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Title: Effect of expertise on shoulder and upper limb kinematics, electromyography and estimated muscle forces during a lifting task.

Running head: Expertise effect on shoulder biomechanics

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Abstract

Objective: To highlight working strategy between expert and novice manual handlers, based on recordings of shoulder and upper limb kinematics, electromyography, and estimated muscle forces during a lifting task.

Background: Novice workers involved in assembly, manual handling and personal assistance tasks are at higher risk of upper limb musculoskeletal disorders. However, few studies have investigated the effect of expertise on upper limb exposure during workplace tasks.

Method: Sixteen experts in manual handling and sixteen novices were equipped with 10 electromyographic electrodes to record shoulder muscle activity during a manual handling task consisting of lifting a box (8 or 12 kg), instrumented with three six-axis force sensors, from hip to eye level. Three-dimensional trunk and upper limb kinematics, hand-to-box contact forces and electromyography were recorded. Then, joint contributions, activation levels, and muscle forces were calculated and compared between groups.

Results: Sternoclavicular-acromioclavicular joint contributions were higher in experts at the beginning of the movement, and in novices at the end, while the opposite was observed for the glenohumeral joint. EMG activation levels were 37% higher for novices but predicted muscle forces were higher in experts.

Conclusion: This study highlights significant differences between experts and novices in shoulder kinematics, electromyography, and muscle forces, hence the importance of providing effective work guidelines to ensure the development of a safe handling strategy.

Application: Shoulder kinematics, electromyography, and muscle forces could be used as an ergonomic tool to identify inappropriate techniques that could increase the prevalence of shoulder injuries.

Keywords: Biomechanics, Biomechanical models – shoulder, Forces and moments, Manual materials handling, Musculoskeletal system (musculoskeletal disorders, cumulative trauma disorder)

Précis: Shoulder biomechanics were assessed in 16 experts in manual handling and 16 novices to highlight musculoskeletal risk factors related to working expertise. Movement strategies of novices may result in increased injury risk, as confirmed by EMG analyses. This study highlighted injury risk factors that could be used for training purposes in industry.

Abbreviations

deltant	Anterior Deltoid
deltlat	Lateral Deltoid
deltpost	Posterior Deltoid
DoF	degree-of-freedom
ECDF	Empirical cumulative distribution function
EMG	Electromyography
ES	Effect size
isp	Infraspinatus
MSDs	Musculoskeletal Disorders

MVC	Maximal voluntary contraction
pect	Pectoralis Major
ssp	Supraspinatus
subs	Subscapularis
uptrap	Upper Trapezius
%trial	Percentage of the trial

Introduction

Shoulder musculoskeletal disorders (MSDs) are a major health problem in industry, costing 28 B$/year in Western countries (Panariello et al., 2019; Yasobant & Rajkumar, 2014), representing about 40% of all costs toward the treatment of work-related injuries. Risk factors for shoulder injuries include assembling or manual handling which requires repetitive work, elevated arm posture, constrained workplaces, and periods of sustained muscle activity (Côté, 2014; Hanvold et al., 2015; Mathiassen, 2006; Mayer et al., 2012). Novice workers are at an increased risk of injury (Hill, 2014), and more prone to develop shoulder MSDs than expert workers, perhaps due to use of safer working strategy (Breslin & Smith, 2005; Häkkänen et al., 2001), and a larger motor variability than novices (Madeleine et al., 2008).

Previous work on working strategy adaptions in expert workers have primarily focused on the lower back pain and MSDs, with little focus on the shoulder joint. Authier et al., (1996) observed that expert workers tilted boxes more than novices in various phases of handling when transferring boxes from a platform to a four-wheel cart. This strategy reduced the duration of the phase during which the load was fully supported by the participant, and the length of the path of the load. The experts' working strategies also reduced the compression force at the L5/S1 level and the shoulder flexor moments by 20% and 16%, respectively (Gagnon, 1997). In addition, the distance from the load to the lumbar region (L5/S1) was reduced in experts, thus decreasing the net moments (Gagnon, 2003). Transfer time and load path were also reduced, potentially improving efficiency and safety. Furthermore, Plamondon et al., (2014) showed an effect of expertise on posture-related variables, particularly when the box was handled from the ground level. Unfortunately, none of these studies focused on overhead tasks and it remains unknown if such working strategies may also prevent shoulder MSDs or, on the contrary, be detrimental. Previous studies have shown the importance of working strategy adaptations to perform and maximize the safety of physical tasks, leading to the development of strategies for reducing the risk of low back MSDs. Determining if working strategy differences exist for the shoulder, which could perhaps differentiate expert handlers from novices, would make it possible to characterize optimal postures and strategies on which to train novice handlers. Such strategies might limit their exposure to the identified shoulder MSDs risk factors (Jeong et al., 2018).

According to Garg and Kapellusch, (2009), the relationship between shoulder injuries and load or posture is complex and requires quantitative measures of musculoskeletal stress on the shoulder. In addition, investigations should consider the task as a dynamic one, especially those where the arms reach above the head level (Garg & Kapellusch, 2009). In repetitive work tasks, participants compensated for reduced shoulder physical capacity caused by muscle fatigue through strategy on their posture and muscle activity compensations that enabled them to maintain task performance (McDonald et al., 2019; Pritchard et al., 2019). The large number of degrees of freedom at the upper extremity makes it possible to employ a great variety of compensatory strategies during repetitive and fatiguing tasks (Mulla et al., 2018). In overhead lifting tasks, previous studies observed that prime movers during abduction and flexion are the most affected by overhead position (Grieve & Dickerson, 2008). Martinez et al., (2019) also showed a higher wrist, elbow, and glenohumeral joint contribution in women compared to men during an overhead lifting task, while Bouffard et al., (2019) found a sex differences in shoulder electromyographic (EMG) activations during the same task. Additionally, Martinez et al., (2020) recently showed that women generate higher musculoskeletal loads than men when lifting a box above shoulder height. However, the effect of expertise was not considered in these studies. In addition, existing studies on the shoulder and upper limb during material handling rarely combine EMG and kinematic data to estimate joint and muscle dynamics, both of which may be important factors for MSDs risk.

Therefore, the objective of this study was to highlight the biomechanics characteristics of the shoulder that differentiate experts from novices during a lifting task using recordings of shoulder kinematics and EMG, as well as estimated muscles activations and muscles forces both estimated using a musculoskeletal model. It was hypothesized that the differences in the joint contributions to the box elevation, as well as the general kinematic movement strategy (e.g. box closer to the body) would suggest that experts employ a lower-risk lifting strategies than novices (Plamondon et al., 2010, 2012). It was also expected that there would be lower overall arm and shoulder EMG activation in experts. Similarly, the muscle activations estimated by the musculoskeletal model, as well as the estimated forces were expected to be lower in experts. The use of the musculoskeletal model to assess muscle activation is complementary to EMG measures and can improve the interpretation of results since it includes a larger set of muscles.

Method

Participants

Two groups of participants were recruited. The first group consisted of 16 expert male manual labourers, familiar with the task investigated in the present study (≥ 5 years of experience with a low lifetime incidence of injuries, and no injury in the year preceding the study; 36.4±7.9 years old; 176.1±6.4 cm; 84.0±13.6 kg). The second group consisted of 16 novice male manual labourers (between 3 and 6 months of experience with no incidence of injury in the year preceding the study; 25.5±2.4 years old; 178.3±8.1 cm; 77.5±9.01 kg). There was neither significant height difference ($t(30)=-0.82$, $p=0.42$) nor weight difference ($t(26.08)=1.50$, $p=0.15$) between the two groups. The significant age difference ($t(19.68)=5.72$, $p<0.001$) should not affect the results of this study since no mechanical or kinematic differences were found in previous studies between groups aged between 22-28 (equivalent to our novice group) and 32-38 years (equivalent to our expert group) (Roldán-Jiménez & Cuesta-Vargas, 2016; Shojaei et al., 2016). In addition, we think that novice workers may be younger than expert workers in true occupational conditions and we believe that this difference is acceptable. Participants were free of MSDs or any significant disability related to their upper limb and back as assessed by the Disabilities of the Arm, Shoulder and Hand questionnaire (Hudak et al., 1996) and the Quebec Back Pain Disability Scale (Kopec et al., 1995). The Physical Activity Readiness Questionnaire was administered prior to the experiment (Thomas et al., 1992). After receiving instruction on the experimental protocol, participants read and signed a written informed consent. The protocol was approved by our institutional Ethics Committee (16-014-CERES-D).

Instrumentation

An 18-camera motion system analysis (Vicon, Oxford, UK) was used to record (100 Hz) 34 reflective markers positioned on the trunk and the dominant side of participants (as detailed in Martinez et al., (2019)) in line with the Jackson et al., (2012) shoulder model

(Figure 1A)). Participants were also equipped with surface EMG electrodes (Trigno EMG Wireless System, Delsys, USA) positioned according to the SENIAM recommendations (Hermens et al., 2000) after shaving and cleaning of the skin. Muscle activity of the deltoids (anterior, lateral, and posterior), biceps and triceps brachii, upper trapezius and pectoralis major of the dominant side were recorded at 2000 Hz. Since rotator cuff muscles are frequently affected by MSDs (Milgrom et al., 1995; Silverstein et al., 2002; Yamamoto et al., 2010), intramuscular EMG electrodes were also inserted into the infraspinatus, supraspinatus, and subscapularis muscles using sterile fine needles and following procedures of previous studies (Kadaba et al., 1992; Perotto, 2011) (Figure 1A). No participant complained of discomfort in their movements after a short period of familiarization. Electrode placements were validated through visual inspection of EMG signals during 10 submaximal voluntary contractions (Table 1 in Appendix).

[Please insert Figure 1 here]

Figure 1: (A) Position of EMG electrodes: anterior deltoid (1), lateral deltoid (2), posterior deltoid (3), biceps brachii (4), triceps brachii (5), upper trapezius (6), pectoralis major (7), supraspinatus (8), infraspinatus (9), subscapularis (10). (B) Three-dimensional view of the instrumented box with locations of three six-axis force sensors (S1, S2, S3). (C) Task setup: participants lifted boxes between the table and an adjustable shelf adjusted to eyes level.

Experimental Procedures

Participants performed 10 maximal voluntary contractions (MVC) in a random order for EMG normalization purposes in accordance with the recommendations of Dal Maso et al., (2016), who identified the combination of isometric contractions most likely to reach a level of 90% of the participants' absolute maximum (Table 1 in Appendix). For each contraction, two tests were performed back-to-back with a 1-minute rest period in between. After the two tests for a given contraction, a rest period of 90-seconds was given to participants before the contractions for the next muscle. The EMG activities were collected for 5-seconds for each test. A static trial was then collected, and based on previous recommendations (M. Begon et al., 2007; Michaud et al., 2016), functional movements were performed to locate joint centers and axes of rotation used to personalize the kinematic model developed by Jackson et al., (2012).

After these prerequisite trials to locate of joint centers and rotational axes, participants performed the experimental task. The participants were asked to move an instrumented box (height×width×length: 20.5×37.7×30.5 cm) from a table (height: 73 cm) to a storage shelf adjusted at each participants' eye level (height: 166.4±3.2 cm), without any instruction on the working technique required to perform the lifting task. The table and the shelf were facing each other and separated by 1 meter (Figure 1C). The box was placed at the middle of the table using a cross mark. The deposit position was also marked off in the middle of the shelf. Our instrumented box had no handles and was covered with cardboard to replicate boxes typically used in the workplace. The lateral and anterior faces of the box were instrumented with three six-axis force sensors to record hand-to-box contact forces as shown in Figure 1B (Sensix, Poitiers, France). The beginning and ending of the trials were automatically detected at the time point when participants applied a force greater than or equal to 5 N, and inferior to 5 N respectively on the instrumented box. The box mass was either 8 kg or 12 kg. Six trials with each mass were performed in a randomized order with respect to the box mass, making for a total of 12 lifting trials. A 30-second rest period was given after each lift. The lifting movement was split into three phases: the pulling (1-20% of the trial duration), lifting (21-60%) and deposit (61-100%) phases (Martinez et al., 2019) (Figure 1C).

Data Processing

Kinematic data

For each participant, a personalized 25 degree-of-freedom (DoF) kinematic model was defined (see Appendix). Generalized coordinates ($\mathbf{q}$) that follow the International Society of Biomechanics recommendations (Wu et al., 2005) were estimated using an extended Kalman filter algorithm (Fohanno et al., 2014). The reference configuration ($\mathbf{q}^{REF} = \mathbf{0}$) of the pelvis, thorax, sternoclavicular and acromioclavicular joints was defined from the static position trial. Glenohumeral, elbow, and wrist joint reference orientations were corrected so that the glenohumeral and elbow longitudinal local axes were aligned with those of the thorax, and the glenohumeral, elbow, wrist mediolateral local axes were oriented according to the scapular plane, as in Martinez et al., (2019).

Individual joint contributions to the box elevation were calculated simultaneously on all the angles constituting an articulation. They were used to quantify lifting movements by consecutively resetting the joint angles to their reference position (Martinez et al., 2019) (Figure 2A-B). The reference position (joint angle=0 degrees) was defined during the participants' static trial (standing in the anatomical position). As the heights of the shelf were adjusted according to participants' anthropometry, the joint contribution to the box centroid elevation was normalized to participants' eye (100%) levels with 0% being the height of the table. The box elevation and the box-thorax distance were calculated over time and averaged for comparison purpose. The latter represents the distance between the centroid of the box and the centroid of the trunk markers in medio-lateral and antero-posterior axes. The box-thorax distance was normalized to participants' height.

[Please insert Figure 2A here]

$$
\begin{aligned}
\text{calculate height}(\mathbf{q}) &= H|_{WR/EL+GH+SC/AC+TR/PE} && (1)\\
\text{reset } q_{WR/EL} &= q_{WR/EL}^{REF} &&\\
\text{calculate height}(\mathbf{q}) &= H|_{GH+SC/AC+TR/PE} && (2)\\
H|_{WR/EL} &= \text{Eq}(1) - \text{Eq}(2) &&\\
\text{reset } q_{GH} &= q_{GH}^{REF} &&\\
\text{calculate height}(\mathbf{q}) &= H|_{SC/AC+TR/PE} && (3)\\
H|_{GH} &= \text{Eq}(2) - \text{Eq}(3) &&\\
\text{reset } q_{SC/AC} &= q_{SC/AC}^{REF} &&\\
\text{calculate height}(\mathbf{q}) &= H|_{TR/PE} && (4)\\
H|_{SC/AC} &= \text{Eq}(3) - \text{Eq}(4) &&\\
\text{reset } q_{TR/PE} &= q_{TR/PE}^{REF} &&\\
\text{calculate height}(\mathbf{q}) &= 0 && (5)\\
H|_{TR/PE} &= \text{Eq}(4) - \text{Eq}(5) &&
\end{aligned}
$$

Figure 2: (A) Illustration of the various joints' contribution at a given location. (B) The contribution of each joint (H|i) to the box elevation was computed by successively resetting joint angles to their reference orientations (q_i^{REF}). Joint contribution refers to the amount of box elevation achieved by each group of joints, namely pelvo-thoracic (PE/TR), sternoclavicular-acromioclavicular (SC/AC), glenohumeral (GH), and wrist-elbow (WR/EL) joints.

EMG data

All filters mentioned hereafter were second order zero-lag Butterworth filters. EMG data were filtered using a 20-425 Hz band-pass filter and a 60 Hz stop-band filter to remove electrical noise contamination. Data were then zero-aligned by subtracting the mean signal value, before being full-wave rectifying and low-pass filtering with a cut-off frequency of 5 Hz to extract EMG envelopes. EMG envelopes were normalized to their corresponding muscle's maximum voluntary activation obtained during MVC to obtain a percent activation value (Table 1, Appendix). EMG activations of participants were summed over time to represent the sum of activation.

Musculoskeletal model

The musculoskeletal analysis (i.e., scaling, inverse kinematics, inverse dynamics and static optimization) were performed using the OpenSim software API (Delp et al., 2007) and batch processed using Pyosim (https://github.com/pyomeca/pyosim) and Pyomeca (https://github.com/pyomeca/pyomeca), two custom-made open source Python libraries. The generalized coordinates were estimated by inverse kinematics from a custom upper extremity model that derived from the Wu et al., (2016) model (details in Appendix). Then, muscle activations and forces (expressed in percentage of MVC (%MVC) and Newton, respectively) were estimated using static optimization from the generalized coordinates and external forces measured by the instrumented box (Anderson & Pandy, 2001; Erdemir et al., 2007), by minimizing the sum of squared muscle activations and residual actuators (Appendix). Finally, the glenohumeral joint reaction forces were calculated and expressed in the local coordinate system of the glenoid. In the end, three groups of MSDs risk indicators were extracted from the previously described data analysis and are presented in Table 1. The experiment was video-recorded and those recordings were qualitatively used when necessary to facilitate interpretation of results.

Table 1: Groups of MSDs risk indicators and outcome measures related to the hypotheses attached to the objectives.

Indicator type	Outcome measures	References
Kinematic	Joint contributions to box elevation Box elevation Box-thorax distance	(Martinez et al., 2019; André Plamondon et al., 2012)
Electromyography	Sum of EMG activations EMG muscle activations	(Bouffard et al., 2019)
Musculoskeletal model	Estimated muscle activations Estimated muscle forces	(Anderson & Pandy, 2001; Erdemir et al., 2007)

Statistical Analysis

All variables were time normalized (1000 data points) for each subject to allow direct comparison. Each trial began and ended when participants first applied (5 N threshold), and first ceased to apply force on the box, respectively. All variables for the experts and novices were compared using statistical parametric mapping (Pataky, 2010). This method avoids information loss associated with standard methods which reduce time series into a single data point (e.g. mean or median), while controlling for type α-error due to multiple comparisons. A two-way ANOVA with expertise and box-mass as factors, with repeated measures on the box-mass factor were applied to each joint group (i.e., wrist-elbow, glenohumeral, sternoclavicular-acromioclavicular, and pelvis-thorax joints) contribution. The effect of mass on joint contributions for each level of expertise was also assessed with paired-sample t-tests. Bonferroni corrections were applied across the six post-hoc tests

(p=0.05/6=0.084). Each significant difference was reported with the cluster localisation in term of percentage of the trial (%trial), the mean difference, the p-value, and the Cohen's d (1988) effect size (ES). ES was interpreted as large (ES≥0.8), medium (0.5≤ ES<0.8) or small (ES<0.5). Data distribution was analyzed using an empirical cumulative distribution function (ECDF), which gives the fraction of sample observations less than or equal to a particular value of x. This method allows exploring distribution objectively, without choosing any parameters as opposed to other techniques (*e.g.* number of binning classes for histograms or bandwidth for kernel density estimation). All data processing and statistical analysis were carried out with Matlab™ R2019a (The MathWorks Inc., Natick, MA, USA) and Python 3.7 (Python Software Foundation).

Results

Kinematics

No mass-expertise interaction was found. In the following, all the ES values are interpretable as small except with other indication, and novices are compared to experts. The pelvo-thoracic contribution was 5% higher in novices between 0 and 22%trial (pulling and beginning of lifting phases) (ES=0.38; p<0.001), 2% higher between 48 and 58%trial (lifting phase) (ES=0.34; p=0.003) and between 71 and 87%trial (deposit phase) (ES=0.33; p=0.003). Sternoclavicular-acromioclavicular joint contribution was 8% lower in novices between 0 and 45%trial (pulling and lifting phases) (ES=0.57[medium]; p<0.001) and became 5% higher between 65 and 89%trial (deposit phase) (ES=0.43; p<0.001). The glenohumeral joint contribution was 9% higher in novices between 48 and 58%trial (lifting phase) (ES=0.40; p=0.001), and 9% lower between 77 and 99%trial (deposit phase) (ES=0.50; p<0.001). Finally, the elbow-wrist joint contribution was 3% higher in novices between 0 and 6%trial (pulling phase) (ES=0.38; p=0.002) and 5% higher between 28 and 45%trial (lifting phase) (ES=0.44; p<0.001). However, the elbow-wrist joint contribution became 6% lower in novices between 52 and 69%trial (end of lifting and beginning of deposit phases) (ES=0.49; p<0.001) (Figure 3A).

A mass effect was only found for the pelvo-thoracic joint with a 4% higher contribution between 14 and 28%trial (pulling and lifting phases) with the 8 kg box (ES=0.36; p=0.001). However, the pelvo-thoracic joint contribution became 2% lower with the 8 kg box between 63 and 81%trial (deposit phase) (ES=0.37; p=0.001) (Figure 3B).

[Please insert Figure 3 here]

Figure 3: Mean (solid lines) and standard deviation (shaded areas) of joint contributions to the box elevation over time for the wrist and elbow (WR/EL), glenohumeral (GH), sternoclavicular and acromioclavicular (SC/AC), and pelvo-thoracic (TR/PE) joints, for (A) experts (blue) and novices (red), and for (B) the 8 kg box (blue) and the 12 kg box (orange). Gray areas represent time intervals during which there were significant main effects of (A) expertise and (B) box-mass.

Novices lifted the box earlier and beld the box in a more elevated position longer as shown in Figure 4 (significant difference in box elevation between 28 and 79%trial (lifting and deposit phases) (ES=0.53[medium]; p<0.001)). Note that at the end of the deposit phase, novices held the box slightly lower than experts (significant difference in box elevation between 90 and 97%trial (ES=0.47; p=0.025)).

[Please insert Figure 4 here]

Figure 4: Mean (solid lines) and standard deviation (shaded areas) of box elevation over time, for experts (blue) and novices (red). Gray areas represent time intervals during which there were significant main effects.

Novices held the box 1% further from their body between 33 and 55%trial (lifting phase) (ES=0.53[medium], p=0.001) as shown in Figure 5. At the end of the deposit phase (between 86 and 99%trial), novices kept the box 5% closer to their body (ES=0.58[medium], p=0.001).

[Please insert Figure 5 here]

Figure 5: Mean (solid lines) and standard deviation (shaded areas) of box-thorax distance over time, for experts (blue) and novices (red). Gray areas represent time intervals during which there were significant main effects.

Electromyography

Overall, cumulative EMG muscle activation was 37% higher for novices from 45 to 52%trial (lifting phase) (ES=0.51[medium], p=0.01) (Figure 6A). However, cumulative EMG muscle activation distributions were similar between groups (Figure 6B).

[Please insert Figure 6 here]

Figure 6: (A) Sum of EMG muscle activations, and (B) empirical cumulative distribution function (ECDF) of EMG muscle activations by expertise. The ECDF can be represented graphically as the percentile (x axis) associated with each value (y axis); e.g. 70% of EMG data are below an activation of 20% MVC. Solid lines represent participants' mean, and

shaded areas represent standard deviations. Gray areas represent time intervals during which there were significant main effects.

The muscle activation was higher for novices in the anterior deltoid between 43 and 62%trial (lifting and beginning of deposit phase) (ES=0.73[medium], p<0.001), the lateral deltoid between 48 and 63%trial (lifting and beginning of deposit phase) (ES=0.67[medium], p<0.001), the upper trapezius between 47 and 62%trial (lifting and beginning of deposit phase) (ES=0.65[medium], p<0.001), and the supraspinatus between 59 and 77%trial (end of lifting and deposit phase) (ES=0.75[medium], p<0.001) and between 79 and 91%trial (deposit phase) (ES=0.64[medium], p<0.001). The muscle activation was lower for novices in the biceps between 53 and 66%trial (lifting and deposit phases) (ES=0.83[large], p<0.001), the triceps between 95 and 100%trial (deposit phase) (ES=0.66[medium], p<0.001), and the pectoralis between 69 and 79%trial (deposit phase) (ES=0.70[medium], p<0.001) (Figure 7).

[Please insert Figure 7 here]

Figure 7: EMG muscle activations over time, for experts (blue) and novices (red). Solid lines represent participants' mean, and shaded areas represent standard deviations. Gray areas represent time intervals during which there were significant main effects. *Deltant*: anterior deltoid; *deltlat*: lateral deltoid; *deltpost*: posterior deltoid; *uptrap*: upper trapezius; *pect*: pectoralis major; *ssp*: supraspinatus; *isp*: infraspinatus; *subs*: subscapularis.

Musculoskeletal model

The sum of estimated muscle activations and muscle forces, both obtained with the musculoskeletal model, were characterized by two peaks that did not clearly corresponded to different lifting phases. Statistical analyses revealed that novices had a lower estimated muscle activations from 55 to 78%trial (lifting and deposit phases) (ES=0.58[medium], $p<0.001$) (Figure 8A), and a 354 N lower sum of muscle forces from 54 to 77%trial (lifting and deposit phases) (ES=0.58[medium], $p<0.001$) (Figure 8B).

[Please insert Figure 8 here]

Figure 8: Sum of estimated muscle activations (A), and muscle forces (B) estimated using static optimization, with expertise as a main effect. Experts are displayed in blue and novices in red. The solid line represents the mean, and the shaded area represents the standard deviation. Gray areas represent time intervals during which there were significant main effects.

When comparing empirical cumulative distribution functions, estimated muscle activations (Figure 9A) distributed from the 69th to the 97th percentile were 6%MVC lower in novices (ES=0.32, $p<0.001$). Similarly, muscle forces (Figure 9B) distributed from the 68th to the 99th percentile were 25 N lower in novices (ES=0.24, $p<0.001$).

[Please insert Figure 9 here]

Figure 9: Empirical cumulative distribution function (ECDF) of estimated muscle activations (A), and muscle forces (B) calculated from static optimization, with expertise as a main effect. Experts are displayed in blue and novices in red. The ECDF can be represented graphically as the percentile (x axis) associated with each value (y axis); e.g. in (A) 80% of estimated activation data are below an activation of 20% MVC for novices, in (B) 80% of estimated force data are below 90N for novices. The solid line represents the

mean of all muscles sorted ascending and the shaded area represents the standard deviation. Gray areas represent time intervals during which there were significant main effects.

Discussion

This study aimed to highlight the biomechanics characteristics of the shoulder that differentiate novices from experts during an ecological box-handling task (i.e. similar to occupational conditions) using a 3D analysis of upper body kinematics, electromyography, and biomechanical modelling. The main results was that in comparison to novices, experts solicited their lower limbs to a greater extent, limiting the contribution of the entire arm, while keeping the trunk in a more neutral position. This may represent a safer approach from the perspective of overuse injury prevention. Novices were also more prone to lifting the box earlier, and to holding the box in a higher position for a longer duration compared to experts. This strategy resulted in higher EMG muscle activations in novices, especially in anterior and lateral deltoids, upper trapezius, and the supraspinatus.

Positioning in relation to expertise

While the lower body kinematics were not directly measured during the experiment, results showed that the pelvo-thoracic joint contribution (including the pelvis vertical displacement controlled only by lower-limbs) in experts was lower than in novices during the pulling phase. These results suggests a slight knee/ankle flexion was performed to reach the box from the table, which confirm the visual observations made during the experiment. This also corresponds with the findings of Plamondon et al., (2010, 2012), who showed an effect of expertise on posture while reaching for the box, and its impact on the back loading. Experts also demonstrated greater sternoclavicular and acromioclavicular joint contributions, which suggests that experts may have a better stabilization or coordination of the shoulder joint during the pulling and the lifting phases. The lower contribution of the elbow and the glenohumeral joints in experts compared to novices suggests that they held the box closer to their body during these phases (pulling and lifting), which was confirmed by the box-thorax distance measure. This result is in accordance with the results reported by Plamondon et al., (2014) indicating that experts held the box closer to their bodies than novices during a handling task. This technique reduces the moment created by the weight of the box on the shoulder joint, which could therefore reduce stress on the upper limb. This kinematic compensation could also influence the directions of muscle forces, allowing less activation for the same level of joint stability (Arwert et al., 1997). In addition to reducing loading on the spine (Marras et al., 2006), this technique could also be a key factor in reducing shoulder injuries as it limits muscle forces during the most extreme part of the joint range of motion (Kim et al., 2003).

Between the lifting and deposit phases, both groups slightly extended the trunk and lower limbs to increase their reach. This technique would reduce shoulder stress by making greater use of the trunk and lower body during the deposit phase, when the box is held at its maximum elevation (Kim et al., 2003). The lower contribution of the elbow and the glenohumeral joints in experts compared to novices suggests that they held the box closer to their body during these phases, which was confirmed by the box-thorax distance measure, and the higher activation of the anterior and lateral deltoids in novices, as well as the higher biceps activation in experts. The two groups also used a similar technique where shoulder flexion in the sagittal plane accounted for about 60% of the height reached by the box. This was the only phase where novices used the sternoclavicular and acromioclavicular joints more than experts. The higher solicitation of these joints, potentially placing the novices at a higher risk of injury, could be a compensatory strategy to ensure sufficient force to move the box and to allow the arms to potentially go further forward. Such kinematics would cause inadequate strengthening of the shoulder muscles in the long term, which could increase the risk of injury (Ludewig & Reynolds, 2009). This highlight the importance of early intervention for workers before they become accustomed to this problematic kinematic strategy. During the deposit phase, experts also had a greater activation of triceps and pectoralis than novices, while novices had a greater activation of supraspinatus to maintain shoulder stability, placing them potentially at a higher risk of injury.

Our results also showed that novices lifted the box earlier and maintained the box higher than the experts during the half of the total movement duration. This strategy could involve a greater recruitment of the shoulder joint and muscles. Additionally, the lever arm created by the box position relative to the spine may increase the loading in the lumbar region, as shown by Plamondon et al., (2014; 2010). This strategy could also lead to higher loading on the shoulder joints and higher use of rotator cuff muscles (SSP) to maintain the stability, and potentially result in increased risk of injury for shoulder muscles of novices. Visual inspections of videos revealed that experts tend to perform the task in sequence (i.e. turning and then lifting the box) more than novices who combined the multifaceted task at the same time (i.e. lifting the box while turning). This displacement before lifting the box (used by experts) is in accordance with previous workplace health and safety recommendations, such as staying close to the load, pivoting to face the dropping area, and segmenting the task instead of doing the transition as fast as possible (Denis et al., 2013; Graveling et al., 2003). The higher box-thorax distance in experts near the end of the deposit phase could increase the loading on the experts' shoulders. However, the recruited experts did not had a higher muscle activation than novices in the deposit phase and had a low lifetime incidence of injuries. Observations made during the experiment as well as video recording suggested a different strategy was used by the experts, wherein they dropped the box at the end of the deposit phase, presumably as they would do in an industry setting to improve their efficiency. Therefore, this result is probably not a risk factor of injury in experts.

Muscle activations and forces in manual handling

The sum of EMG muscle activations was found to have two peaks (at around 10%trial and at around 75%trial), with a higher local maxima for the second one. This difference in amplitude could be explained by the increase of box elevation, but also by increased muscle activity perhaps employed in an attempt to set the box down in a controlled manner that avoids excessive impact forces (Westerhoff et al., 2009). The greater sum of EMG muscle activation of novices during the lifting phase, and more particularly the higher EMG activation of anterior deltoid, lateral deltoid, upper trapezius, and supraspinatus are in accordance with kinematic findings showing that novices lifted the box earlier and maintained the box in high position longer compared to experts. This strategy could generate muscle fatigue earlier in novices, placing them in a higher risk of injury (Côté, 2014; Hanvold et al., 2015).

Results related to estimated muscle activations and forces are influenced by the model and its limitations. The absence of distinct peaks on the sum of estimated muscle activations (compared to the measured EMG activation data) is probably due to the limitations of the static optimization algorithm used (Gottlieb, 2000). Muscle contraction provides the strength necessary to perform a specific movement, and to stabilize the shoulder joint. Minimizing the sum of activations during static optimization will estimate the dynamic contribution of muscles but will neglect the co-contraction component that is present for stabilization. This is also reflected in the difference between the activations estimated by the model (Figure 8) and those measured experimentally (Figure 6).

The absence of co-activation in the model is also observed in the differences between the distribution of muscle activations estimated by the musculoskeletal model and experimental data. The distribution of estimated activations is somewhat polarized, whereas the measured EMG activations have a more balanced distribution throughout the spectrum. The contribution of synergistic muscles is under-estimated in the musculoskeletal analysis which could explain the limited activation of these muscles and higher activation in agonist muscles.

Limitations

Limitations come mainly from musculoskeletal modelling. First, muscles have been simplified as a set of lines of actions. Their respective trajectories have been validated using basic movements (Wu et al., 2016). These trajectories might however, not be physiological throughout the whole trial during manual handling tasks. Second, generic muscle parameters were used. Since the model scaling was limited to a geometric one, the muscle properties did not express the individuality of each participant (n=32), nor the variability between the two groups in terms of muscle properties (e.g. isometric strength and optimal fibre length). The implementation of a calibration process (Appendix) after the anthropometric scaling using an EMG informed algorithm could be implemented to improve the personalization of the models (Lloyd & Besier, 2003; Wu et al., 2016). The use of an EMG informed algorithm has been found to predict activation patterns more accurately for the glenohumeral joint muscles during a lifting task as this algorithm accounts for co-contraction (Assila et al. 2020). However, this approach is sensitive to the calibration process, and seems to overestimate the glenohumeral joint reaction forces. Thus, further work is needed to improve the calibration process to improve this method results. Finally, the limited activation of various muscles could also be a result of the static optimization as it has been reported to underestimate the activation of antagonist muscles (Kian et al., 2019).

The results of static optimization also depend on the force data collected by the instrumented box. The instrumented box was specially created for this study to measure forces at many points, while offering a multitude of gripping possibilities. Although it was designed to be similar to boxes a worker would encounter, the instrumented box had a less rigid frame. Three load cells were connected to an internal frame for a total mass of 8 kg, with weight added to the centroid to achieve 12 kg. Noise in the load cell data was apparent and could have resulted from internal connections that were not ideally rigid (especially at the impact of the deposit phase) and which could not be easily eliminated by filtering the signals without risk of losing its important characteristics (*e.g.* peaks expected when the box is placed on the shelf).

With regard to joint kinematics, soft tissue artefacts may influence shoulder kinematics. In accordance with previous findings (Begon et al., 2017; Michaud et al., 2017), a multibody kinematic optimization was used with the Jackson et al. (2012) model and a thorax-sized ellipsoid was added, to prevent penetration of the thorax by the scapula. As we were comparing two populations, we considered that a visual validation of the scapula kinematics is sufficient to discuss the differences in muscles activation tendencies, and thus draw conclusions as to the effect of expertise on injury risk.

It is possible that the age played a role in differences in muscle activation patterns between groups. However, it is most likely that novice workers would be younger in age than their expert counterparts and so we believe that this difference is acceptable.

Conclusion

Differences in shoulder joint health according to expertise level must be considered as a complex multi-causal phenomenon. Work technique is one of the many factors that may contribute to differences in injuries related to expertise. Considering experts as reference, (as novice workers are often exposed to higher risks of injury), our results suggest that bending the knees to reach the box would be safer for the shoulder, as well as for the back. Bringing the box closer to the body during a handling task is also likely a safer strategy. In addition, when needed, performing the displacement with the load closer to the body is likely safer than lifting the load while pivoting. This could decrease the contribution of the prime mover muscles as well as the stabilizer.

Key points

- Sternoclavicular-acromioclavicular joint contributions were higher in experts at the beginning of the movement, and in novices at the end.
- The glenohumeral joint contribution was higher in novices at the beginning of the movement, and in experts at the end.
- EMG activation levels were higher in novices, placing them in a higher risk of injury.
- Estimated muscle activations and forces were higher in experts.

Author Contributions

EG drafted the manuscript. RM was involved in the data collection, analyzed data, and was involved in the critical revision of the manuscript for intellectual content. NA was involved in the data analysis and in the critical revision of the manuscript for intellectual content. EMD was involved in the data collection and was involved in the critical revision of the manuscript for intellectual content. JDM was involved in the data analysis and in the critical revision of the manuscript for intellectual content. FDM and MB, the lead scientists, helped in all facets of the project. All authors read and approved the final manuscript.

Conflict of Interest

The authors have no conflict of interest to report.

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Appendix

Submaximal contractions and MVC tests

Table 1: Description of the submaximal contractions and MVC tests

Target muscle	Names	Poses	Instructions
DeltA	Shoulder flexion 90º	Seated	Arm flexed at 90º, palm of the hand facing down. Arm flexion with resistance at the elbow.
DeltL	Shoulder abduction 90º	Seated	Arm abducted at 90º, palm of the hand facing down. Arm abduction with resistance at the elbow.
DeltP	Prone extension 90º	Prone	Arm horizontally abducted at 90º, elbow flexed at 90º. Horizontal arm abduction with resistance at the elbow.
Biceps	Elbow flexion 90º	Seated	Arm at the side, elbow flexed at 30° in supination. Elbow flexion with resistance at the wrist.
Triceps	Elbow extension	Seated	Arm at the side, elbow flexed at 30° in supination. Elbow extension with resistance at the wrist.
UpTrap	Abduction 90º	Seated	Arm abducted at 90º, neck side-bent to the same side, head rotated toward the opposite side, palm of the hand facing down. Arm abduction with resistance at the head and elbow.
Pec	Palm press	Seated	Arms flexed at 90º, elbows lightly flexed, palms of the hands together. Pressing hands together with no external resistance.
SSP	Abduction 0º	Side-lying	Arm at the side, palm of the hand facing down. Arm abduction with resistance at the wrist.
ISP	External rotation 0º	Side-lying	Arm at the side, elbow flexed at 90º. Arm external rotation with resistance at the wrist.
Subs	Lift-off test	Prone	Back hand in contact with the upper lumbar spine. Arm internal rotation with resistance at the hand.

To calculate MVC of each muscle, all MVC trials were used. Data were sorted in decreasing order and the MVC value was determined as the median of the first second in the resulting signal. This list accounts for each of the MVC listed in Table 2 in Dal Maso et al., (2016), for the muscles of interest in this study.

Data processing: Kinematic data

Centres of rotation of the pelvis, trunk and wrist joints were located using SCoRE algorithm (Ehrig et al., 2006) and the sternoclavicular, acromioclavicular and glenohumeral joints were located according to bony landmarks (Michaud et al., 2016). The flexion and pronation-supination elbow axes of rotation were defined using the SARA algorithm (Ehrig et al., 2006). Then, a 25 degree-of-freedom (DoF) kinematic model was generated from the static acquisition and the located joint centres/axes (pelvis and thorax [6 DoF each], sternoclavicular and acromioclavicular joints [3 DoF each], glenohumeral joint [3 DoF], elbow and wrist joints [2 DoF each]). A thorax-sized ellipsoid fitting the area browsed by the scapula was added to the model to better estimate the scapular kinematics (Michaud et al. 2017).

Data processing: Custom Wu shoulder model

Arm muscles

Two lines of action for the biceps brachii, and the long head of the triceps brachii were added to the model to account for the contribution of the arm muscles to the glenohumeral joint.

Wrapping objects

We modified the wrapping objects to avoid sudden changes in muscle trajectories, lighten the model and duplicate objects to prevent using a single object for several muscles. Wrapping object dimensions were modified as needed while preserving the muscles lengths. The active quadrants of the wrapping objects have been identified to reduce singular points. Ellipsoidal objects have been reduced to a minimum, and replaced by cylindrical objects. This change should reduce the computation time, without influencing the trajectories for our range of motion.

Muscle lengths

We modified the normalized muscle lengths to maintain them within a physiological range [0.5;1.5]. We analysed muscle lengths during high amplitude trials for all participants to identify muscles with low (generation of minimal effort) or high (high passive force) lengths. The normalized lengths of these muscles have been modified by changing the optimal fiber lengths and/or changing the dimensions of the wrapping objects. The modifications were made, while respecting the initial values of the lever arms of each muscle with respect to each degree of freedom. The modified muscles are the anterior serratus anterior, the rhomboid and the pectoralis minor.

Muscles abbreviations

BICB	biceps brachii short head
BICL	biceps brachii long head
CORB	coracobrachialis
DELT1	anterior deltoid
DELT2	lateral deltoid
DELT3	posterior deltoid
INFSP	infraspinatus
LAT	latissimus dorsi
LVS	levator scapulae
PECM1	pectoralis major superior
PECM2	pectoralis major medial
PECM3	pectoralis major inferior
PMN	pectoralis minor
RMJ1	rhomboid major superior
RMJ2	rhomboid major inferior
RMN	rhomboid minor
SBCL	subclavius
SRA1	serratus anterior superior
SRA2	serratus anterior medial
SRA3	serratus anterior inferior
SUBSC	subscapularis
SUPSP	supraspinatus
TMAJ	teres major
TMIN	teres minor
TRIC	triceps brachii
TRP1	upper trapezius
TRP2	middle trapezius superior
TRP3	middle trapezius inferior
TRP4	lower trapezius

Briefly, the alterations to the model were done in an iterative way, comparing the evolution of the muscle length and moment arms of each muscle to those of the original model for all participants. Modifications were made only when we could observe a non-physiological muscle trajectory in the original model (e.g., double wrapping, non-respect of the wrapping constraint). The Wu et al., (2016) shoulder model allows for unprescribed scapular motion. No scapulothoracic rhythm on the scapula was imposed. We used the same marker positions as in Jackson et al., (2012) and optimized the markers weighting for the inverse kinematics step. We based these choices on the results reported by Blache & Begon, (2018).

Data processing: Static optimisation

Residual actuators were added to the wrist, elbow, glenohumeral, acromioclavicular, sternoclavicular as well as at the base of the model (thorax) and the box. These actuator forces compensate for simplifications in the present model configuration (such as the absence of a lower body) that might prevent the solver from converging on muscle forces that correspond to the prescribed kinematics and external forces (Hicks et al., 2015).

Data processing: Calibration process

The calibration process aims to personalize parameters related to muscle contraction dynamics. While the scaling process insures anthropometrical scaling, it can not express differences between participants in the maximal isometric force of the muscle or the fiber optimal length. Consequently, the predicted forces using a generic scaled or a subject-specific scaled models can be significantly different (Wu et al., 2016). These parameters needs to go through an additional tuning step. This step is a numerical optimization that seeks to minimize the tracking error of the joint moments. Wu et al., (2016) used the maximal voluntary contraction test for this calibration, considering that the muscles that contribute positively to the joint moment are fully activated, whereas the others are not activated. Lloyd & Besier (2003) used the experimental EMG to actuate the model and tuned the muscle activation and contraction dynamics to generate the moment calculated with inverse dynamics. While both methods have particular limitations related to the hypotheses used, they remain relatively costly from a computational point of view, particularly for studies with large number of participants.

Box speed

[Please insert Figure 10 here]

Figure 10: Box speed in the vertical direction as a function of box elevation. Novices moved the box faster than experts and with constant acceleration.

Density of predicted activation

The density of predicted activation of each muscle (Figure 11 left) shows that many muscles have low activation (100% of time < 20% MVIC), especially for SBCL, TRP4, RMJ1, PECM3, LAT, RMJ2, RMN, DELT3, TRP3, tric_long, SRA3, TMAJ, TMIN. The five muscles most activated were TRP1, SUBSC, PECM1, bic_l, INFSP, each with a large activation range. The density of muscle forces for each muscle (Figure 11, right panel) show similar results with many muscles lightly solicited (100% of time < 100 N) (SBCL, TRP4, RMJ1, PECM3, LAT, RMJ2, RMN, DELT3, TRP3, tric_long, SRA3, TMAJ), and a similar muscle group with high forces (TRP1, SUBSC, PECM1, bic_l, INFSP).

[Please insert Figure 11 here]

Figure 11: Distribution of predicted muscle activations (left panel), and muscle forces (right panel) calculated from static optimization for each muscle. Muscles are sorted in decreasing order. The distribution is approximated using Kernel Density Estimation, and normalized so that the sum of each distribution is equal to one.

Figures

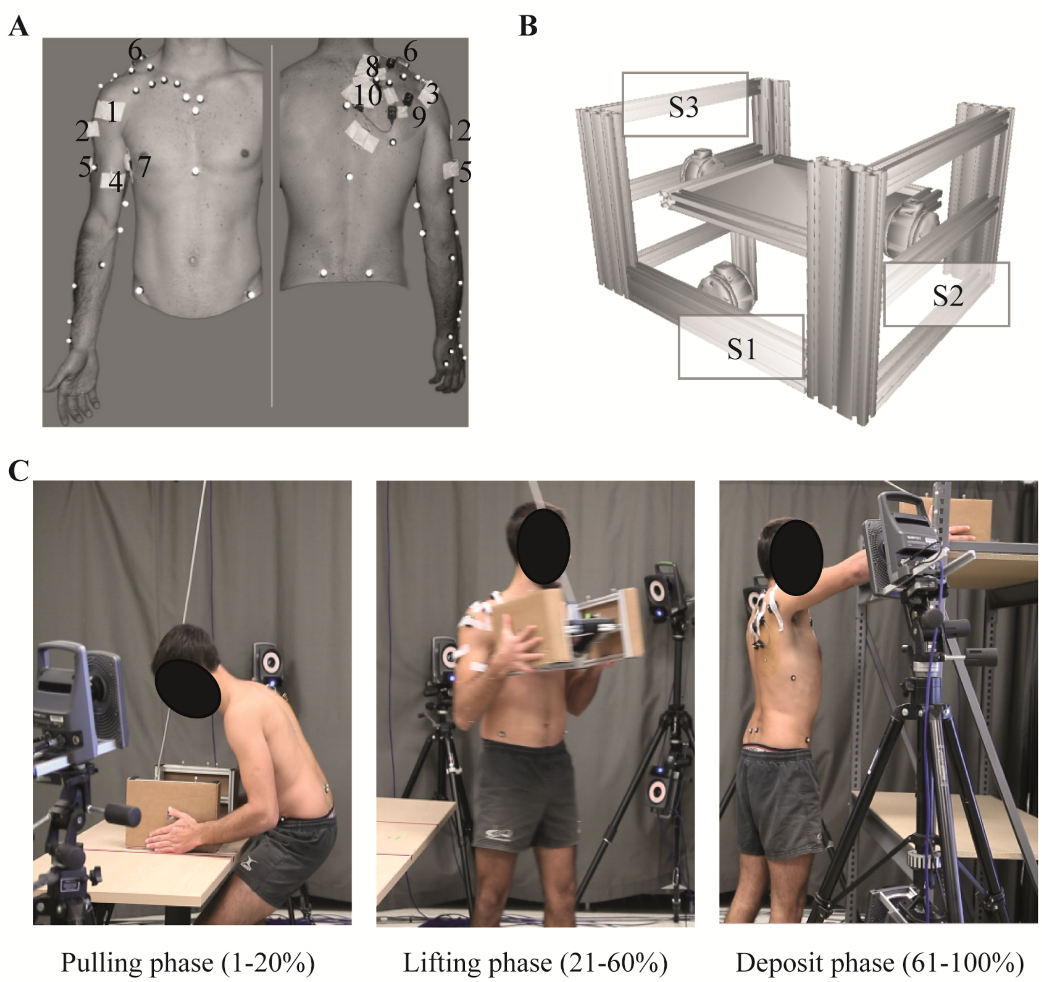
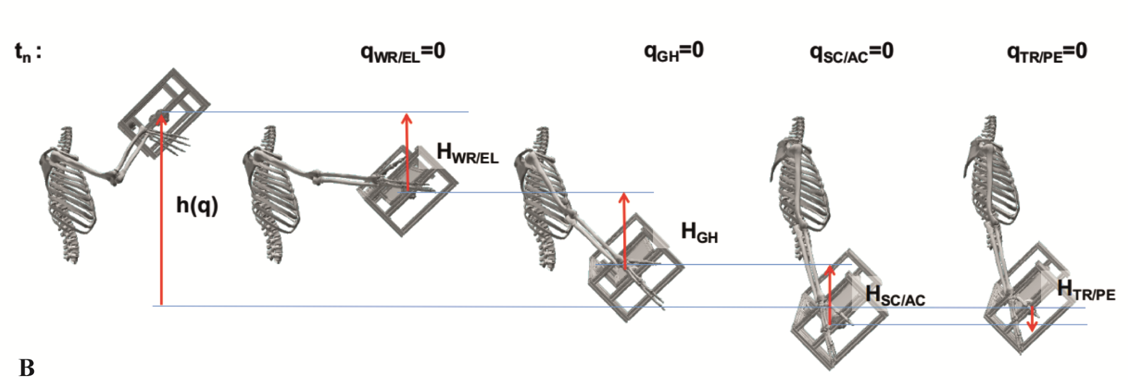


Figure 1

A



B

Figure 2A

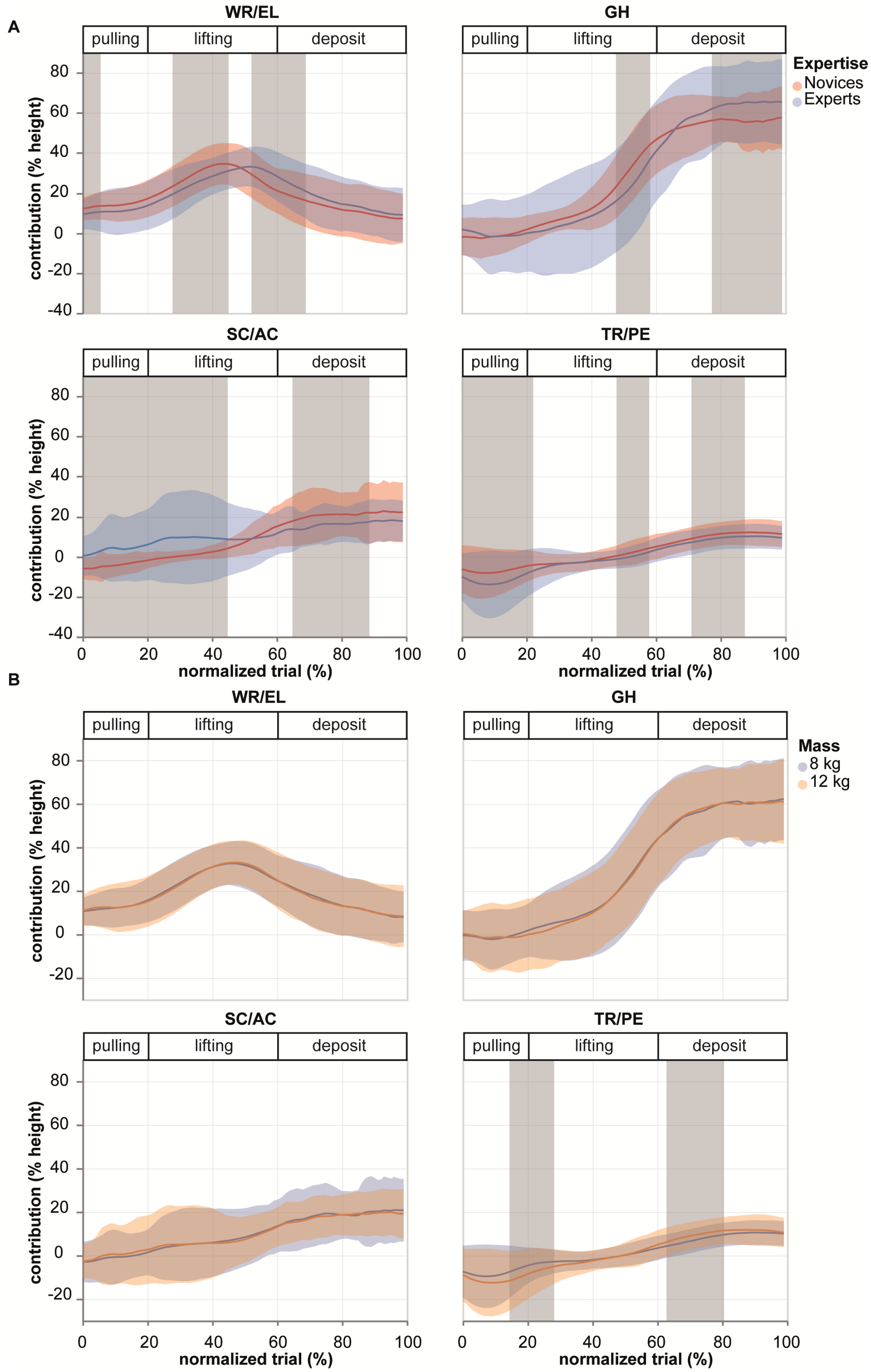

A
WR/EL
GH
SC/AC
TR/PE
pulling
lifting
deposit
Expertise
Novices
Experts
contribution (% height)
normalized trial (%)
B
Mass
8 kg
12 kg

Figure 3

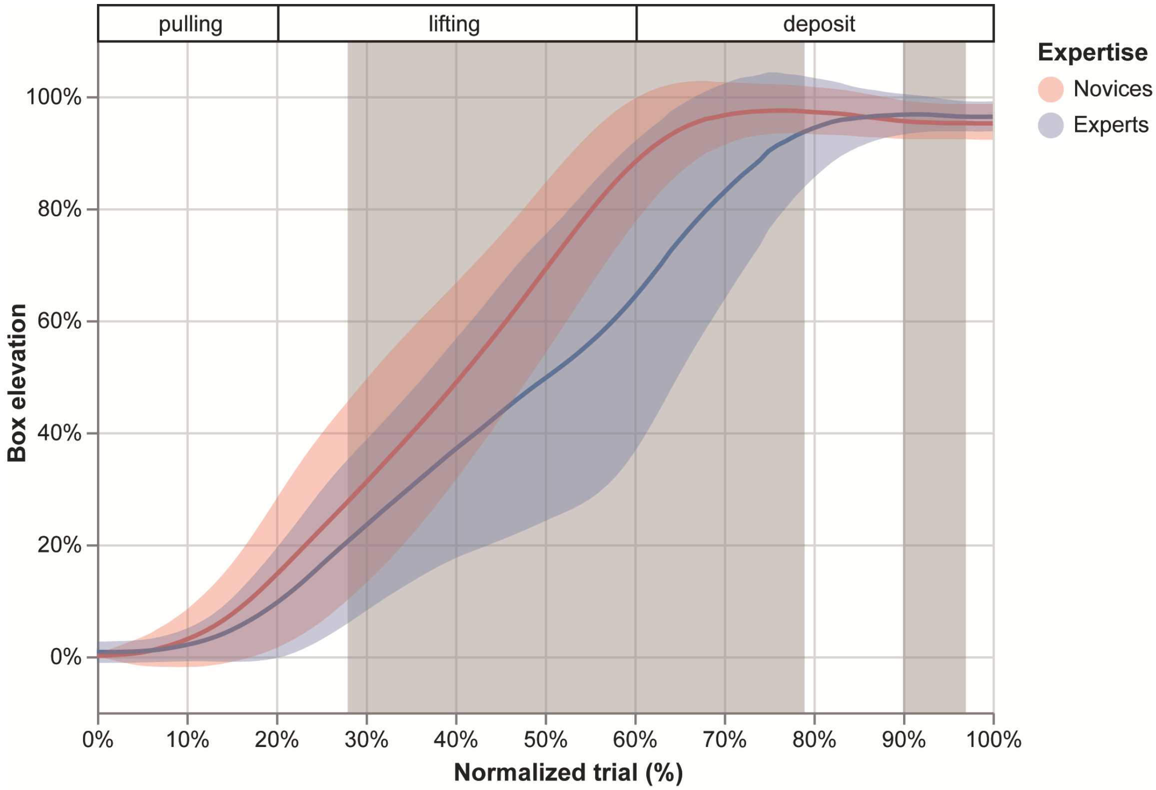

pulling
lifting
deposit
Expertise
Novices
Experts
100%
80%
60%
40%
20%
0%
Box elevation
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Normalized trial (%)

Figure 4

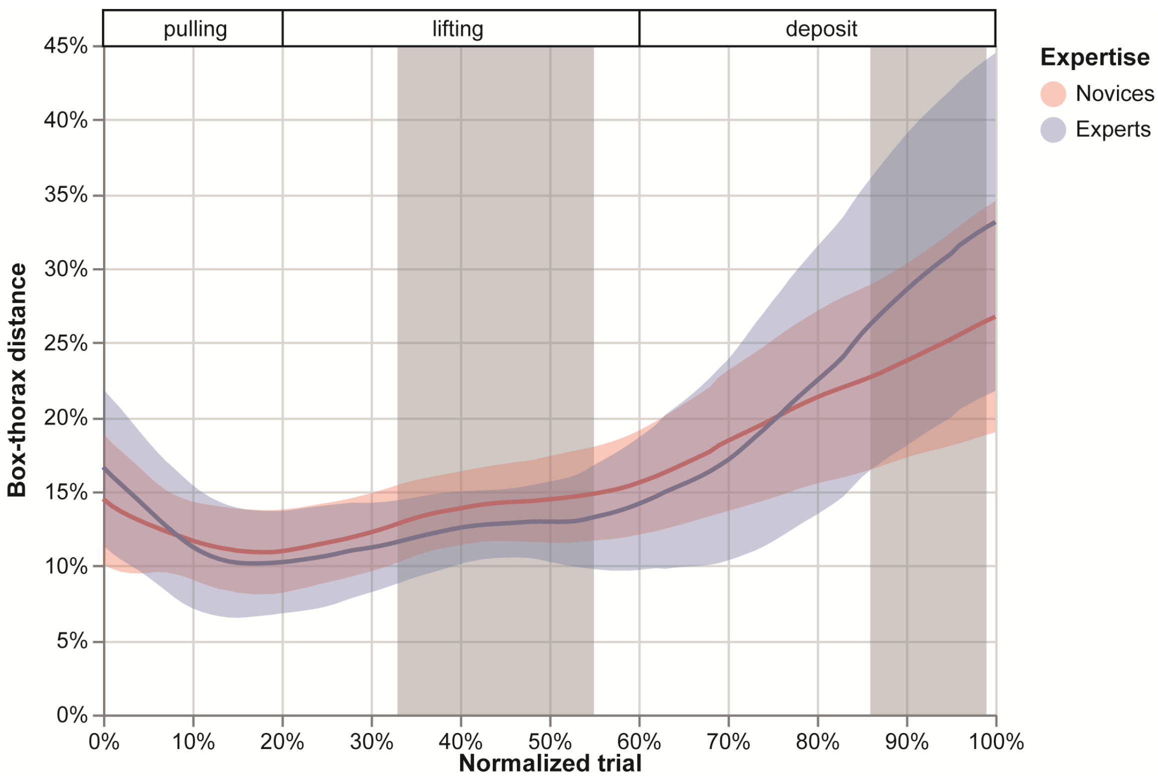


Figure 5

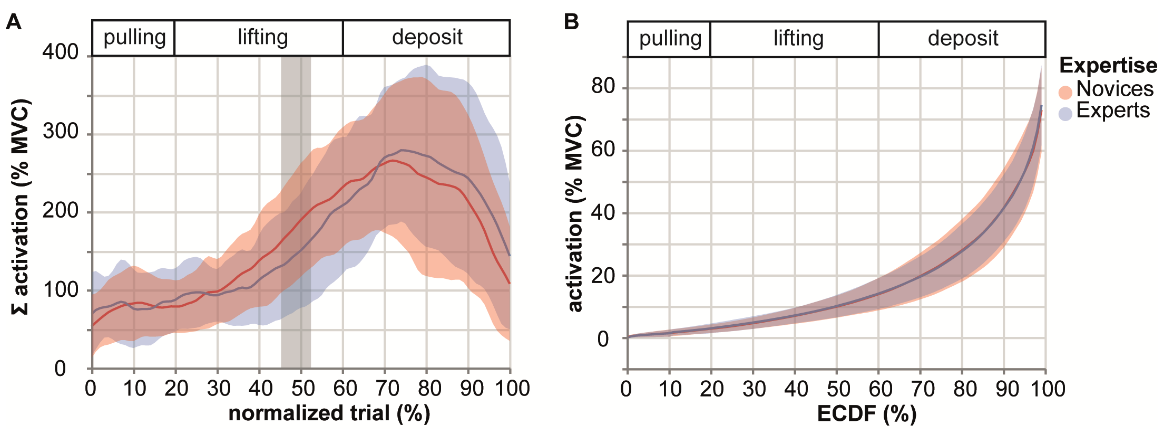


Figure 6

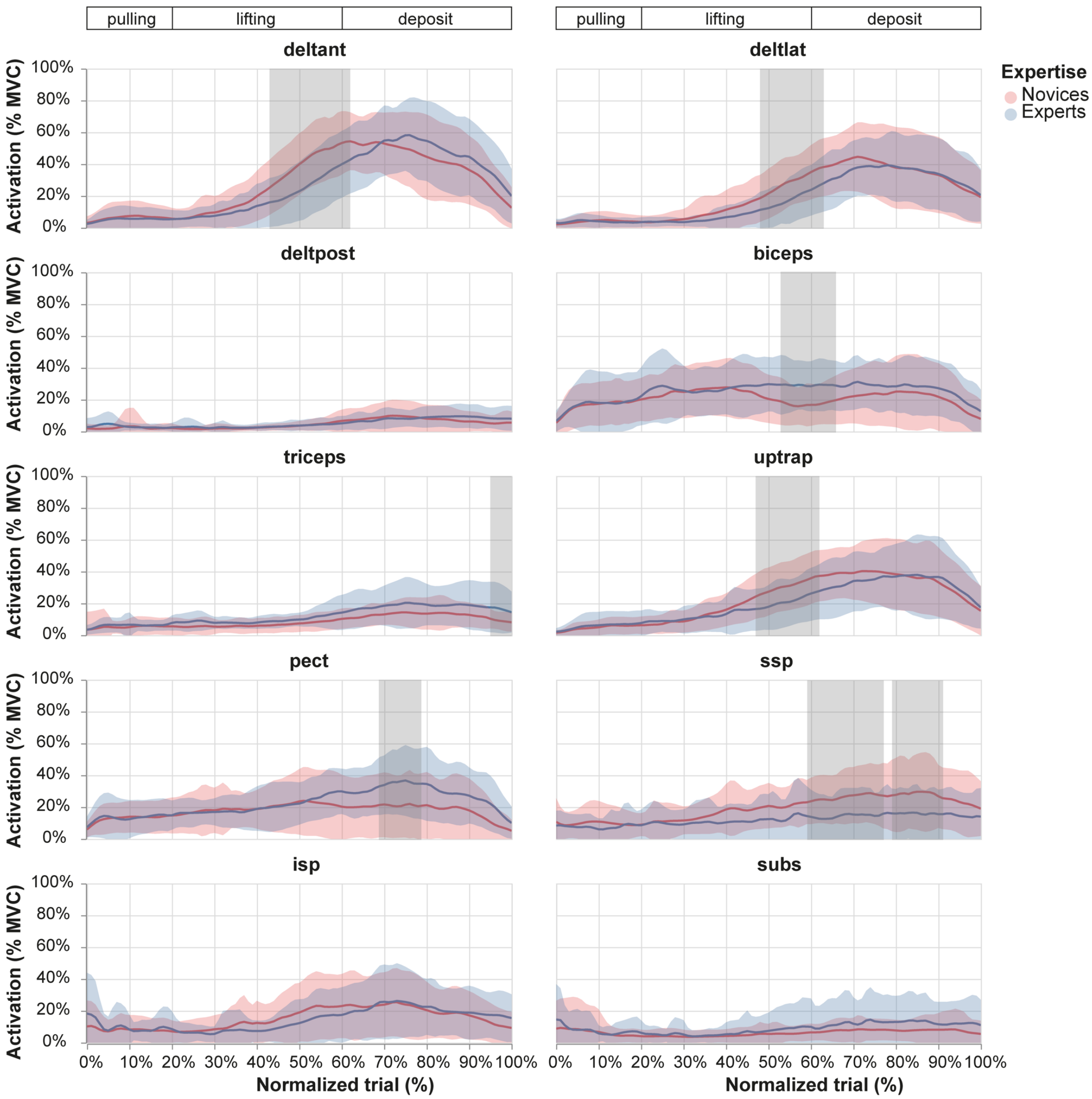

pulling
lifting
deposit
deltant
deltlat
deltpost
biceps
triceps
uptrap
pect
ssp
isp
subs
Activation (% MVC)
100%
80%
60%
40%
20%
0%
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Normalized trial (%)
Expertise
Novices
Experts

Figure 7

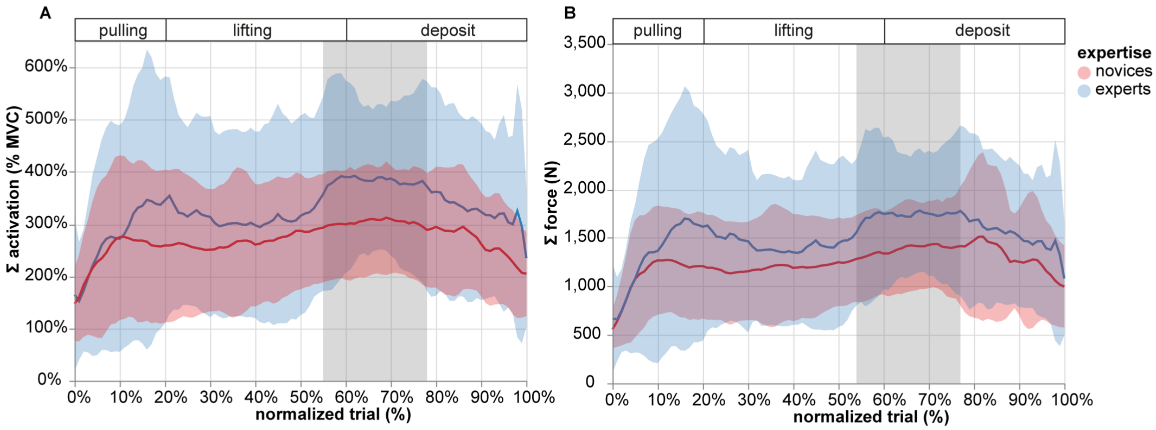


Figure 8

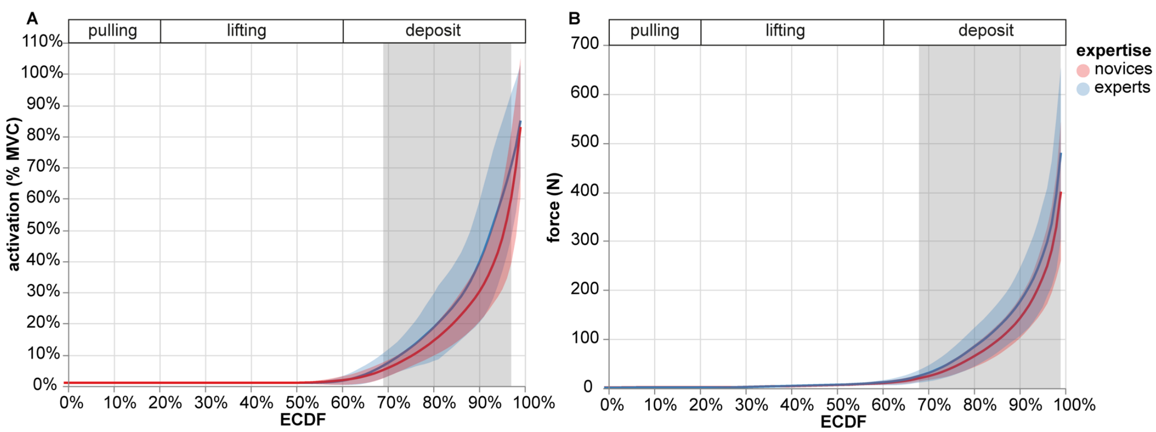


Figure 9

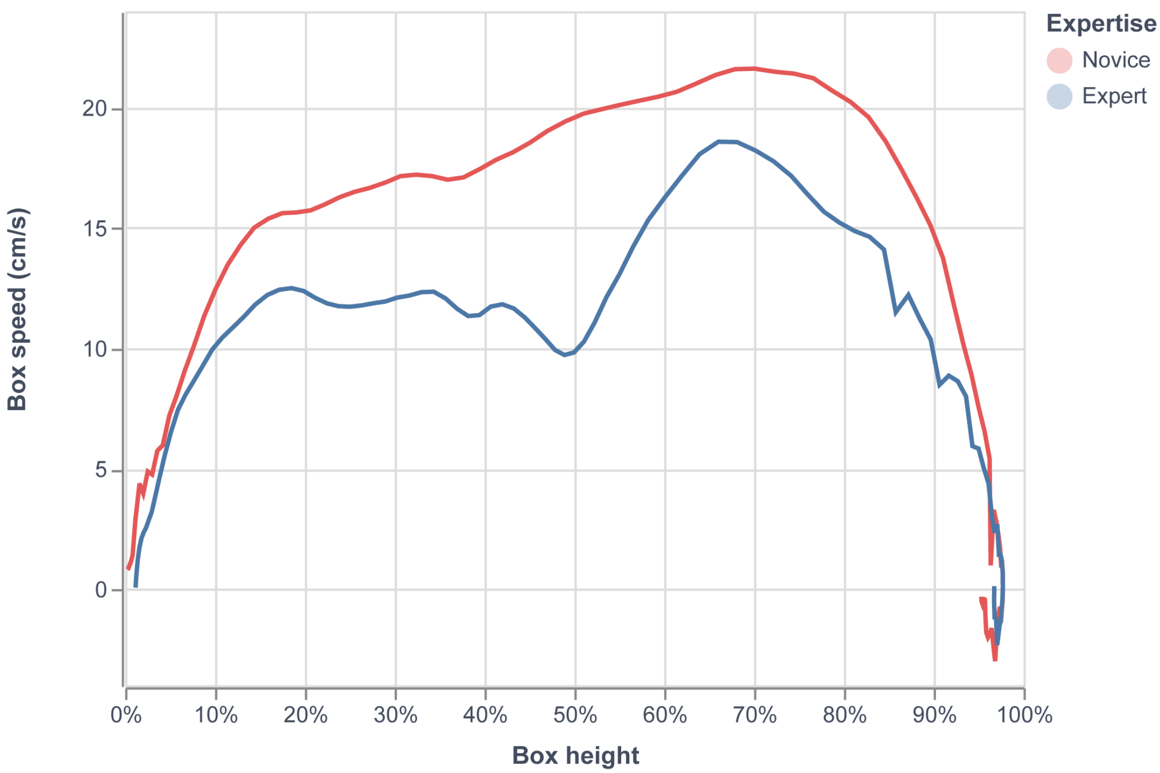

Expertise
Novice
Expert
Box speed (cm/s)
20
15
10
5
0
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Box height

Figure A1

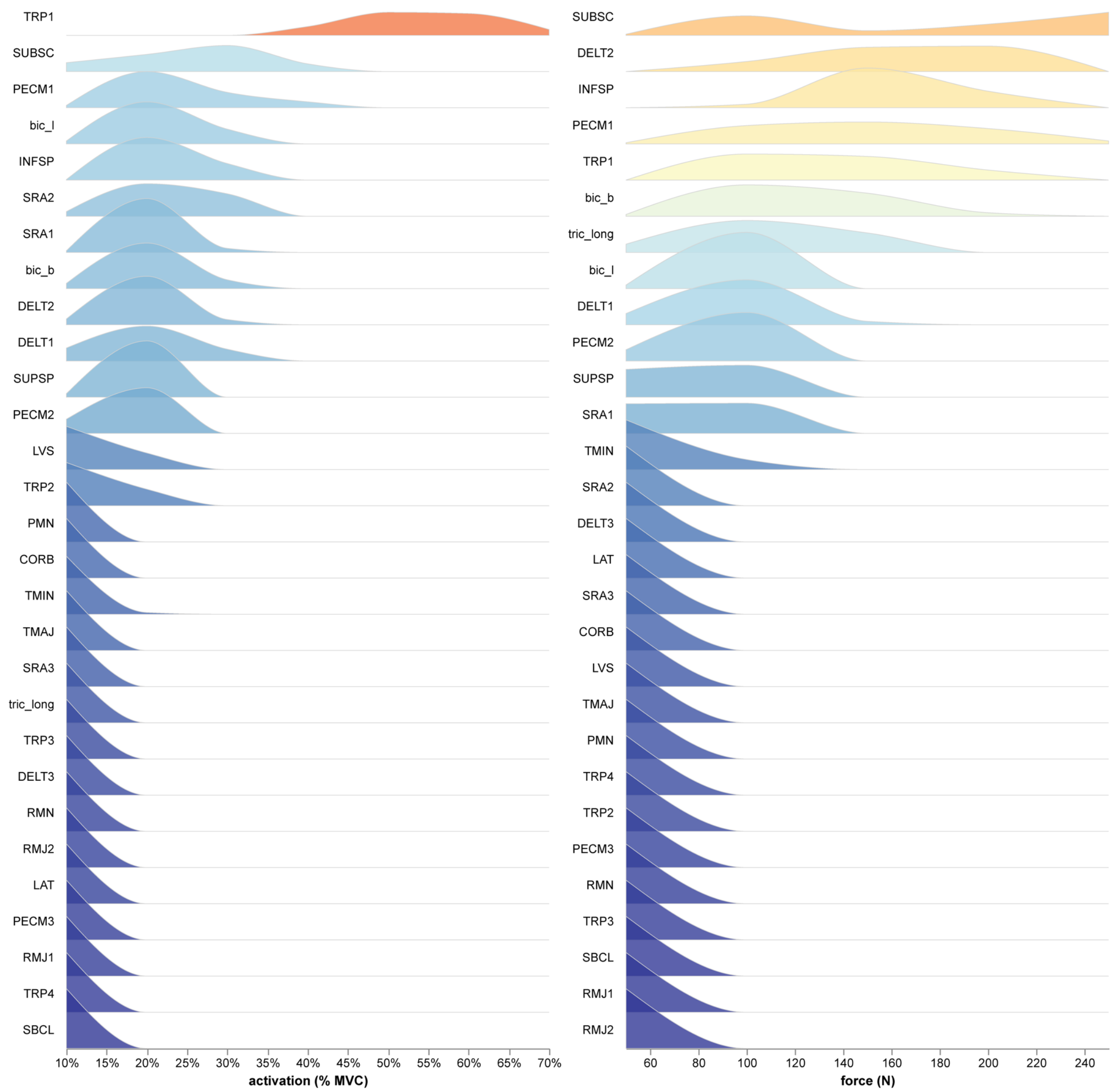

TRP1
SUBSC
PECM1
bic_l
INFSP
SRA2
SRA1
bic_b
DELT2
DELT1
SUPSP
PECM2
LVS
TRP2
PMN
CORB
TMIN
TMAJ
SRA3
tric_long
TRP3
DELT3
RMN
RMJ2
LAT
PECM3
RMJ1
TRP4
SBCL
10% 15% 20% 25% 30% 35% 40% 45% 50% 55% 60% 65% 70%
activation (% MVC)
SUBSC
DELT2
INFSP
PECM1
TRP1
bic_b
tric_long
bic_l
DELT1
PECM2
SUPSP
SRA1
TMIN
SRA2
DELT3
LAT
SRA3
CORB
LVS
TMAJ
PMN
TRP4
TRP2
PECM3
RMN
TRP3
SBCL
RMJ1
RMJ2
60 80 100 120 140 160 180 200 220 240
force (N)

Figure A2