with their dominant arm hanging vertically and freely at their side. The pinch meter was placed on a table, which was customized to the appropriate height, allowing participants to press their thumb on the meter with the wrist in a near-neutral position and without the need to lean or raise their shoulders.
3) For the **screwing task**, participants stood holding a screwdriver in their dominant hand, with their elbow positioned at approximately a 100-degree angle with the wrist in ulnar deviation. The screwdriver was inserted into a nozzle connected to the moment meter, which was securely fixated on a table adjusted to the participant's height. During the exertion, participants turned the screwdriver outward (supination), with the direction of the moment standardized to represent outward movement, regardless of which hand was used.
4) For the **key-pinching task**, participants were seated in a chair, holding the meter between their thumb and index finger with the wrist in a neutral position, as if holding a key. The elbow was positioned at a 90-degree angle, kept close to the body, and supported by the chair's armrest.

During both thumb- and key-pinching tasks, participants were specifically instructed to use only the force from their hand and forearm, avoiding leaning or any use of body weight.

2.3. Measurement of exerted force

The exerted force during the gripping task was measured using a dynamometer (G200, Biometrics Ltd, Newport, UK) with a sampling rate of 50 Hz. The exerted moment (the term was used interchangeably as force for the convenience in this study) during the screwing task was measured using a moment meter (Mecmesin static moment meter ST, Chauvin Arnoux Mätsystem, Täby, Sweden) at 100 Hz, with the direction of the moment standardized. Both the key-pinching and thumb-pinching forces were quantified using a pinch meter (P200, Biometrics Ltd, Newport, UK) at 100 Hz.

2.4. Measurement of muscle activity

Muscle activity was recorded using self-adhesive bipolar electrodes with gel (Ag/AgCl electrodes, N-00-S/25, Ambu, Penang, Malaysia) and captured by a data logger (DataLog MWX8, Biometrics Ltd, Newport, UK). Signals were sampled at 1000 Hz per channel using a 24-bit A/D converter embedded in the logger.

Three sEMG placements were used: extensor, flexor, and through-forearm (Fig. 3). The extensor sEMG was placed one-third of the forearm's length from the elbow, above the area surrounding the m.

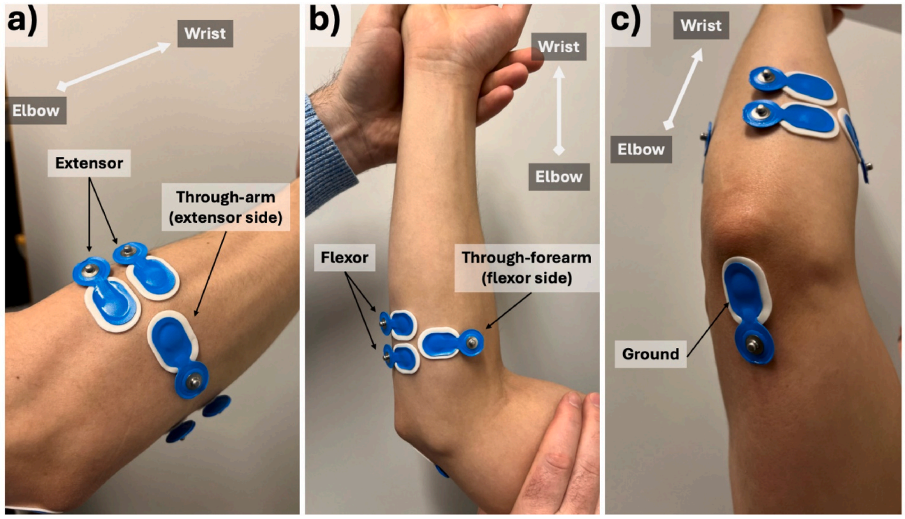

Fig. 3. The placements of the sEMG electrodes on the right arm. Each placement is illustrated as such: extensor (a), flexor (b), through-forearm (a,b), and ground (c). The orientation of the arm is indicated by a light-grey arrow.

extensor carpi radialis longus and brevis, with a center-to-center electrode distance of 2 cm (Fig. 3a; Nordander et al., 2004). The flexor sEMG was placed over the belly of the m. flexor digitorum superficialis, also with a center-to-center distance of 2 cm (Fig. 3b) (Takala and Toivonen, 2013). For the through-forearm placement (Fig. 3a and b), one of the bipolar electrodes was positioned over the m. extensor digitorum communis, while the other electrode was placed 1.5 cm lateral to the flexor sEMG electrodes (Takala and Toivonen, 2013).

Ground electrodes were positioned above the olecranon process on both the distal forearm and humeral areas (Fig. 3c).

2.5. Signal processing

The sEMG measurement was processed following a modified version of a previous study (Fan et al., 2022; Hansson et al., 2000). The sEMG signals were initially filtered using a digital bandpass filter (20–400 Hz) to isolate relevant frequencies, followed by a notch filter to remove environmental noise at 50 Hz and its harmonics. The resulting signals formed the base sEMG data. The noise level was determined as the minimum root mean square (RMS) value calculated from the base sEMG data during the resting period of the calibration phase, using a 2.375-s moving RMS window on the processed data. To determine each participant's maximal voluntary electrical activity (MVE), the base sEMG data from the gripping task's MVC period was extracted and filtered using a 0.5-s moving RMS window. The filtered data were then power-subtracted to remove noise using the formula $\sqrt{x_i^2 - x_0^2}$, where x_0 represents the noise level. The highest RMS value from the resulting data during the gripping MVC period was recorded as the participant's MVE. To calculate muscle activity levels during each task and exertion level, the base sEMG data for each exertion level was first rectified using a 0.125-s moving RMS window, with the noise level similarly power-subtracted. The resulting sEMG data were then normalized to the individual's MVE and expressed as a percentage of MVE (%MVE), representing the normalized muscle activity. The muscle activity level for each exertion level was obtained as the median value of the normalized muscle activity during the corresponding exertion period.

Similarly, force data were processed by an 8 Hz low-pass filter to the raw signals and saved as the base force data. The base force data were then denoised by subtracting the minimal value during the 10-s resting part during the MVC period at the beginning of each task and normalized to the MVC of the task, expressed as a percentage of MVC (%MVC). Eventually, the exerted force level for each exertion level was derived as the median value of the normalized force value during the corresponding exertion period. For each subject, task, and intensity level, a single numeric value was derived for physical exertion and for each corresponding EMG placement.

2.6. Statistics

All analyses related to muscle activity (%MVE), perceived exertion (OMNI-RES score), and exerted force (%MVC) were done within subgroups stratified by task.

The descriptive results of muscle activity were first presented, which include the group median and quartiles of muscle activity of each sEMG placement within each exertion level under each task. To test if there were significant differences of muscle activity measured by the three EMG placements under each perceived exertion level, Friedman tests were used. The core analyses in this study were two-fold.

1) Perceived exertion and exerted force were estimated using three sEMG placements. Following the approach of a previous study (Barański et al., 2024), polynomial mixed-effects models were employed to estimate both outcomes. In these models, muscle activity was treated as the fixed effect, while subjects were modeled as random effects. The assumption of homogeneity was evaluated using Levene's test, which was satisfied. The Shapiro-Wilk test indicated violations of normality in approximately one-third of the fitted models. Still, mixed-effects models are considered generally robust to such violations (Schielzeth et al., 2020), which allows the analysis to proceed. Polynomial terms were added progressively to the models, and model comparisons were performed to determine the necessity of higher-order terms. The final models are structured as follows:

   a Perceived Exertion Model:

$$\text{OMNI-RES}_{ij} = \begin{pmatrix} \beta_0 + u_{0i} \\ \beta_1 + u_{1i} \\ \beta_2 + u_{2i} \end{pmatrix} \begin{pmatrix} 1 \\ \text{EMG}_{ij} \\ \text{EMG}_{ij}^2 \end{pmatrix} + \epsilon_{ij}$$

where OMNI-RES_{ij} represents the perceived exertion for the subject i and task j, EMG_{ij} is the muscle activity level, β_0, β_1, β_2 are the fixed effects coefficients, and u_{0i}, u_{1i}, u_{2i} are the random effects for the subject i. The term ϵ_{ij} denotes the residual error.

   b Exerted Force Model:

$$\text{Force}_{ij} = \begin{pmatrix} \beta_0 + u_{0i} \\ \beta_1 + u_{1i} \\ \beta_2 + u_{2i} \end{pmatrix} \begin{pmatrix} 1 \\ \text{EMG}_{ij} \\ \text{EMG}_{ij}^2 \end{pmatrix} + \epsilon_{ij}$$

where Force_{ij} represents the exerted force for the subject i and task j, EMG_{ij} is the muscle activity level, β_0, β_1, β_2 are the fixed effects coefficients, and u_{0i}, u_{1i}, u_{2i} are the random effects for the subject i. The term ϵ_{ij} denotes the residual error.

After fitting, the inter-task variances of the coefficients of the models were calculated to estimate the consistence of models from each sEMG placement across different tasks.

2) To explore the relationship between the three sEMG placements, Pearson correlations were calculated between each pair of sEMG placements, both within each task and across all tasks. Afterward, a secondary exploration was conducted by examining the contribution of extensor and flexor activities to through-forearm activity. To do so, a linear mixed-effects model was used, with z-score transformed muscle activity levels (calculated within each task of each participant):

$$\text{Through-forearm}_{ij} = \begin{pmatrix} \beta_1 + u_{1i} \\ \beta_2 + u_{2i} \end{pmatrix} \begin{pmatrix} \text{Extensor}_{ij} \\ \text{Flexor}_{ij} \end{pmatrix} + \epsilon_{ij}$$

where $\text{Through-forearm}_{ij}$, Extensor_{ij}, Flexor_{ij} represent the through-forearm, extensor, flexor muscle activity level for subject i and task j, β_1, β_2 are the fixed effects coefficients, and u_{1i}, u_{2i} are the random effects for subject i. Intercepts were excluded under the assumption that when both muscles' activities are zero, the through-forearm should be simultaneously zero. The term ϵ_{ij} denotes the residual error.

3. Results

3.1. Prediction of perceived exertion from sEMG placements

Overall, muscle activity from all three sEMG placements increased monotonically with rising perceived exertion levels. Among the placements, muscle activity from the extensor was consistently higher than that of the flexor across all tasks and perceived exertion levels. The through-forearm placement showed muscle activity that was intermediate between the extensor and flexor placements at lower perceived exertion levels across all four tasks. However, at higher perceived exertion levels, the through-forearm placement exhibited greater muscle activity than both the extensor and flexor placements during the screwing and thumb-pinching tasks, while remaining intermediate for the gripping and key-pinching tasks (Table 2).

When predicting perceived exertion levels from muscle activity, the polynomial mixed-effects models for all sEMG placements explained over 80 % of the variance across all tasks. Notably, the model based on the through-forearm placement consistently explained more than 90 % of the variance, with three tasks reaching around 95 %, outperforming the other two placements (Fig. 4).

The standard deviations (SDs) of the residuals were approximately 1 for the gripping, screwing, and thumb-pinching tasks, and less than 2 for the key-pinching task. When comparing the sEMG placements, the through-forearm placement exhibited the lowest residual SDs, indicating more precise predictions (Fig. 4).

To compare the consistency of models across different tasks and subjects, the inter-task variances of the model coefficients and the random factor coefficients were shown in Table S1 (Appendix). Overall, using the fixed effects as references, models from all three sEMG placements exhibited from low to moderate inter-task (1 %–66 %) and inter-subject (22 %–75 %) variability (excluding few extreme values for the insignificant intercepts). However, the differences between the placements were inconsistent. No single sEMG placement consistently outperformed the others; each showed strengths in certain tasks but underperformed in others.

3.2. Prediction of exerted force from sEMG placements

The prediction of exerted force from muscle activity showed strong fits of models across all four tasks, with explained variances (R^2) mostly exceeding 95 % (0.95) and most SDs of the residuals less than 10 %MVC. Among the three sEMG placements, models based on the through-forearm sEMG consistently explained the largest proportion of variance across all tasks, with three tasks achieving $R^2 > 0.98$ and the key-pinching task reaching $R^2 > 0.96$, albeit marginally. Additionally, model residuals from the through-forearm placement were the lowest across all tasks, with three tasks showing residuals below 5 %MVC and the key-

Table 2
Group medians of the 50th percentile muscle activity at different perceived exertion levels from the three sEMG placements across various tasks (N = 16).

Task	Perceived exertion level	Extensor (%MVE)		Flexor (%MVE)		Through-forearm (%MVE)		Friedman	Ext vs Fle	Ext vs Thr	Fle vs Thr
		Median	[Q1-Q3]	Median	[Q1-Q3]	Median	[Q1-Q3]	p	p	p	p
Grip	**0 (Rest)**	7.2	[5.0–11.4]	1.1	[0.4–2.0]	2.5	[1.6–3.4]	**<0.001**	**<0.001**	**0.008**	**0.040**
	2 (Easy)	12.9	[7.0–19.4]	3.1	[1.8–6.3]	5.7	[3.2–7.4]	**<0.001**	**<0.001**	**0.024**	**0.024**
	4 (Moderate)	29.0	[15.0–31.5]	11.5	[8.5–13.6]	14.5	[9.8–17.1]	**<0.001**	**<0.001**	0.102	0.102
	8 (Hard)	42.4	[27.6–53.7]	28.6	[17.1–53.0]	34.5	[22.1–46.9]	0.444	0.648	1.000	1.000
	10 (Maximum)	82.7	[80.9–87.0]	85.1	[81.3–86.4]	83.8	[80.0–86.6]	0.779	1.000	1.000	1.000
Key-pinch	**0 (Rest)**	2.2	[1.3–3.6]	0.3	[0.2–0.9]	1.3	[0.9–1.5]	**<0.001**	**<0.001**	0.472	**0.001**
	2 (Easy)	6.6	[3.7–12.8]	0.7	[0.5–2.0]	3.1	[1.9–3.9]	**<0.001**	**<0.001**	**0.040**	**0.008**
	4 (Moderate)	14.2	[7.4–20.2]	2.3	[1.5–7.2]	7.3	[5.1–11.6]	**<0.001**	**<0.001**	0.335	**0.004**
	8 (Hard)	25.8	[18.2–33.6]	7.9	[4.2–12.9]	19.0	[12.6–23.9]	**<0.001**	**<0.001**	1.000	**0.002**
	10 (Maximum)	46.8	[36.7–66.6]	18.9	[15.3–22.9]	42.2	[33.2–54.9]	**<0.001**	**<0.001**	1.000	**<0.001**
Screw	**0 (Rest)**	4.6	[2.7–6.8]	1.9	[1.3–3.1]	2.7	[2.1–6.0]	**0.002**	**0.001**	0.231	0.231
	2 (Easy)	12.6	[6.0–16.9]	10.8	[6.4–17.3]	10.4	[7.2–18.5]	0.829	1.000	1.000	1.000
	4 (Moderate)	20.5	[10.2–30.5]	20.0	[15.2–35.6]	27.3	[18.8–43.0]	**0.010**	0.648	**0.008**	0.231
	8 (Hard)	36.0	[28.4–56.9]	49.0	[35.4–63.7]	59.4	[44.9–78.3]	**0.010**	0.231	**0.008**	0.648
	10 (Maximum)	74.0	[60.9–91.0]	77.5	[60.8–92.2]	93.3	[85.5–107.4]	**0.050**	1.000	0.102	0.102
Thumb-pinch	**0 (Rest)**	1.2	[0.4–2.4]	0.5	[0.3–0.7]	1.2	[1.0–1.5]	**<0.001**	**<0.001**	1.000	**<0.001**
	2 (Easy)	4.6	[2.3–7.0]	2.6	[1.2–4.0]	4.4	[2.9–8.1]	**0.039**	0.231	1.000	**0.040**
	4 (Moderate)	8.8	[4.9–14.3]	5.8	[4.2–9.5]	10.9	[7.0–16.2]	**0.028**	0.335	0.867	**0.024**
	8 (Hard)	19.5	[16.3–26.9]	16.9	[11.6–22.3]	26.4	[18.5–33.5]	**0.039**	1.000	0.231	**0.040**
	10 (Maximum)	47.0	[31.1–72.2]	32.8	[25.5–42.3]	57.2	[43.7–62.3]	0.099	0.231	1.000	0.155

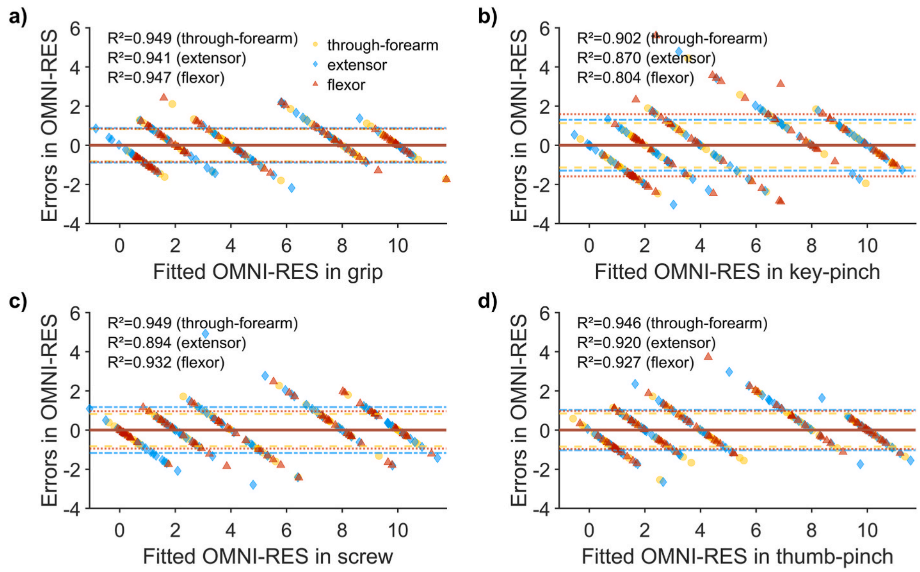

Fig. 4. Residual plots of the mixed-effects models predicting perceived exertion levels (shown as OMNI-RES scores) from muscle activity across the four measured tasks.

pinching task below 8 %MVC (Fig. 5).

Despite the high R^2 values and low residuals observed across individual models, inter-subject and inter-task variability was prominent in all three sEMG placements. For instance, in the model for the extensor during gripping, the SD of the slope due to the random effect (subject) was 0.87, which accounted for 48 % of the fixed-effect slope (1.82), indicating substantial variability between individuals. Similarly, task-specific differences were evident, as seen in the extensor model, where the slope during key-pinching (3.83) was more than double that during gripping (Table S2 in Appendix).

Despite the noticeable variability, among the three sEMG placements, the through-forearm placement demonstrated relatively low inter-subject variability (20 %–73 % of the corresponding fixed effects) across most tasks, and in some cases, it exhibited the lowest variability, outperforming the extensor (18 %–103 %) and flexor (26 %–152 %) placement. Additionally, the through-forearm (2 %–91 %) and extensor (2 %–98 %) placement showed a similarly low to moderate inter-task variability ratio relative to gripping for the fixed factors, while the flexor placement had the highest ratio in all tasks (137 %–626 %) (Table S2 in Appendix).

3.3. Correlations between sEMG placements

Further analysis of the correlations between the 50th percentile muscle activity revealed strong linear relationships across all three sEMG placements in all four tasks (all $r > 0.97$) (Table 3).

Additionally, a linear mixed-effects model of z-score standardized muscle activity indicated that the through-forearm activity can be expressed as a linear combination of the extensor and flexor activity. The contributions of the extensor and flexor varied across different tasks, suggesting task-specific differences in the role of each muscle group (Fig. 6).

4. Discussion

This study highlights that sEMG can effectively predict both

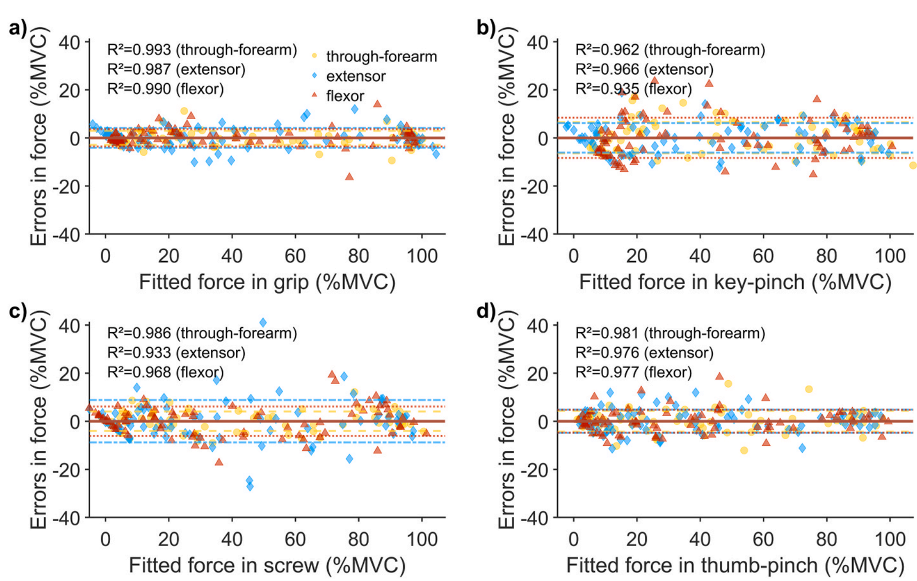

Fig. 5. Residual plots of the mixed-effects models predicting exerted force from muscle activity across the four measured tasks.

Table 3
Pearson correlations of the 50th percentile muscle activity between the three sEMG placements across different tasks.

Section	Extensor vs flexor	Through-forearm vs extensor	Through-forearm vs flexor
Grip	0.985 [0.975–0.975]	0.979 [0.973–0.973]	0.990 [0.991–0.991]
Key pinch	0.990 [0.958–0.958]	0.989 [0.981–0.981]	0.977 [0.984–0.984]
Screw	0.970 [0.943–0.943]	0.971 [0.964–0.964]	0.990 [0.984–0.984]
Thumb pinch	0.992 [0.987–0.987]	0.992 [0.991–0.991]	0.991 [0.987–0.987]
All	0.846 [0.809–0.809]	0.905 [0.877–0.877]	0.922 [0.877–0.877]

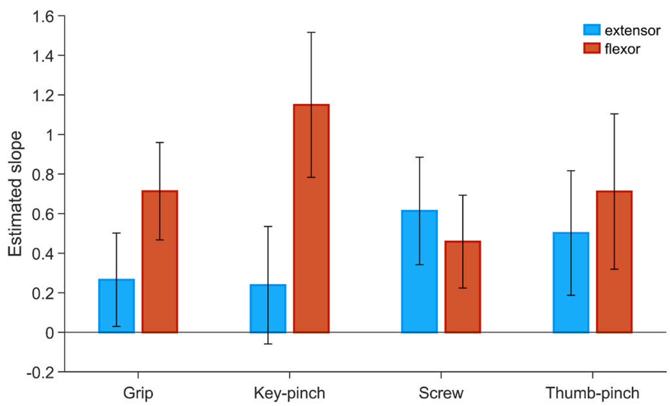

Fig. 6. Slopes of the extensor and flexor activity in the z-score standardized linear mixed-effects models for the through-forearm activity across different tasks. Whiskers represent the lower and upper boundaries of the estimated slopes.

perceived exertion (i.e., OMNI-RES levels) and normalized exerted force with good fitness and low errors. Among the three sEMG placements evaluated, the through-forearm placement consistently explained the largest proportion of variance and produced the lowest residuals across all four tasks (except for estimating the exerted force in keypinching), making it a reliable option for estimating both perceived exertion and exerted force. Despite notable inter-subject and inter-task variability observed across all placements, the through-forearm placement demonstrated the lowest inter-subject variability in most tasks, outperforming the extensor and flexor placements in this regard.

Additionally, strong correlations were observed among the three sEMG placements—extensor, flexor, and through-forearm. Specifically, through-forearm muscle activity was closely correlated with a linear combination of extensor and flexor activity, with the relative contributions of each varying depending on the task.

4.1. Predicting perceived exertion and exerted force

Our findings demonstrate that through-forearm sEMG can predict perceived exertion and normalized exerted force with high fitness ($R^2 >$ 96 %) and low errors (<5 % MVC for three tasks, and <8 % MVC for key-pinching) across all placements and tasks, showcasing its utility of monitoring exertions in work tasks.

Similar results have been observed in previous studies. Barański et al. reported that when predicting grip force using a single sEMG channel placed on the flexor, models based on RMS yielded high R^2 values (>0.8), with prediction errors below 10N across a 20–100N force range (Barański et al., 2024). Although their study focused on absolute force rather than %MVC, the results align closely with ours.

However, inter-task variability remains a critical factor, as evidenced by the relative variance in model parameters across tasks, particularly when comparing tasks like gripping and key-pinching. In practical settings, tasks often involve complex transitions between sub-tasks, which may reduce prediction accuracy. While the current data and results cannot precisely determine the extent to which task order affected the outcomes, the significant differences in parameter values between tasks—and the fact that these differences did not follow a monotonic trend along the temporal sequence—strongly suggest the presence of inter-task variability.

Several studies have attempted to mitigate this by increasing the number of sEMG channels to capture broader muscle activity patterns. For example, Wang et al. (2023) employed five sEMG channels to identify the task and predict exerted force, achieving a 74 % precision in force category prediction. Bardizbanian et al. (2020) used a 12-channel sEMG armband, yielding an error rate of 2.5 %–8 % MVC during finger contractions. Similarly, Chihara and Sakamoto (2021) utilized an 8-channel armband device, estimating container weights (ranging from 2 to 20 kg) with average absolute errors of 1.5 kg. However, Martinez et al. (2020) demonstrated that increasing the channel density beyond 16 may not significantly improve prediction accuracy. For applications where fewer channels are desired, alternative methods, such as integrating sensors like accelerometers (Mao et al., 2023b) or pre-defining primary task types, may offer solutions. In clinical studies, the simplicity and cost-effectiveness of sensors often determine the feasibility of including more participants, further emphasizing the need for simple, convenient, and efficient methods in predicting force during real tasks.

Besides inter-task variability, inter- and intra-subject variability in the prediction of perceived exertion and exerted force is also important to consider. Although normalization has partially reduced this variability, individual differences in muscle engagement during the same tasks remain. Studies by Jarque-Bou et al. (2024) have shown that muscle activity patterns can vary significantly inter- and intra-subject even under identical force exertion and task conditions. These findings highlight the inevitable presence of both inter- and intra-subject variability. While normalization by MVCs helps, it may not suffice entirely. Further research is needed to explore alternative normalization techniques or methods to minimize the impact of this variability on research outcomes.

4.2. sEMG measurement via through-forearm placement

Further analysis revealed that through-forearm activity was linearly correlated with both extensor and flexor activity (Fig. 6). This finding is consistent with previous studies on muscle synergy in humans, where signals from the central nervous system are distributed across muscles according to a pre-learned synergy pattern (Bizzi and Cheung, 2013; Geng et al., 2020). According to the theory, different muscles were activated in a predetermined and linear combination in various tasks.

Following this theoretical framework, the through-forearm placement appears to capture aspects of underlying muscle synergies. Across different tasks, the extensor and flexor muscles—acting as antagonists—engage in distinct combinations, whereas within a single task, their activation patterns remain relatively consistent. If muscle engagement across tasks is conceptualized as a vector in a multidimensional space defined by the load of individual muscles, the direction of the vector may represent the relative contribution of each muscle (i.e., the synergy), while the magnitude reflects the overall exerted force. Within a given task, force variations would thus manifest as changes in vector length along a fixed direction.

When measuring activity from a single muscle, noise and task-related disturbances can obscure changes in overall force, making it difficult to accurately estimate the vector magnitude from one component alone. In contrast, capturing a combined signal—such as through the through-forearm placement—offers a more integrated representation, effectively filtering out irrelevant noise and focusing on task-relevant changes. This may explain the modest but consistent advantage observed with the through-forearm configuration, particularly when the estimated variable is perceived workload which is more relative and in tasks where the relative contributions of extensor and flexor muscles differ significantly (Fig. 5).

This conceptual model also aligns with findings from Takala and Toivonen (2013), where the through-forearm placement demonstrated greater stability in estimating muscle activity across varying wrist postures within the same task. Since wrist posture affects muscle length and induces signal variability, a placement that captures the overall magnitude of muscle synergy may be less sensitive to such disturbances and better suited for robust force estimation. If this theory holds, the placement of electrodes in the through-forearm approach may be more tolerant to the mis-location, and increasing the number of electrodes circumferentially around the forearm and integrating their signals could further improve precision and reduce dependence on specific electrode placement over individual muscles. Further studies could investigate how electrode location within the through-forearm placement influences the outcomes.

It is important to note, however, that this model does not account for all observed patterns. For instance, in the key pinch task, the through-forearm placement performed marginally—though not necessarily significantly—worse than the extensor alone. This suggests that combining signals may introduce noise from the less informative or more variable muscle component. Moreover, the extent to which this model applies to dynamic and complex real-world tasks remains uncertain. Further research is necessary to evaluate the reliability of this theoretical framework and to assess the practical applicability of the through-forearm placement in occupational and clinical settings.

4.3. Methodological consideration

Compared to Takala's work (Takala and Toivonen, 2013), our study expanded the range of tasks, allowing for greater generalization of results to common work-related activities. Fatigue is known to impact force prediction (Wang et al., 2021). While the order of tasks in our study was not randomized, several measures were taken to mitigate potential fatigue effects. First, participants rested for several minutes between tasks, providing sufficient time for muscle recovery and limiting the influence of fatigue on results. Second, the fixed task order alternated between pinching movements, which primarily engage hand muscles, and gripping and screwing tasks, which emphasize forearm muscles, allowing specific muscle groups to rest between exertions. Third, comparisons between sEMG placements were performed within each task, ensuring consistent pre-task workloads and controlling for fatigue-related variability.

The quadratic models selected through an incremental model comparison process produced promising results, aligning with previous research (e.g., Barański et al. (2024)). This incremental approach effectively balanced the risks of overfitting with the need to capture the non-linear relationship between perceived exertion and muscle activity. Our study also benefits from a demographically balanced dataset, which minimizes potential biases induced by demographic factors.

Additionally, our findings reveal that the through-forearm placement reflects a task-dependent, linear combination of extensor and flexor activity. This provides valuable insight into the nature of through-forearm measurements, suggesting that they capture integrated muscle activity across multiple muscle groups while varying according to task demands.

4.4. Limitations

One limitation of our study is that force was normalized by task, which may, therefore, influence the practicality of the resulting models. Although this approach helped control task-specific variations, its impact on the predictive power of the models in real-world cases remains unclear. Furthermore, the number of tasks in this study was limited, and real-world hand movements are far more complex and diverse. In practice, hand movements often involve quick transitions between different motions, which may not be fully captured by our protocol. Even though our study aimed to expand the scope beyond simple gripping tasks, future studies will need to employ more innovative methods to capture the full dynamic range of hand movements. Additionally, transitions between motions and tasks may introduce variations in sEMG signals independent of exerted force. These variations can result from factors such as skin or clothing displacement, changes in muscle length due to wrist posture, and muscle engagement for movement stabilization. Moreover, other factors regarding measurement, such as calibration methods, data preprocessing, and filtering, or individual factors can all influence predictability of the results (Abdoli-Eramaki et al., 2012; Bao et al., 1995; Boyer et al., 2023; Clancy et al., 2002; Merletti and Hermens, 2004). Therefore, further research is needed to quantify the real-world impact of these movement-related factors on sEMG signal magnitude in details.

4.5. Practical implications

Our findings suggest that through-forearm sEMG can feasibly predict perceived and exerted force in controlled laboratory settings, consistently explaining the largest proportion of variance and producing the lowest residuals in predicting both perceived exertion and exerted force across all four tasks. However, strategies to account for inter-task and inter-subject variability are crucial. Acquiring task types for specific occupations at any stage of the measurement or conducting task-specific model calibrations could help mitigate inter-task variability. Regarding inter-subject variability, calibrations based solely on resting and maximal contractions may be insufficient. Incorporating normalization techniques, such as using progressively increasing contraction scales instead of a single maximal voluntary contraction, could enhance model accuracy.

Finally, if a single-channel sEMG approach is preferred, the choice of sEMG placement should be guided by the study's objectives. For assessing muscle-specific workload, the sEMG should be placed on the target muscle (e.g., extensor or flexor). Whereas if the goal is to estimate overall workload or perceived exertion, the through-forearm placement may be more appropriate, as it captures signals from multiple muscles.

5. Conclusion

Our findings underscore the reliability of sEMG, particularly through-forearm placement, in estimating both perceived exertion and exerted force. However, limitations such as inter-task and inter-subject variability were identified, suggesting the need for further studies to explore compensatory methods for applying quadratic sEMG modeling on single-channel sEMG measurements in real-world settings. Additionally, the study suggests that through-forearm placement captures integrated muscle activity from multiple muscles, making it a slightly better option than muscle-specific placements for estimating physical workload in the hand and forearm. In practical applications, the choice of sEMG placement should align with the study's specific objectives: through-forearm placement is better suited for general exertion predictions, while muscle-specific placements are more appropriate for assessing muscle-specific risks.

CRediT authorship contribution statement

Xuelong Fan: Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Johan Rydgård:** Writing – review & editing, Methodology, Investigation. **Liyun Yang:** Writing – review & editing, Data curation. **Peter J. Johansson:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, Conceptualization.

Declaration of interests

There are no conflicts of interests to declare.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve the language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Funding sources

This work was supported by AFA Insurance, Sweden [Ref.no. 200070].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We appreciate AFA Insurance for funding the study [Ref.no. 200070]. We thank the Unit of Occupational and Environmental Medicine at Uppsala University Hospital for their support with participant recruitment and for providing the location for the experiment. We also extend our gratitude to all the participants for their time and effort.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apergo.2025.104699.

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