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Identification of movement phenotypes from occupational gesture kinematics: Advancing individual ergonomic exposure classification and personalized training

Emilia Scalona [a,*], Doriana De Marco [b], Laura Ferrari [c,d], Ilaria Creatini [e], Elisa Taglione [e], Giuseppe Andreoni [f], Maddalena Fabbri-Destro [c], Pietro Avanzini [c], Nicola Francesco Lopomo [c,g]

[a] Dipartimento di Scienze Medico Chirurgiche, Scienza Radiologiche e Sanità Pubblica (DSMC), Università Degli Studi di Brescia, Viale Europa 11, 25123, Brescia, Italy
[b] Dipartimento di Medicina e Chirurgia, Università Degli Studi di Parma, Parma, Italy
[c] Consiglio Nazionale Delle Ricerche, Istituto di Neuroscienze, Parma, Italy
[d] School of Advanced Studies, Università di Camerino, Camerino, Italy
[e] Centro di Riabilitazione Motoria, INAIL, Volterra, Italy
[f] Dipartimento di Design, Politecnico di Milano, Milano, Italy
[g] Dipartimento di Ingegneria Dell'Informazione, Università Degli Studi di Brescia, Brescia, Italy

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ABSTRACT

The identification of personalized preventive strategies plays a major role in contrasting the occurrence of work-related musculoskeletal disorders. This requires the identification of distinct movement patterns within large samples and the attribution of a proper risk level to each identified movement phenotype. We assessed the feasibility of this approach by exploiting wearable inertial measurement units to estimate the whole-body kinematics of 43 healthy participants performing 18 reach-to-manipulate movements, which differed based on the object's position in the space and the type of manipulation required. Through unsupervised clustering, we identified multiple movement phenotypes graded by ergonomic performance. Furthermore, we determined which joints mostly contributed to instantiating the ergonomic differences across clusters, emphasizing the importance of monitoring this aspect during occupational gestures. Overall, our analysis suggests that movement phenotypes can be identified within occupational motor repertoires. Assigning individual performance to specific phenotypes has the potential to inform the development of more effective and tailored interventions.

1. Introduction

Work-related musculoskeletal disorders (WMSDs) have significant implications for global health and social care systems, constituting a primary cause of sick leave across various professions and serving as a major component of occupational diseases (Eurofound, 2015). In the United States and Europe, WMSDs account for more than one-third of all lost working days, resulting in an estimated financial burden of around \$50 billion (Kang et al., 2014). The etiology of WMSDs is multifaceted, involving a complex interplay of individual characteristics, psychosocial factors, and physical factors within the "worker-task-environment" triad (Hogan et al., 2013). Consequently, addressing this challenge necessitates a collaborative approach to mitigate the adverse impacts of WMSDs. This involves the development of methods capable of profiling exposure risks, facilitating standardized early-stage diagnosis, and providing effective interventions (Arezes and Serranheira, 2017; Sultan-Taïeb et al., 2017; Van Eerd et al., 2016). By adopting such an approach, the detrimental consequences of WMSDs can be minimized, leading to improved occupational health and well-being.

In the existing literature, primary prevention methods primarily concentrate on interventions aimed at directly mitigating physical risk factors associated with work organization and workplace design (David, 2005; Manghisi et al., 2017; van der Beek et al., 2017). However, despite notable advancements in workplace safety measures, such as the implementation of exoskeletons, workers remain vulnerable to work-related musculoskeletal disorders (WMSDs) due to the inherent nature of their tasks involving repetitive arm movements, physically demanding actions, and awkward postures (Manghisi et al., 2017;

* Corresponding author.
E-mail address: emilia.scalona@unibs.it (E. Scalona).

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Rimmele et al., 2023). Various observational methods have been proposed to address biomechanical exposures in work environments (David, 2005; Li and Buckle, 1999; Takala et al., 2010) and are investigated in surveys of quantifying ergonomic tools used in the UK (Dempsey et al., 2005), in Australia (Lowe et al., 2019) and Canada (Beliveau et al., 2022). These include: i) the NIOSH (National Institute for Occupational Safety and Health) scale, which assesses carrying and lifting activities (Murphy, 2002); ii) the OCRA (OCcupational Repetitive Actions) method (Colombini and Occhipinti, 2006) targeting low loads at high frequency; iii) the OWAS (Ovako Working Posture Analysing System) (Karhu et al., 1977), RULA (Rapid Upper Limb Assessment) (McAtamney and Nigel Corlett, 1993), and REBA (Rapid Entire Body Assessment) (Hignett and McAtamney, 2000) methods, which analyze overall posture and movement quality. A primary drawback of these approaches is their focus on specific body postures or work actions, limiting their broader applicability. To address this limitation, Schaub et al. (2013) endeavored to overcome specificity issues by developing the Ergonomic Assessment Worksheet (EAWS), aiming to provide a comprehensive ergonomic score that encompasses a broader range of workers' activities. Nevertheless, one notable drawback of the aforementioned methods is their reliance on well-trained field experts to conduct meticulous and time-consuming analyses, resulting in the potential for bias in the decision-making process (Lenzi et al., 2019).

Wearable technologies have gained significant popularity, including within the working environment, for addressing physical ergonomics and conducting biomechanical risk assessments. This advancement has led to swift analysis, enhanced reliability, and objective results (Andreoni et al., 2022; Ranavolo et al., 2018, 2020; Stefana et al., 2021). By leveraging wearable technologies, ergonomic assessments can be conducted on specific motor tasks and postures, such as the Method for Movement and Gesture Assessment (MMGA), which was developed by Andreoni et al. (2009) as an extension of the LUBA (Loading on the Upper Body Assessment) method (Kee and Karwowski, 2001). These approaches can be particularly useful for classifying discomfort experienced by individuals (Andreoni et al., 2009).

Within this context, wearable devices offer opportunities for interventions targeting individual behavior in order to reduce exposure to occupational risks, specifically through Individual Working Practice (IWP) (van de Wijdeven et al., 2023). Among the various categories of IWP interventions, van de Wijdeven et al. emphasize the importance of training and motor skills (van de Wijdeven et al., 2023). However, there is currently no consensus on the effectiveness of ergonomic training in reducing musculoskeletal symptoms, as well as the transfer of training and knowledge for inducing behavioral changes (Liu et al., 2022). One of the causes of this lack of consensus could be ascribed to the lack of standardization in identifying risk factors and training strategies (Rodrigues Ferreira Faisting and de Oliveira Sato, 2019).

In addition to addressing behavioral aspects, training can also focus on improving motor skills, taking into account different implicit/explicit learning strategies (Hodges and Franks, 2002; Patel et al., 2017) and inter/intra-individual variability in performing specific motor tasks, which can influence the success of these approaches (Hogan et al., 2014). Gaudez et al. reviewed motor control theories and highlighted the role of intrinsic movement variability in task completion within occupational environments (Gaudez et al., 2016). More recently, Oomen et al. explored kinematic consistency in workers performing repetitive manual tasks, emphasizing that motor variability is specific to the degrees of freedom involved in the task (Oomen et al., 2022). The inherent variability of the motor system, such as variations in postures and trajectories during task execution, may provide an opportunity to manage variation within the occupational context (Srinivasan and Mathiassen, 2012). Proper training of workers can minimize ergonomic risk without compromising performance. From a motor control perspective, executing motor tasks involves the coordination of different muscles and joints, and human movement is characterized by general invariant laws (Hogan and Flash, 1987; Hogan and Sternad, 2007; Viviani and Flash, 1995). Biomechanical analysis of actions performed with the same goal by different individuals shows high variability between subjects due to the natural redundancy of the motor system organization (D'Ausilio et al., 2015; Hilt et al., 2017; Kilner, 2011). Furthermore, it is important to recognize that the "worker-task-environment" triad directly influences motor control within the working environment (Newell, 1986).

In order to differentiate individual movement competencies and target specific training interventions, the assessment of time-series whole-body movement strategies can be beneficial. Principal Component Analysis (PCA) is one of the pattern recognition tools most frequently used in this context. PCA allows for the identification of principal movement patterns by reducing data and explaining variance within kinematic datasets (Armstrong et al., 2019; Brandon et al., 2013; Federolf et al., 2014; Ross et al., 2018; Troje, 2002). An additional advantage of using PCA is its support for unsupervised machine learning methods for cluster analysis, which can detect and interpret differences in individuals' motor strategies (Deluzio et al., 2014). Clustering has proven useful in biomechanical analysis for grouping participants with similar kinematic patterns, also known as "phenotypes" (Bennetts et al., 2013; Gilles and Wild, 2018; Remedios et al., 2020; Sawacha et al., 2010).

Based on these considerations, we hypothesized that different motor phenotypes can be extracted from the analysis of kinematics time series recorded during the execution of actions underlying many occupational gestures and that such phenotypes could correspond to different levels of ergonomic quality, thus reflecting a different exposure to injuries or insurgence of WMSDs.

To test these hypotheses, we collected full-body kinematics data from 43 healthy participants while they performed reach-to-manipulate tasks using wearable technologies. Participants were then grouped into clusters based on the similarity of their motor strategies, and the quality of their movements was assessed using a validated ergonomic index, namely the MMGA. Additional kinematic performance indexes were used to determine the contribution of each joint to the discomfort experienced. Finally, each identified motor phenotype was evaluated with respect to overall discomfort and the associated risk of developing WMSDs.

2. Material and methods

2.1. Participants

Forty-three healthy volunteers (31 females, 12 males, mean age 25.1 years old) were enrolled in the study. All the participants reported no previous history of neurological disorders or recent orthopedic injuries. All participants were right-handed according to the Edinburgh Handedness Inventory (Oldfielf, 1971). The local ethics committee approved the study (Comitato Etico dell' Area Vasta Emilia Nord, 10084, 12.03.2018), which was conducted according to the principles expressed in the Declaration of Helsinki. Each participant provided written informed consent before the experimental sessions.

2.2. Experimental setup

The participants were instructed to perform a motor task involving reaching and manipulating nine soft spheres, each with a diameter of 6 cm, placed on a 2 × 1 meter rack consisting of three rows and three columns (Fig. 1), adapting the paradigm proposed in (Andreoni et al., 2010). The distance between the columns was set at 40 cm. The placement of the soft spheres within the three rows was determined based on the participant's anthropometric measurements: the three spheres in the lower position were consistently placed 6 cm above the floor, the three spheres in the middle position were positioned at the participant's pelvis height, and the three spheres in the top position were moved to a position corresponding to the participant's height plus 10 cm. These nine positions will be referred to in the text using an abbreviation, with the

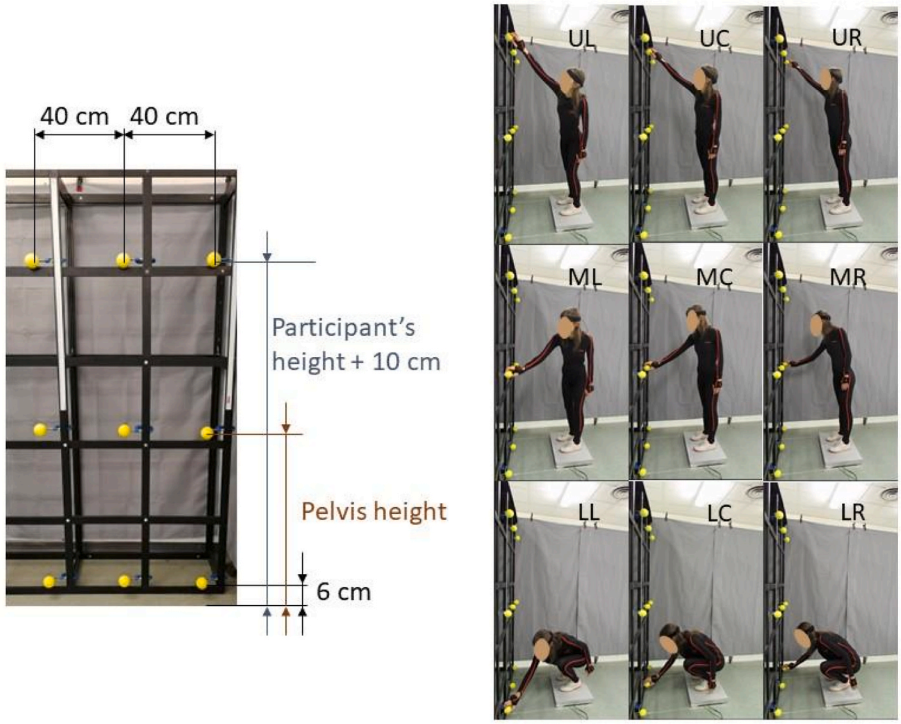

Fig. 1. Experimental setup. Participants were asked to reach and manipulate 9 spheres placed on a 2 × 1 meters rack, formed by 3 rows and 3 columns.

first letter indicating the vertical position (i.e., "L" for lower, "M" for middle, "U" for upper), and the second letter indicating the horizontal position (i.e., "L" for left, "C" for central, "R" for right). The participants stood in front of the rack with their feet positioned behind a reference cross, which was placed at a distance equivalent to the length of their forearm plus 30 cm, in order to make the task more challenging.

Full-body kinematics data were captured using a system based on wearable inertial measurement units (IMUs, Xsens MVN Link, with motion capture software MVN Analyze, 2021, version 2021.0.0). The IMUs were positioned on the body segments according to the manufacturer's protocol, with a total of 17 sensors used to track the movement of 23 body segments, including the head, neck, eighth and tenth thoracic vertebrae, third and fifth lumbar vertebrae, right and left shoulders, right and left arms, right and left forearms, right and left hands, pelvis, right and left thighs, right and left shanks, right and left feet, and right and left forefeet. Before recording, a calibration procedure was conducted to align the motion trackers with the participant's body segments. The sampling frequency was set at 240 Hz. Additionally, to facilitate ergonomic assessments, the movement of the participants was recorded on video from a lateral perspective.

2.3. Experimental design

Participants were asked to reach and grasp each sphere by performing two types of manipulation tasks, i.e., rotation and squeezing. The rotation task consisted of rotating the sphere three times clockwise with the right hand. More specifically, the spheres have been pierced and embedded in a pivot around which they can rotate, and the participant would rotate the sphere, leave it to return the wrist to a neutral position, and rotate it again. The squeeze task consisted of squeezing the sphere 3 times with the right hand. We enrolled only right-hand participants to avoid left-handed people resulting in separate clusters. These specific movements were chosen to simulate potential occupational activities, or at least some primitives common to several occupational activities.

Participants performed five repetitions of each movement for a total of 90 movements (i.e., 5 repetitions x 9 sphere positions x 2 tasks). The order of the sphere's position to reach was randomized across participants and the operators tell the position to participants each time. For both tasks, the participants started from a static standing position with their arms resting by their sides. Participants stood still on a force platform (6 cm above the ground) and had to perform the task without crossing the reference cross placed on the platform with the tape, and without lifting their feet completely off the platform. Once the sphere manipulation is completed, the subjects return to the starting position.

2.4. Data analysis

Data file.mvnx was first exported by using the dedicated software. Three-dimensional information concerning position, velocity, acceleration of segments, joint angles, and the body center of mass (COM) position were extracted by using a dedicated processing and analysis pipeline (Matlab2018a; MathWorks Inc.). Before additional data processing, the start and end frames for each trial were determined. In particular, we focused only on the reaching phase of the movement to evaluate whether the postural motor strategies change according to the different goals, i.e., the location of the spheres. The reaching phase was segmented according to the tangential velocity of the hand (Michaelsen et al., 2004). The temporal boundaries of the reaching phase were identified as the times at which the hand speed surpasses and returns below 5% of the peak speed (reaching start and end, respectively).

For the movement strategies characterization, we selected ten segment 3D (antero-posterior, medio-lateral, longitudinal) positions: pelvis, 8th thorax vertebra, left and right hip, left and right knee, shoulder, elbow, wrist, and body COM (Remedios et al., 2020). For each segment Participants' trajectory data were divided by their standing height to normalize for inter-participant anthropometric variance (Ross et al., 2018). In Matlab, the trajectory data were moved to the origin of the left ankle coordinate system to reduce the variance in trajectory data associated with each participant's relative positioning with respect to the global coordinate system obtained from the calibration procedure. Trials were segmented and resampled to a normalized 0-to-100% time interval within reaching duration. Successively, each time series were averaged among 5 repetitions for each participant and each task. To verify that the average curves were representative of the trials within subject, each single trial was compared with the average curve using the Linear Fit Method (LFM) (Iosa et al., 2014). In fact, LFM allows to assess waveform similarity by calculating the linear regression between the dataset under investigation and returning information about the scaling factor (a_1), the weighted average offset (a_0), and the strength of the linear relationship, i.e., R^2. When $R^2 > 0.5$ the assumption of linearity is considered valid, and the curves could be considered temporally lined up (Di Marcoa et al., 2018). All R^2 values are larger than 0.9, thus documenting that the average curves are indeed highly representative of the individual trials.

The time-normalized segment and COM positions were then prepped for PCA. PCA was applied on each segment trajectory data set to perform data reduction and identify the features able to capture most of the variability of the dataset. The time-series trajectory was organized in a n x m matrix where n represents the number of participants (43 participants) and m the temporal observations throughout the cycle (101). For each segment trajectory, the score of the 1st PC was retained for clustering analysis. We selected the first PC since it usually captures a magnitude feature and describes the pattern of greatest variance within the data (Brandon et al., 2013).

The vector of PC scores relative to each segment was concatenated resulting in a p x q matrix ($p = 43$ participants, $q = 30$ trajectories) which was input into a k-means cluster analysis. K-means uses an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid overall cluster. The Euclidean distance was chosen in forming the cluster and an optimal number of clusters k was selected for each task and position. To determine k, the silhouette plot for k ranging from 2 to 5 is generated to evaluate which solution generates clusters that are better separated than previous solutions. The k-means were applied to each dataset, running 100 repetitions to increase the likelihood of the data converging to an optimum.

MMGA approach was used as a discomfort index for each participant and task to find differences among cluster strategies in terms of ergonomic features of the movement (Andreoni et al., 2009). This index accounts for three factors: a) the joint angles kinematics; b) an articular coefficient of discomfort for each joint; c) a coefficient estimating the "weight" of the ergonomic contribution of each joint to the movements. It is defined and calculated as follows: the joint angle curves are normalized to 100 points and used for the score computation. Joint angles were estimated from the IMUs and, the following were considered: wrist, elbow, knee, and ankle flex-extension; shoulder and hip flex-extension, intra-extra rotation and abd-adduction; trunk flex-extension, rotation, and lateral bending. Successively, a coefficient of discomfort for each joint, and each time percentage, is computed through a spline fitting of the discomfort ranks proposed by (Kee and Karwowski, 2001) for varying joint motions; the contribution of each joint is weighted on the mass of the distal body district participating to the movement. The mass of body segments was estimated by referring to the anthropometric tables proposed by (Zatsiorsky, 1983). For more details on index calculation see (Andreoni et al., 2009). The MMGA scoring takes into account the contribution of both the upper and the lower body segments and weights their intervention according to the mass involved. High values of MMGA indicated great ergonomic discomfort. The MMGA was calculated for each task, each participant, and each repetition and then averaged among the 5 repetitions.

Since MMGA is a synthetic index, we further computed the joint displacement w1 (Lorenzini et al., 2022) for each joint and the degree of freedom to define which joints for each cluster were the most responsible for the ergonomic discomfort. For each joint angle curve, w1 was computed considering its absolute values and the corresponding upper and lower boundaries, as defined in the literature (Whitmore et al., 2012). The aim of monitoring each joint displacement was to detect wherever the body configurations that participants adopt to perform the tasks could be considered as "not ergonomic". This index ranges from 0 to 1, with 1 underlining that the joint is in proximity to the maximum limits and, thence, this specific task should be avoided. The joint displacement was specifically computed for the following joint angles: trunk abduction, trunk rotation, trunk flexion/extension, right shoulder ab/adduction, right shoulder intra/extrarotation, right shoulder flexion/extension, right elbow flexion/extension, right wrist flexion/extension, right and left hips ab/adduction, right and left hips intra/extrarotation, right and left hips flexion/extension, right and left knees flexion/extension, right and left ankle dorsi/plantarflexion. The w1 corresponding to each joint angle was calculated for each task, each participant, and each trial and then averaged among the 5 performed trials. Only in the tasks in which MMGA showed a significant difference between/among the cluster groups, the w1 variables were evaluated to characterize the movement.

2.5. *Statistical analysis*

The ergonomic scoring criteria, i.e., MMGA and w1 served as dependent variables in one-way ANOVA models or t-tests. Cluster assignment served as the independent variable (i.e., the number of levels depends on the number of clusters). An alpha value of 0.05 was set. A Bonferroni post-hoc comparison was used to determine significant differences in dependent measures between clusters. Cohen's d or partial eta squared (η^2) was calculated as a measure of effect size for t-test and ANOVA, respectively.

3. Results

To assess the reliability of the proposed PCA approach, we analyzed the average value of the explained variance for each first component and their standard deviation for each task and position, as reported in Table 1.

As highlighted, the average explained variance of the first component among all joint trajectories is high with values ranging from 80 to 96 percent.

The k-means identified k = 2 as the optimal number for the Squeeze in the UC, UR, MC, and LR positions and the Rotation in the UL, UC, UR, and LR positions. For the Rotation LL and LC the number of clusters is equal to 3. Four clusters were identified for the Squeeze UL, MR, LL, and LC positions and Rotation MC and MR. Finally, for Squeeze and Rotation ML, the optimal number of clusters was 5. A summary of the clustering results is reported in Table 2.

Considering the MMGA index, the main effect of cluster assignment was detected for Squeeze and Rotation in the UC, LL, LC, and LR positions.

In Fig. 2 are reported the visual representation of the emergent difference in terms of motor strategies adopted by the participants closer than the centroid of each cluster for the rotation UC and LC, respectively.

Table 1
Mean and standard deviation of the explained variance (%) of the first principal component among joint trajectories for each task and each position.

Position	Rotation	Squeeze
LC	84.70 (5.19)	83.22 (5.71)
LL	83.21 (6.23)	79.83 (6.70)
LR	82.29 (6.22)	81.09 (6.20)
MC	95.48 (4.79)	94.73 (4.73)
ML	93.22 (5.72)	92.41 (6.00)
MR	95.93 (3.32)	94.24 (3.85)
UC	94.91 (5.88)	93.70 (6.10)
UL	90.10 (7.69)	89.76 (7.81)
UR	91.73 (5.73)	88.77 (7.28)

Table 2
Number of clusters according to the different object locations and required task (R = rotation; S = squeeze). The letter in the row indicates the vertical position ("L" for lower, "M" for middle, "U" for upper), while the letter in the column indicates the horizontal position ("L" for left, "C" for central, "R" for right). In **bold** are the positions where the number of clusters for the squeezing task was different from that one identified for the rotation task; underlined are the positions where the effect of the cluster assignment reflects on the MMGA index.

	L	C	R
U	***R* = 2 |*S* = 4**	*R* = 2 |*S* = 2	*R* = 2 |*S* = 2
M	*R* = 5 |*S* = 5	***R* = 4 |*S* = 2**	*R* = 4 |*S* = 4
L	***R* = 3 |*S* = 4**	***R* = 3 |*S* = 4**	*R* = 2 |*S* = 2

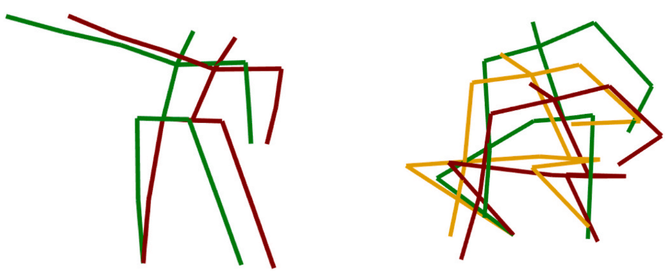

Fig. 2. Lateral perspective visualization of the reconstructed posture at the end of the reaching phase considering the participant closer than the centroid from each cluster. In the left panel is reported Rotation Upper Central task and in the right Rotation Lower Central is reported. The different colors represent the cluster assignment. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

3.1. Squeeze and rotation UC

Considering the squeezing task, the MMGA values relative to the two cluster groups (Fig. 3a) were statistically different (t (41) = 3.16; p = 0.003, Cohen's d = 1.01). Cluster 2 showed a higher mean value of MMGA than cluster 1, indicating that the participants belonging to cluster 2 executed the task with greater discomfort from an ergonomic point of view. Considering the joint displacement w1, the following joint angles were different between the two clusters: trunk abduction (t (41) = 3.20; p = 0.002, Cohen's d = 1.22), trunk flexion (t (41) = 2.71; p = 0.009, Cohen's d = 1.00), right shoulder abduction (t (41) = 2.95; p = 0.005, Cohen's d = 0.95), right hip abduction (t (41) = 3.23; p = 0.002, Cohen's d = 1.26), right hip flexion (t (41) = 3.45; p = 0.001, Cohen's d = 1.03), and left knee flexion (t (41) = 2.92; p = 0.005, Cohen's d = 0.65). Mean and standard error relative to the angle w1 are reported in Fig. 3c. These results are in line with the MMGA since the mean values of the variables of cluster 2 are always higher than cluster 1. Trunk and right shoulder abduction seem to be the most involved joint in the execution of this task.

In the rotation task, the two groups differed in the MMGA values (Fig. 3b) as well (t (41) = 2.55; p = 0.014, Cohen's d = 0.80). Considering the joint displacement w1, the following joint angles were different between the two clusters: trunk abduction (t (41) = 2.46; p = 0.018, Cohen's d = 0.83), right shoulder abduction (t (41) = 3.05; p = 0.004, Cohen's d = 0.94), right hip abduction (t (41) = 3.13; p = 0.003, Cohen's d = 1.00) and left knee flexion (t (41) = 2.27; p = 0.028, Cohen's d = 0.62). Mean and standard error relative to the angle joint displacements are reported in Fig. 3d. The results of the rotation task are in line with the squeeze task indicating that cluster 2 performed the movement with a high discomfort and the joint angles that mainly contribute to the general discomfort of the movement are the trunk and right shoulder abduction.

3.2. Squeeze and rotation LL

In the squeeze LL task, a main group effect of cluster assignment emerged for the MMGA values (F (3,36) = 8.28; p < 0,001; partial η^2 = 0.41). Post hoc comparisons revealed that cluster 4 had systematically higher values than cluster 1 and cluster 2 (both p < 0.001) indicating that participants of cluster 4 reached the target less comfortably with respect to participants of clusters 1 and 2. The mean and standard error of the MMGA grouped according to cluster assignment are reported in Fig. 4a. Considering the joint displacement w1, only two joint angles were different among the four clusters: trunk abduction (F (3,36) = 4.21; p = 0,011; partial η^2 = 0.26; post-hoc: cluster 2 lower than cluster 4, p = 0.010), and right hip abduction (F (3,36) = 3.96; p = 0.022; partial η^2 = 0.23; post-hoc: cluster 1 lower than cluster 3, p = 0.032). Moreover, only the w1 relative to the trunk abduction seems to be in line with the results of MMGA since cluster 4 showed the highest values of this parameter. Mean and standard error relative to the angle joint displacements is reported in Fig. 4c.

In the rotation, a main group effect among the three clusters assignment emerged for the MMGA values (F (2,39) = 17.03; p < 0.001;

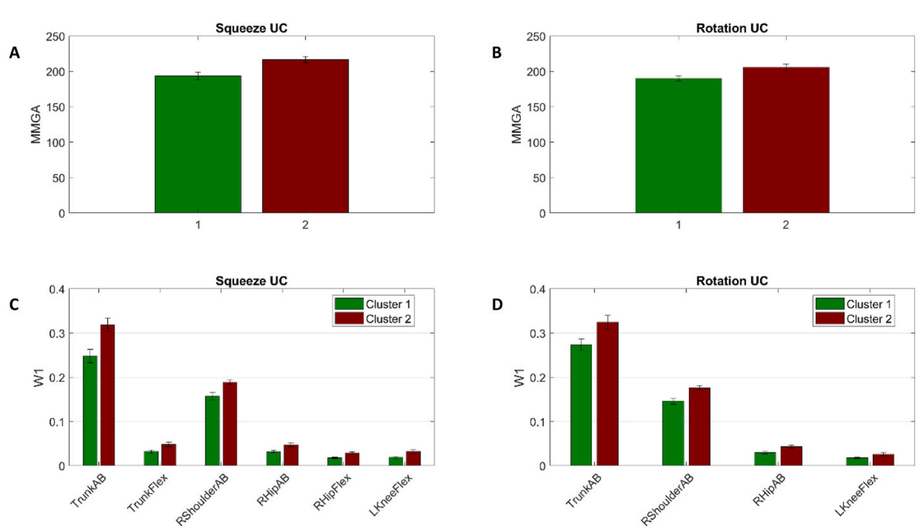

Fig. 3. Panels A and B report the mean and standard error of MMGA values relative to the two clusters (green bars for cluster 1 and red bars for cluster 2) in the squeeze and rotation Upper Central (UC) tasks, respectively. Panel C and D report the mean and standard error of w1 values relative to the joint angles that showed a significant difference between the two groups in the UC squeeze and rotation tasks, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

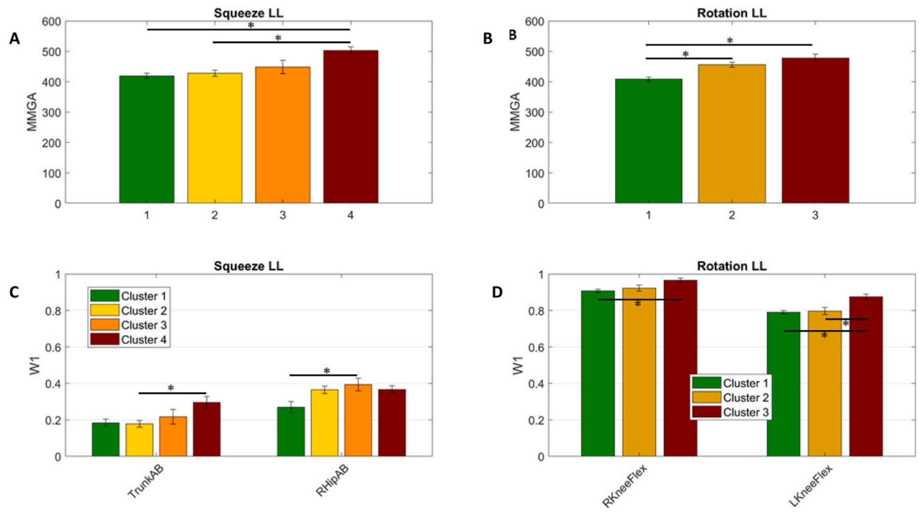

Fig. 4. Panel A reports the mean and standard error of MMGA values relative to the four clusters (green bar for cluster 1, yellow bar for cluster 2, orange bar for cluster 3, and red bar for cluster 4) in the squeeze Lower Left (LL) tasks. Panel B reports the mean and standard error of MMGA values relative to the three clusters (green bar for cluster 1, mustard-colored bar for cluster 2, and red bar for cluster 3) in the rotation LL tasks. Panels C and D report the mean and standard error of w1 values relative to the joint angles that showed a main group effect among the four groups for the squeeze task and among the three groups for the rotation task. Asterisks indicate significant post-hoc comparisons. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

partial $\eta^2 = 0.46$). Post hoc comparisons revealed that cluster 1 had systematically lower values than cluster 2 and cluster 3 (both $p < 0.001$) indicating that the postures assumed by the participant of cluster 1 are more comfortable than the other 2 groups. The mean and standard error of the MMGA grouped according to the cluster assignment are reported in Fig. 4b. Considering the joint displacement w1, the most involved joints are the knees. In fact, main effect was found for the right knee flexion ($F(2,39) = 5.18$; $p = 0.010$; partial $\eta^2 = 0.21$; post-hoc: cluster 1 lower than cluster 3, $p = 0.007$), and the left knee flexion ($F(2,39) = 9.78$; $p < 0.001$; partial $\eta^2 = 0.33$; post-hoc: cluster 1 lower than cluster 2 and cluster 3, $p < 0.001$ and $p = 0.002$, respectively). Mean and standard error relative to the angle joint displacements are reported in Fig. 4d. The high w1 values indicate that both knees are the joints most responsible for the discomfort of this task.

3.3. Squeeze and rotation LC

In the squeeze LC task, a main group effect of cluster assignment emerged for the MMGA values ($F(3,39) = 7.62$; $p < 0.001$; partial $\eta^2 = 0.37$). Post hoc comparisons revealed that cluster 1 had systematically lower values than cluster 2, cluster 3, and cluster 4 ($p = 0.022$, $p < 0.001$ and $p = 0.014$). Mean and standard error of the MMGA grouped according to cluster assignment are reported in Fig. 5a. Considering the joint displacement w1, the following angles were different among the four clusters: right shoulder rotation ($F(3,39) = 3.38$; $p = 0.016$; partial $\eta^2 = 0.22$; post-hoc: cluster 3 lower than cluster 1, $p = 0.014$), right hip abduction ($F(3,36) = 4.27$; $p = 0.010$; partial $\eta^2 = 0.24$; post-hoc: cluster 1 lower than cluster 2 and cluster 3, $p = 0.014$ and $p = 0.029$), right knee flexion ($F(3,39) = 7.86$; $p < 0.001$; partial $\eta^2 = 0.37$; post-

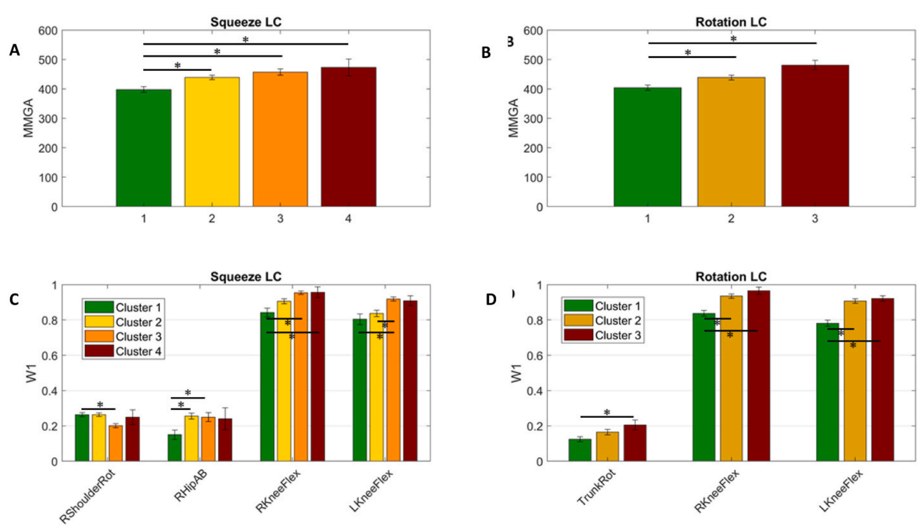

Fig. 5. Panel A reports the mean and standard error of MMGA values relative to the four clusters (green bar for cluster 1, yellow bar for cluster 2, orange bar for cluster 3, and red bar for cluster 4) in the squeeze Lower Central (LC) tasks. Panel B reports the mean and standard error of MMGA values relative to the three clusters (green bar for cluster 1, mustard-colored bar for cluster 2, and red bar for cluster 3) in the rotation LC tasks. Panels C and D report the mean and standard error of w1 values relative to the joint angles that showed a main group effect among the four groups for the squeeze task and among the three groups for the rotation task. Asterisks indicate significant post-hoc comparisons. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

hoc: cluster 1 lower than cluster 3 and cluster 4, $p < 0.001$ and $p = 0.033$), and the left knee flexion ($F(3,39) = 5.88$; $p = 0.002$; partial $\eta^2 = 0.31$; post-hoc: cluster 3 higher than cluster 1 and cluster 2, $p = 0.002$ and $p = 0.036$, respectively). Mean and standard error relative to the angle joint displacements w1 are reported in Fig. 5c. The knees are the main ones responsible for the ergonomic discomfort of this task and show the same trend of MMGA index in which participants of cluster 1 perform the task with less ergonomic discomfort.

In the rotation, a main group effect among the three clusters assignment emerged for the MMGA values ($F(2,37) = 11.17$; $p < 0.001$; partial $\eta^2 = 0.37$). Post hoc comparisons revealed that cluster 1 had systematically lower values than cluster 2 and cluster 3 ($p = 0.026$ and $p < 0.001$). The mean and standard error of the MMGA grouped according to the cluster assignment are reported in Fig. 5b. Considering the joint displacement, the most involved joints are the trunk and the knees. In fact, main effects were found for the trunk rotation ($F(2,36) = 4.50$; $p = 0.017$; partial $\eta^2 = 0.19$; post-hoc: cluster 1 lower than cluster 3, $p = 0.023$) the right knee flexion ($F(2,36) = 16.07$; $p < 0.001$; partial $\eta^2 = 0.46$; post-hoc: cluster 1 lower than cluster 2 and cluster 3, both $p < 0.001$), and the left knee flexion ($F(2,36) = 20.42$; $p < 0.001$; partial $\eta^2 = 0.53$; post-hoc: cluster 1 lower than cluster 2 and cluster 3, both $p < 0.001$). Mean and standard error relative to the angle w1 are reported in Fig. 5d. These results confirmed those of the squeeze task.

3.4. Squeeze and rotation LR

Considering the squeezing task, the MMGA values relative to cluster 1 are lower than the values of cluster 2 (Fig. 6a) showing a statistical difference ($t(36) = 5.18$; $p < 0.001$; Cohen's $d = 1.72$). Considering the joint displacement, the following joint angles were different between the two clusters: trunk abduction ($t(36) = 3.13$; $p = 0.003$; Cohen's $d = 0.98$), right shoulder abduction ($t(36) = 2.34$; $p = 0.024$; Cohen's $d = 0.77$), right hip abduction ($t(36) = -2.63$; $p = 0.012$; Cohen's $d = 0.96$), and right hip flexion ($t(36) = -2.71$; $p = 0.010$; Cohen's $d = 1.00$). Means and standard errors relative to the angle joint displacements are reported in Fig. 6c. In particular, the right hip flexion showed the highest values of w1 but the values of cluster 1 are higher than cluster 2 and this is in contrast with the results of the MMGA scores.

In the rotation task, the two groups differed in the MMGA values (Fig. 6b) ($t(41) = 2.87$; $p = 0.006$; Cohen's $d = 0.86$), with cluster 1 lower than cluster 2. Considering the joint displacement, the following joint angles were different between the two clusters: trunk abduction ($t(41) = 3.69$; $p < 0.001$; Cohen's $d = 1.11$), right hip abduction ($t(41) = -4.62$; $p < 0.001$; Cohen's $d = 1.52$), right ankle flex ($t(41) = 2.94$; $p = 0.005$; Cohen's $d = 0.88$) and left ankle flexion ($t(41) = 2.54$; $p = 0.014$; Cohen's $d = 0.78$). Mean and standard error relative to the angle joint displacements w1 are reported in Fig. 6d. In this case, the right and left ankle flexion are most involved in the discomfort of the task.

4. Discussion

The primary aim of the present study was to determine whether kinematic patterns for a sample of healthy participants during the execution of whole-body reach-to-manipulate tasks could be classified into homogeneous subgroups, according to their movement phenotype. After isolating prototypical motor strategies using pattern recognition (i.e., PCA) and clustering technique (i.e., k-means), we further tested whether these motor phenotypes embedded also a different level of ergonomic risk, quantitatively evaluated in terms of maintained posture and performed tasks. Finally, we back-projected the different levels of ergonomic quality onto the joint kinematics, so as to reveal which body districts played a major role in driving movement discomfort and in assuming human awkward or unfavorable postures.

4.1. Clusters and their variability

The unsupervised clustering approach identified a different number of clusters (range 2–5) according to the to-be-reached object position and the type of manipulation requested to the participants (see Table 2). In other words, the inter-subject variability inherent to the movement performance led to the identification of several movement phenotypes, mostly reflecting the different motor strategies adopted by our participants. It is not trivial that the object position and even more the type of manipulation impacted the number of clusters. Indeed, the first factor was manipulated to test the same manipulative action while perturbing the balance and postural control of the participants. Thus, we somewhat expected that some positions could have been more prone to highlight a richness of movement phenotypes/ergonomic attitudes. Examining cluster numerosity, one can easily note that the middle positions are the ones showing the largest number of clusters (13 for rotation and 11 for squeezing), while the upper positions show the smallest ones (6 for rotation, 8 for squeezing). It is thus tempting to hypothesize that more constrained postural conditions (e.g., objects in upper positions, in which participants must stretch their body to reach a distant point)

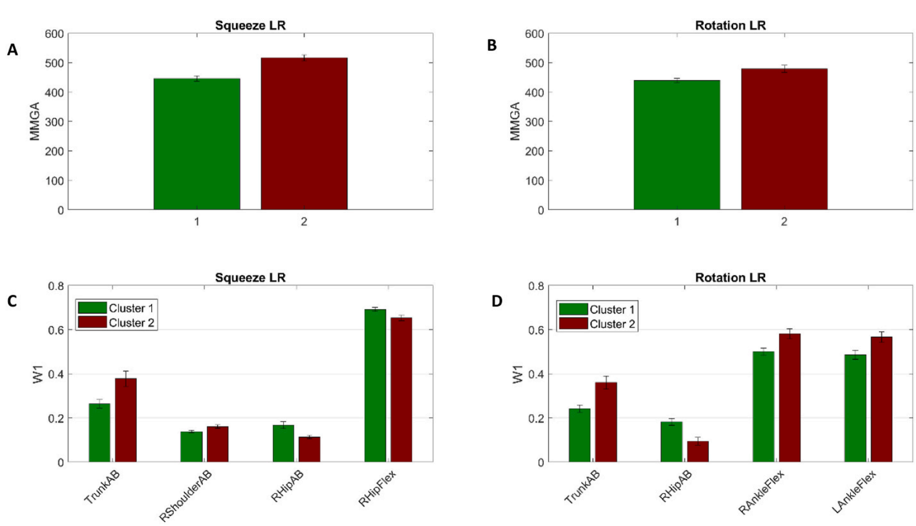

Fig. 6. Panels A and B report the mean and standard error of MMGA values relative to the two clusters (green bars for cluster 1 and red bars for cluster 2) in the squeeze and rotation Lower Right (LR) tasks, respectively. Panels C and D report the mean and standard error of w1 values relative to the joint angles that showed a significant difference between the two groups in the LR squeeze and rotation tasks, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

could lead to a lower variability of kinematic behavior, or at least to easier modeling of such variance. Conversely, movements less demanding from an ergonomic point of view would favor a larger variability, with a higher richness of movement patterns. The same line of reasoning seems not applicable to the horizontal position, with left, central, and right positions not highlighting reproducible differences.

For each object position, participants had to perform two types of manipulations, and interestingly this factor impacted on the cluster numerosity in most of the positions. Here, we must consider that the two manipulations reasonably required the realization of different forces and torques at the hand-object interface, thereby involving the whole kinetic chain - down to the feet - in order to balance and maintain the body posture (Pienciak-Siewert et al., 2020). Moreover, the two manipulations necessitated different coordination strategies at the motor control level, affecting the management of tasks outside the sagittal plane and possibly resulting in distinct anticipatory and compensatory postural adjustments (Aimola et al., 2011; Li et al., 2017; Pienciak-Siewert et al., 2020). These factors could contribute to the implementation of different movement phenotypes within the participants' motor strategies.

4.2. Ergonomic assessment: MMGA

As underlined by Remedios et al. (2020), a clustering approach per se is not able to identify "bad" or "good" movers. Therefore, in order to associate movement strategies with an overall ergonomic discomfort, we chose to use the MMGA approach since it represents a proper extension of the LUBA model including dynamic tasks and posture, and, further, it has been recently used as a reference method in the estimation of mechanical energy expenditure and mechanical efficiency within the ergonomic context (Wang et al., 2018). Moreover, the MMGA approach can be based on the exploitation of wearable technologies – as we used in this study – so as to have quantitative information about joint kinematics. The use of wearable sensors to monitor and analyze biomechanical data represents a promising approach to preventing or mitigating WMSDs; by continuously tracking and analyzing workers' movements, posture, and exposure levels, these systems – providing a multi-parametric and quantitative framework - can identify risky patterns and provide personalized feedback to help workers adjust their behavior and reduce their biomechanical risk (Ranavolo et al., 2018, 2020; Stefana et al., 2021). Through our clustering analysis, we found that different movement strategies significantly influenced the overall discomfort experienced by the participants in four out of the nine defined object positions, considering both tasks. These results suggested that MMGA is often different among phenotypes, but not necessarily able to distinguish across all groups, especially when a moderate effect was observed as in the case of targets that require minimal ergonomic discomfort. In particular, the upper central (UC) position and the three lower positions (LL, LC, and LR) were particularly impacted.

When requiring both the squeezing and the rotation action on the object placed in the UC position, strategies classified in Cluster 2 showed a higher mean value of MMGA than those classified in Cluster 1, indicating that the participants belonging to the first cluster executed both the tasks with greater discomfort from an ergonomic point of view, despite the central position of the object. Considering LL and LC positions we found a difference in the identification of the overall number of the clusters between squeezing and rotation tasks; however, Cluster 4 for the rotations and Cluster 3 for the squeezing actions presented higher average values of MMGA, underline also in this case the presence of different motor strategies which led to less comfortable dynamic executions and postures. Interestingly in the last analyzed position, i.e., the LR, we found that the participants classified in Cluster 2 always presented a higher average value of MMGA, when considering both the realized tasks.

Before delving into the specific joints that contributed most to this ergonomic modulation, it is important to note that we did not observe the consistency in assigning participants to clusters across the 18 tasks. In other words, the ergonomic quality of motor performance appeared to be more task-specific than subject-specific. This finding suggests that the interpretation of results is not driven by a group of "good movers" across tasks but rather highlights the necessity of individualized training and preventive interventions in occupational therapies. It emphasizes that ergonomic performance cannot be generalized across different movements within a subject and underscores the importance of tailoring interventions to specific tasks and individuals.

4.3. Contribution of the single joint to the overall discomfort

Finally, we introduced w1, an additional quantitative index concerning the normalized joint displacement, to define the contribution of each joint and the corresponding degree of freedom to the overall ergonomic discomfort (Lorenzini et al., 2022).

Specifically, when requiring both the squeezing and the rotation action on the object placed in the UC position, the participants classified in Cluster 2 presented the trunk more abducted and flexed, the right shoulder and hip more abducted and the left knee more flexed with respect to those classified in Cluster 1 (see Fig. 2 left panel for a visual representation of the emergent differences in movement). From the biomechanical perspective, the most important contributions in the realization of this task are indeed given by an increase of 15–20% abduction of the trunk and a corresponding rise in the excursion of the abduction of the right shoulder, which are risk factors underlined also by the international technical standards (ISO 1128 (SA, 2011)); the other joint variations are mainly due to compensatory strategies required to maintain a coherent posture.

Considering the tasks in the LL and LC positions, the flexion of both knees was higher in the cluster corresponding to the higher value of MMGA and presenting a value close to 1, thus underlining the important contribution to the discomfort of these joints. In the LC position, we found also a different contribution of the trunk rotation, mainly due to the need for maintaining the postural equilibrium during the execution of this task. On the other hand, when considering the squeezing action, in both LL and LC positions, we must underline little discrepancies between the MMGA clusters and those corresponding to the significant joints. Anyhow, these reductions are extremely small if compared to the absolute value of the w1 index, above all, when considering knee joints. Therefore, different grades of the knee flexion characterized phenotypes of the movements facing down positions except for the LR which present some discrepancies with the MMGA scores. In fact, in this position, there was a decrease in right hip abduction and flexion in Cluster 2 during squeezing and a decrease in right hip abduction during rotation action. On the other hand, we have to underline that from the biomechanical perspective, most of the contribution to the discomfort, in this case, was due to the ankle flexion and a variation in the trunk abduction of about 40% between Cluster 1 and Cluster 2.

As we expected, then confirmed by the analysis, the movements toward the upper vs lower position will recruit body segments differently. More precisely, the joint angles contributing to discomfort varied depending on the specific task. However, the trunk, right shoulder, right hip, and knees were consistently identified as the most involved joints in rotation and squeezing movements. Notably, an increase in overall joint displacement in the trunk and shoulders was associated with a higher level of discomfort. This finding is in line with previous research indicating that excessive joint angles in these regions can increase the risk of musculoskeletal disorders during manual handling tasks in various occupational contexts (Goubault et al., 2022; Hajaghazadeh et al., 2019; Mayer et al., 2012; Silvetti et al., 2015, 2017, 2020). Furthermore, knee flexion was specifically associated with discomfort in the lowest position, especially during the rotation task. This observation aligns with previous studies highlighting that movements involving squatting or kneeling positions can lead to altered movement patterns and increased stress on the knee joints. Factors such as sex differences can also contribute to variations in muscle activation, joint torque, and overall biomechanical stress on the knees (Buchman-Pearle et al., 2021; Kingston and Acker, 2018; Pejhan et al., 2020; Tennant et al., 2018), further raising the level of biomechanical risk. Overall, these findings emphasize the importance of considering specific joint angles and movement patterns in relation to discomfort and biomechanical risk during occupational tasks. Understanding the contributions of different joints and their potential implications for musculoskeletal health can inform the development of targeted interventions and ergonomic guidelines to mitigate the risk of work-related musculoskeletal disorders.

4.4. Potential applications and limitations

The applicability of these findings exceeds the mere identification of the movement phenotype associated with the individual subject motor performance. Indeed, examining the preventive strategies within occupational medicine, also the observation of occupational gestures can be integrated into training procedures to bias the workers' motor system and promote the level and stability of their work-related motor skills. Such an approach has been largely validated in clinical and pre-clinical contexts (Rizzolatti et al., 2021), and proved efficient in ameliorating the subjects' performance both behaviorally (Bazzini et al., 2022), in terms of temporal tuning of the EMG activity (Bazzini et al., 2023) and cortical excitability responses (Nuara et al., 2023), also favoring the outcome of musculoskeletal impairment (De Marco et al., 2021). In addition, to reproduce as comprehensively as possible the "worker-task-environment" triad indicated as a key promoter of motor control within the working environment (Newell, 1986), recent studies proposed to show occupational gestures in virtual reality, thus reproducing not only the kinematic features of the specific gesture but also its three-dimensional aspect and the surrounding, work-specific environment (Scalona et al., 2022). In light of these considerations, a point of interest that needs to be addressed is whether the kinematics of the to-be-observed gestures can be controlled also for their ergonomic quality, thus using action observation to bias not only the performance of the end-effectors (e.g. arms and hands) but also the overall postural attitude of the trainee, with significant applications for the prevention of work-related musculoskeletal disorders.

A few limitations must be acknowledged in our study. The first one concerns the generalizability of our findings, which is hurdled by two different aspects. On one side, we recruited a moderately small size sample of healthy volunteers, thus the identified movement phenotypes cannot be regarded as representative of the whole population, but rather as proof that it is possible to distinguish movement-specific patterns even within a moderately-sized group of participants. A further limit is related to the simplicity of the requested movements. Although these movements are prototypical tasks that a worker can deal with during "on-field" interactions (Andreoni et al., 2009), future studies should test more complex working tasks which can be representative of the whole spectrum of manual handling tasks, including lifting, as underlined by Armstrong and Fischer (2020), without forgetting that different movement phenotypes could emerge only upon specific types of motor activity (Oomen et al., 2022). Finally, as occupational movement strategy is influenced by several factors also related to the external environment (Newell, 1986), an on-field assessment would be advised to maximize the reliability of the findings.

Considering the overall clustering strategy, it is worth underling that the number of retained principal components directly affects the variance included in the analysis (Remedios et al., 2020); in fact, in general, for clustering purposes the need for a reduction in dimensionality leads to a compromise in the retention of the principal components, sufficient to explain the overall variance of the movement (e.g. (Armstrong and Fischer, 2020),) and this choice can limit the possibility to better understand the intra-subject variability.

Finally, the variables selected for the cluster and the statistical analysis are indeed related through the kinematic chain; this could have partially influenced the obtained results in the clustering phase. Anyhow, this relation is not linear and it is also influenced by the motor control features of each subject. Future studies should involve a modeling approach that introduces forces and moments which could help to better assess the general ergonomic risk within the identified cluster related to movement phenotypes.

5. Conclusion

Overall, in this study an unsupervised clustering technique was employed to underline the presence of distinct movement phenotypes during the realization of occupational tasks and associate them with specific levels of ergonomic discomfort. The results obtained in this work provided an important preliminary basis for supporting this main hypothesis by exploiting wearable technologies and established methodologies for assessing the ergonomic risk during the execution of motor tasks and maintenance of postures. Furthermore, the main findings of this study pave the way to define a proper methodological framework addressing the need for training the workers to achieve optimal biomechanical strategies in terms of minimizing overall ergonomic risk. Indeed, this approach provides a valuable tool for researchers and ergonomists, enabling them to enhance their understanding of the relationship between motor control and musculoskeletal risk even when considering diverse occupational tasks.

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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.

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