Consistent individual motor variability traits demonstrated by females performing a long-cycle assembly task under conditions differing in temporal organisation

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A B S T R A C T

Research suggests an association between motor variability (MV) during repetitive work and work-related musculoskeletal disorders (MSDs). However, whether MV control is a consistent individual trait, even across working conditions or tasks, remains unknown. This study assessed whether individual MV traits were consistent during complex work performed under different temporal conditions.

Fifteen women performed cyclic assembly under four conditions differing in pace and organisation (line-type, batch-type). MV of trapezius muscle activity and upper arm elevation was quantified and partitioned into variance components.

For all MV metrics, a non-zero between-subjects variance was found, indicating consistent individual MV traits across conditions. Variance between subjects was higher for electromyography (EMG) MV metrics compared with kinematic metrics.

Our results showed individuals exhibited consistent MV traits across working conditions differing in pace and production process. Further research is needed to understand whether MV is an individual predictive factor for MSD onset or progression.

1. Introduction

Repetitive work is generally accepted to be associated with increased risk of work related musculoskeletal disorders (MSDs), particularly in the shoulder and hand-arm regions for short work-cycle tasks performed over a major part of the day (Bernard, 1997; Buckle and Devereux, 2002; Larsson et al., 2007; National Research Council, 2001). Despite modern ergonomic improvements, repetitive work remains common in many sectors, for example, food processing (Juel-Kristensen et al., 2002; Madeleine et al., 2008b; Ohlsson et al., 1994) and packing (Leclerc et al., 2001), light assembly, clothing and shoe industries (Leclerc et al., 2001), factory work (Fallentin et al., 2001), animal pelt skinning (Tabata-baeifar et al., 2017) and for super market cashiers (Leclerc et al., 2001).

Individuals performing the same repetitive work have been shown to differ in terms of MSD susceptibility (Kilbom and Persson, 1987; Nordander et al., 2016, 2013; Veiersted et al., 1993). Individual motor variability (MV) traits may be an underlying contributing factor to this individual susceptibility (Madeleine, 2010; Madeleine et al., 2003; Mathiassen, 2006; Mathiassen et al., 2003; Sandlund et al., 2017; Veiersted et al., 1993). MV is the spatiotemporal dispersion of joint movements, joint coordination, and muscle activation levels between successive repeats of a same task (Srinivasan and Mathiassen, 2012). MV is an inherent property of the motor control system that is even present when an individual attempts to perform identical repeats of a task (Newell and Corcos, 1993). MV is present for highly controlled repetitive tasks, characteristic of cyclic assembly work, as has been previously shown both in the lab (ex. (Granata et al., 1995; Hammarskjöld et al., 1990; Jackson et al., 2009; Srinivasan et al., 2015a; Van Dienen et al., 2001)) and in the field (ex. (Christensen et al., 2000; Fethke et al., 2007; Moller et al., 2004)). MV occurs despite a worker consistently maintaining ‘perfect’ performance or production since successful task executions can be accomplished via myriad movement combinations and muscle recruitment strategies.

MV magnitude has been shown to differ across workers (Mathiassen et al., 2010; Madeleine et al., 2003; Mathiassen, 2006; Mathiassen et al., 2003; Sandlund et al., 2017; Veiersted et al., 1993). MV is the spatiotemporal dispersion of joint movements, joint coordination, and muscle activation levels between successive repeats of a same task (Srinivasan and Mathiassen, 2012). MV is an inherent property of the motor control system that is even present when an individual attempts to perform identical repeats of a task (Newell and Corcos, 1993). MV is present for highly controlled repetitive tasks, characteristic of cyclic assembly work, as has been previously shown both in the lab (ex. (Granata et al., 1995; Hammarskjöld et al., 1990; Jackson et al., 2009; Srinivasan et al., 2015a; Van Dienen et al., 2001)) and in the field (ex. (Christensen et al., 2000; Fethke et al., 2007; Moller et al., 2004)). MV occurs despite a worker consistently maintaining ‘perfect’ performance or production since successful task executions can be accomplished via myriad movement combinations and muscle recruitment strategies.

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et al., 2003; Srinivasan et al., 2015a; Van Dienen et al., 2001). Workers who perform work in a highly stereotyped way, either due to a natural predisposition or due to learned patterns, have been proposed to be at higher risk for developing MSDs than workers who utilise the flexibility offered by the motor system and are more variable in the way they perform work – the so-called ‘Repeater and Replacer Hypothesis’ (Sandlund et al., 2017). Individual MSD susceptibility based on the extent of MV is in line with prominent muscle recruitment theories. Consider first, the ‘Cinderella Hypothesis’ (Hagg, 1991), which suggests motor units are recruited in a consistent order to increase tension in a muscle, and subsequently de-recruited in the opposite order – that is, motor units with the lowest recruitment threshold are the first ‘on’ and last ‘off’, and are therefore likely to experience increased MSD risk. When a repetitive task is performed, individuals who perform the task in a highly stereotyped way (i.e. repeaters) will place a high demand on the low-threshold fibres in the muscle(s) that are consistently recruited. In contrast, individuals who demonstrate higher motor variability (i.e. replacers) either by shifting activity within a muscle (Fallà and Farina, 2007; Farina et al., 2008; Thorn et al., 2002) or between muscles (Palmer et al., 1995) may be at lower risk for MSDs. Redistribution of muscle activity between fibres within a muscle may reflect a mechanism to counteract fatigue (Fallà and Farina, 2007) and may occur according to the principal of motor unit substitution (Westgaard and De Luca, 1999), which suggests a varying recruitment threshold of motor units depending on their activation history. Assessing MV in muscle activity recordings may therefore serve as a proxy measurement for different types of muscle recruitment substitution patterns, and help identify low-MV subjects at increased risk of ‘Cinderella-prone’ low-threshold fibre injury.

For the repeater-replacer hypothesis to hold true, individual MV traits must be consistent: that is, a particular individual must be consistent in demonstrating low MV (i.e. a ‘repeater’) or high MV (i.e. a ‘replacer’) across cycles, days, paces, production process and, ultimately, different tasks. However, the extent to which individual MV traits are so generally consistent it is not yet known. To date, consistent individual variability traits have been confirmed across cycles for several short-cycle repetitive tasks, including walking (Konig et al., 2014) and pipetting (Sandlund et al., 2017; Srinivasan et al., 2015a). Individual MV traits were further shown to be consistent between days for the pipetting task (Sandlund et al., 2017) and for a repetitive short-cycle screwing task (Luger et al., 2019). Whether individual motor variability traits remain consistent for more complex repetitive tasks, for tasks differing in temporal organisation (i.e., differing in pace or production process), or across completely different tasks remains unknown.

The aim of this study was, therefore, to determine if consistent individual MV traits were evident in female workers performing a long-cycle assembly task under four temporal organisation conditions that differed in pace and production process. We hypothesized that a unique component of variance between subjects would be evident in MV metrics, indicating consistent individual MV traits. Further, we hypothesized that some individuals would consistently demonstrate higher magnitudes of MV across MV metrics, as captured by the relative magnitude of within-subject variance on these metrics, while others would consistently demonstrate lower amounts of MV across MV metrics.

2. Methods

Data were collected as part of a larger study, which received ethical approval from the Internal Review Board at the Liberty Mutual Research Institute for Safety.

2.1. Participants

Healthy, right-handed women, aged 18–45 years, were recruited from the greater Boston area via newspaper announcement. All recruits completed a health questionnaire and signed an informed consent. Recruits were excluded if they reported having had repeated feeling of numbness, tingling, or pins and needles sensations in their hands, forearms, elbows or neck during the preceding six months, or had a history of MSDs or rheumatoid conditions. A total of 23 candidate women met the inclusion criteria and participated in a job training phase; of these, 15 passed the timed proficiency test and entered the experimental phase (see Section 2.2). The 15 participants had mean age 33.3 years (SD 9.1, range 18–45), mean stature 1.66 m (SD 0.06, range 1.58–1.75), mean mass 69.9 kg (SD 16.3, range 45.4–113.4) and mean body mass index of 25.4 kg/m² (SD 5.4, range 17.7–39.2).

2.2. Experimental task and conditions

Participants performed a simulated industrial assembly task in which they removed a base plate from an ‘in-box’, placed the plate in a wooden jig, drove screws into four holes in the plate using a counter-balanced pneumatic drill (nine holes were present and subjects were required to select the four correct locations), turned over the assembly product, added four spacers (1 per screw), placed a top plate over the spacers, fastened the top plate in place using one wing nut per screw (as seen in Fig. 1), and placed the completed product in an ‘out-box’. The assembly task comprised gross motor movements, including reaching, and fine motor skills, including aligning screws with threaded holes. The experimental workstation and final assembly product are shown in Fig. 2.

To assess the impact of temporal organisation on MV, four conditions differing in pace and production process were created. A pre-determined cycle time was calculated for the work task using the Maynard Operation Sequence Technique (MOST©) (Zandin, 1990) methods-time measurement (MTM) system. To simulate industrial work time pressures akin to those experienced by workers paid on piecework, an average performance time standard of 110 MTM pacing was selected (i.e. 110% as fast as the operational pre-determined standard time) for all fixed-pace conditions. Three assembly paces (self-paced, 110 MTM, 120 MTM), and two production process (batch and assembly-line) were considered. The degree of autonomy for each condition was determined by both pace (ex. minimal breaks were afforded at 120 MTM) and production process (higher autonomy with batch-type than line-type work).

The four conditions were:

SP - Self-paced. Participants were instructed to work as if paid on piece-work at a pace sustainable for 8-h. No fixed production pace was imposed.

B-110 - Batch-type. All components and a clock were provided at the beginning of the work bout and participants were instructed to complete 36 assemblies within 30 min (equivalent to an average pace of 110 MTM, 51s average cycle time).

L-110 - Line-type. New components were provided at the start of each new cycle based on 110 MTM pacing (36 assemblies, 51s average cycle time).

L-120 - Line-type with forced breaks. New components were provided at the start of each new cycle based on 120 MTM pacing, and a 15s break was inserted after every sixth assembly cycle (equivalent to an average pace of 110 MTM pacing, 46s average cycle time).

2.3. Training and experimental protocols

To ensure task familiarity under all conditions, candidates completed three training days, concluding with a 10-min proficiency test. Only candidates demonstrating proficiency at 120 MTM gained entry to the experimental phase of the study. This proficiency cut-off was deemed to indicate secure proficiency at 110 MTM pacing and was required for the L-120 condition. During both the training and experimental phases, visits were interspaced by a minimum of one day and a maximum of four days.

During the 2-day experimental phase, participants worked in 30-min
bouts, alternating between assembly and disassembly (not used in the current paper) interspersed by 15 min rest breaks. The SP condition was scheduled first on day 1 and last on day 2. The L-110 condition was randomly scheduled on both days, then conditions B-110 and L-120 were randomly assigned in the two remaining slots.

2.4. Experimental measures

2.4.1. Kinematics

Movement data were captured using a five camera Eagle system (Motion Analysis, California, U.S.A.), with markers placed atop the distal portion of the acromion process (‘shoulder’) and the lateral epicondyle (‘elbow’) of the right arm – Fig. 1. Upper arm elevation angles were calculated as the angle between the vector joining these markers and a vertical reference vector taken while participants leaned towards their right side until their right arm was hanging vertically, while holding a 1 kg weight in the right hand to assist in ensuring a straight arm (Bernmark and Wiktorin, 2002; Hansson et al., 2006; Leijon et al., 2005).

2.4.2. Electromyography

EMG data were collected from the right trapezius muscle, with electrodes centred 2 cm lateral to the midpoint of the line between C7 and the acromion process (Veiersted, 1991) (Fig. 1). At the recording site, skin was shaved then cleaned with alcohol prior to applying a disposable two snap Ag-AgCl electrode, 2 cm inter-electrode distance, (Noraxon Dual Electrode – Arizona, USA) aligned along the length of the muscle fibers. A single snap ground electrode (Noraxon Single Electrode – Arizona, USA) was positioned atop a prominent thoracic vertebra (usually T1). A rest file and four sub-maximal reference voluntary exertion (RVE) normalisation trials were collected at the beginning of each experimental day. For RVE trials, each subject sat upright, looking straight ahead at a marker positioned at eye level, arms abducted 90° in the frontal plane with elbows fully extended, wrists straight and palms down (Mathiassen, et al., 1995). RVE trials were 15 s in duration (Åkesson et al., 1997; Hansson et al., 2000) interspaced by 30 s of rest. Each subject’s mean amplitude across a stable 10s period from each of the four RVE trials was used to normalise their EMG data.

EMG signals were pre-amplified (gain 500) at a distance of 6.5 cm from the recording site and telemetrically transmitted to the central receiver (Noraxon TeleMyo 2400R, Noraxon, USA). Signals were band-pass filtered (Butterworth 10–500 Hz), A/D converted using a 12 bit National Instruments A/D card and sampled at 1000 Hz. Kinematic data were captured at 50 Hz. All data were continuously monitored in real time to assure data quality and recorded using Evart software (Motion Analysis, California, USA). Synchronized analogue data were collected from limit switches mounted on the out- and in-boxes, signalling the start and stop of each assembly.

2.5. Data selection and processing

Post collection, EMG signals were Butterworth filtered (30 Hz high pass) for minimization of electrocardiogram (ECG) contamination (Drake and Callaghan, 2006), offset corrected, and root-mean-square (RMS) converted (100 ms moving window), then quadratically rest adjusted. All files were visually inspected to ensure good data quality. Kinematic and EMG data were partitioned to individual cycles using the limit switch data. Individual cycles were excluded if they contained: erroneous or missing ‘start’ or ‘stop’ data; participant error(s) which resulted in an incomplete assembly; or obvious non-biological noise.

2.5.1. Motor variability metrics

We included a comprehensive selection of metrics addressing both within- and between-cycle variability, summarized in terms of both means across cycles and dispersions between cycles. A similar selection of variables was used by Luger et al. (2017) in a study of a repetitive pick-and-place task intended to simulate occupational work.

For each cycle, the mean and within-cycle standard deviation of EMG amplitudes (EMGmean, EMGsd) and upper arm elevation angles (UAEmean, UAESD) were calculated. These metrics characterized the central value (mean exposure) and the within-cycle variability, respectively (Mathiassen, 2006).

For each subject, day and condition, summary measures were calculated by averaging across the within-cycle central tendency and variability metrics. For exposure amplitude, a simple average was taken across the set of cycles for each condition on each day (EMGmean of means, EMGsd of sd).
Table 1
Motor variability metrics calculated across cycles for each subject and condition.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Calculation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-value per-cycle metrics&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>EMG&lt;sub&gt;mean of means&lt;/sub&gt;</td>
<td>Mean trapezius EMG amplitude</td>
</tr>
<tr>
<td>2</td>
<td>EMG&lt;sub&gt;mean of SDs&lt;/sub&gt;</td>
<td>RMS mean of the within-cycle standard deviations in EMG amplitude</td>
</tr>
<tr>
<td>3</td>
<td>EMG&lt;sub&gt;SD of means&lt;/sub&gt;</td>
<td>Standard deviation across cycles in mean EMG amplitude</td>
</tr>
<tr>
<td>4</td>
<td>EMG&lt;sub&gt;SD of SDs&lt;/sub&gt;</td>
<td>Standard deviation across cycles of the within-cycle standard deviation in EMG amplitude</td>
</tr>
<tr>
<td>5</td>
<td>UAEA&lt;sub&gt;mean of means&lt;/sub&gt;</td>
<td>Mean UAEA amplitude</td>
</tr>
<tr>
<td>6</td>
<td>UAEA&lt;sub&gt;mean of SDs&lt;/sub&gt;</td>
<td>RMS mean of the within-cycle standard deviations in UAEA</td>
</tr>
<tr>
<td>7</td>
<td>UAEA&lt;sub&gt;SD of means&lt;/sub&gt;</td>
<td>Standard deviation across cycles of mean UAEA</td>
</tr>
<tr>
<td>8</td>
<td>UAEA&lt;sub&gt;SD of SDs&lt;/sub&gt;</td>
<td>Standard deviation across cycles of the within-cycle standard deviation in UAEA</td>
</tr>
<tr>
<td>Point-by-point within-cycle metrics&lt;sup&gt;b&lt;/sup&gt;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>UAEA&lt;sub&gt;mean of PP-SDs&lt;/sub&gt;</td>
<td>RMS mean of point-by-point standard deviations between cycles</td>
</tr>
</tbody>
</table>

<sup>a</sup> To simplify the nomenclature, ‘mean’ is used for both a simple arithmetic mean, used with additive variables (variables 1 & 5), and for RMS mean, used for standard deviation variables (2, 6 & 9). Similarly, SD is used without specifying if it is within within-cycles (ex. 2 & 6), between-cycles (ex. 3, 7, 9), or first within and then between cycles (ex. 4 & 8).

UAEA<sub>mean of means</sub>. For variability, an RMS approach was used to compute the mean of SDs across the set of n cycles for each condition on each day (EMG<sub>mean of SDs</sub>, UAEA<sub>mean of SDs</sub>), for example:

\[
\text{UAEA}_{\text{mean of SDs}} = \sqrt{\frac{\sum_n \text{UAEA}_{\text{SD of SDs}}^2}{n}}
\]

Mean values across participants for each metric were calculated to characterize work under each condition.

Between-cycle variability was calculated as the standard deviation of the mean exposure amplitude across the set of cycles for each condition and subject (EMG<sub>SD of means</sub>, UAEA<sub>SD of means</sub>). Between-cycle variability of within-cycle variability was calculated as the standard deviation of within-cycle variability (EMG<sub>SD of SDs</sub>, UAEA<sub>SD of SDs</sub>) values across the set of cycles for each condition and day (EMG<sub>SD of SDs</sub>, UAEA<sub>SD of SDs</sub>).

All of the above metrics were based on a single-value-per-cycle approach where a single value was used to describe both the average exposure and the within-cycle variability for each cycle, and summary values were subsequently calculated across cycles for each day. While straightforward and representative of the most common current approaches for assessing variability, salient differences in timing between cycles may be missed. Thus, a more rigorous version of the UAEA<sub>SD of means</sub> metric was created using a point-by-point approach to quantify the differences between cycles in UAEAs as a function of time (Srinivasan et al., 2015a).

To examine whether cycle times differed for work conducted under the three experimental work phases (110 MTM, 120 MTM and self-paced), a repeated measures ANOVA for cycle time was conducted.

The total variability of the data set was partitioned according to the mixed effects model (Searle et al., 2006):

\[
E_{\text{cov}} = \mu + \beta_s \cdot \alpha_i = e_{\text{cov}}
\]

where \(E_{\text{cov}}\) is the measured value of the exposure parameter for a specific condition \(c\), subject \(s\) and day \(r\), \(\mu\) is the group grand mean; \(\beta_s\) is the fixed effect due to condition; \(\alpha_i\) is the random effect of subject; and \(e_{\text{cov}}\) is the residual. \(\beta_s\) has, by definition, a sum of zero across all conditions. Both random effects (\(\alpha_i\), \(e_{\text{cov}}\)) were assumed to be independently and identically distributed, to have zero covariance between any pair of values and to have a mean of zero.

To rule out the possibility of a systematic effect of day on dependent variables, paired t-tests with Holm’s correction for multiple comparisons were performed on all metrics for the L-110 and self-paced conditions (p < 0.05 significance criterion).

Since no systematic effect for day was found for any metric, the mixed-effects model was resolved using a REML procedure in JMP® Pro (Version 14, SAS Institute Inc., Cary, NC) to estimate the variance between subjects (\(S^2_{\text{WS}}\), i.e. the variance of \(\alpha_i\)) and between days within subject (\(S^2_{\text{WB}}\), i.e. the variance of \(e_{\text{cov}}\)) with 95% confidence intervals. The fixed effect of condition was also tested, and when significant (p < 0.05), post hoc pairwise comparisons of least squares means using the Tukey-Kramer Honestly Significant Difference tests were performed to determine which specific pairs of conditions differed.

Table 2
EMG and kinematic descriptive metrics by condition.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Average cycle time</th>
<th>EMG&lt;sub&gt;mean of means&lt;/sub&gt; (%RVE)</th>
<th>EMG&lt;sub&gt;mean of SDs&lt;/sub&gt; (% RVE)</th>
<th>UAEA&lt;sub&gt;mean of means&lt;/sub&gt;</th>
<th>UAEA&lt;sub&gt;mean of SDs&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>L-110</td>
<td>45.7&lt;sup&gt;b&lt;/sup&gt;</td>
<td>111.9</td>
<td>56.7</td>
<td>52.1</td>
<td>10.8</td>
</tr>
<tr>
<td>b-110</td>
<td>46.0&lt;sup&gt;a&lt;/sup&gt;</td>
<td>100.7</td>
<td>51.4</td>
<td>51.2</td>
<td>10.9</td>
</tr>
<tr>
<td>L-120</td>
<td>44.5&lt;sup&gt;c&lt;/sup&gt;</td>
<td>122.1</td>
<td>62.5</td>
<td>52.8</td>
<td>11.0</td>
</tr>
<tr>
<td>SP</td>
<td>47.3&lt;sup&gt;a&lt;/sup&gt;</td>
<td>104.9</td>
<td>53.8</td>
<td>51.4</td>
<td>11.2</td>
</tr>
</tbody>
</table>

<sup>a,b,c</sup> Significantly differing conditions indicated by different superscripts.
3. Results

3.1. Work task

Average cycle time across conditions ranged from 44.5s for L-120 to 47.3s for SP work (Table 2). Cycle times for all conditions with predetermined MTM standards (L-110, B-110, L-120) were below the required cycle times (51s for 110 MTM work and 46s for 120 MTM work) indicating the performance standards were met.

A repeated measures ANOVA showed cycle time differed across conditions (p < 0.01). Pairwise t-tests with Holm’s correction for multiple comparisons showed cycle times from the L-120 condition were faster than for all other conditions, and cycle times from self-paced work were slower than all other conditions (Table 2). No difference was found between cycle times for line-type and batch-type work conducted at the 110 MTM pace. These data confirmed that work was performed at three different work paces, as intended.

The average trapezius muscle activity during the assembly task ranged from 105%RVE to 122%RVE and the average upper arm elevation angle ranged from 51 to 53 (Table 2). Work cycles completed under the L-120 condition tended to show the highest amplitude mean and variability across cycles, while work cycles performed at the B-110 condition tended to show the lowest mean amplitude and variability (Table 2).

The effect of condition was statistically significant for most EMG metrics (EMGmean of means - EMGSD of means - EMGSD of SDs) and one kinematic metric (UAEAmean of SDs) - Table 3. Post-hoc analyses for these metrics showed that assembly work performed at 120 MTM pace tended to be more variable than work performed at slower paces, as suggested even by the results shown in Table 2. These data show that the temporal organisation of work could significantly impact the magnitude of MV, particularly for trapezius muscle activity. Further, these data show that the four conditions differed sufficiently that MV changes occurred, as intended.

Table 3: Differences in exposure level and variability between conditions.

<table>
<thead>
<tr>
<th>Variable</th>
<th>F-ratio</th>
<th>Prob.</th>
<th>Pos Hoc Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>EMGmean of means</td>
<td>3.34</td>
<td>0.024</td>
<td>L-120 condition had significantly larger mean amplitude than condition B-110 (MD - 21.32%RVE, 95%CI 1.31–41.31)</td>
</tr>
<tr>
<td>EMGmean of SDs</td>
<td>0.92</td>
<td>0.436</td>
<td>NA</td>
</tr>
<tr>
<td>EMGSD of means</td>
<td>3.90</td>
<td>0.012</td>
<td>L-120 condition had significantly larger variance across cycles in mean amplitude than conditions B-110 (MD 11.07, 95%CI 1.75–20.40) and SP (MD 8.70, 95% CI 0.62–16.77)</td>
</tr>
<tr>
<td>EMGSD of SDs</td>
<td>3.43</td>
<td>0.021</td>
<td>L-120 condition had significantly larger variance between cycles in within-cycle variance than conditions L-110 (MD 1.26, 95% CI 0.08–2.44) and SP (MD 1.32, 95% CI 0.14–2.50)</td>
</tr>
<tr>
<td>UAEAmean of means</td>
<td>1.05</td>
<td>0.378</td>
<td>NA</td>
</tr>
<tr>
<td>UAEAmean of SDs</td>
<td>3.45</td>
<td>0.021</td>
<td>L-120 condition had significantly larger average within cycle SD than from B-110 (MD 0.301, 95%CI 0.012–0.590) and SP (MD 0.276, 95% CI 0.027–0.525)</td>
</tr>
<tr>
<td>UAEA2SD of means</td>
<td>1.05</td>
<td>0.378</td>
<td>NA</td>
</tr>
<tr>
<td>UAEA2SD of SDs</td>
<td>1.54</td>
<td>0.213</td>
<td>NA</td>
</tr>
<tr>
<td>UAEA3mean of PP-SDs</td>
<td>1.15</td>
<td>0.336</td>
<td>NA</td>
</tr>
</tbody>
</table>

MD mean difference.

3.2. Consistency of individual motor variability traits

Individual subjects tended to demonstrate consistent MV levels across days and conditions for all EMG and kinematic MV metrics, suggesting consistent individual MV traits. Consistency across conditions was evident in the clustering of the four markers (representing the four conditions) for each subject for all MV metrics, as shown in Fig. 3 and supplemental data, Fig. 1. In these figures, each marker represents the average of the 36 cycles performed at a condition for a subject for the specific motor variability metric shown in the figure.

The rank order of subjects based on magnitude of variability was also generally consistent across all EMG and kinematic MV metrics, as seen in the relatively consistent ordering of subjects across metrics, as seen on the x-axis in Fig. 3A and B and Supplemental Material Fig. 1A to E. Subjects 5, 7, 10, 14, and 16 consistently ranked in the lower half of all subjects for at least 6 of the 7 MV metrics, and thus demonstrated more repeatable MV traits. Conversely, subjects 2, 6, 11, and 12 consistently ranked in the top half of all subjects for at least 6 of the 7 MV metrics, and thus demonstrated more variable motor control strategies.

The observations of consistent individual MV traits are supported quantitatively by the variance component analyses. For all metrics, with the possible exception of UAEAmean of SDs, the 95% confidence intervals for the between-subject variance component clearly did not contain zero, implying that subjects systematically differed from one another (Table 4, S^2BS with 95% CIs).

For all metrics, a 95% confidence interval not including zero was also found for the within-subject-between-days variance component, implying that a consistent MV difference was found within each subject between days. However, for all EMG metrics and UAEA2SD of means, the non-overlapping 95% confidence intervals for S^2BS and S^2WS indicated that the variance between subjects was markedly higher than the within-subject variance between days. Among these metrics, variance due to subject was 3- to 19-times larger than the variance due to day, underlining the dominance of the between-subject variance, particularly for the EMG metrics. The larger magnitude of between-subject variance compared with within-subject variance for EMG MV metrics is also reflected in the relative sizes of the CVs: CVWS ranged from 0.65 to 0.80 while CVBS ranged from 0.17 to 0.33.

4. Discussion

Individual MV traits were demonstrated by workers performing a long-cycle assembly task under four working conditions differing in temporal organisation. This finding was evident in the consistent rank-order of subjects in MV magnitude across conditions, and in the non-zero between-subjects variance components found for all MV metrics. Previous studies have shown consistent individual MV traits across days for a simple, short-cycle repetitive task (Samani et al., 2015; Sandlund et al., 2017; Srinivasan et al., 2015a); our data now show consistent individual traits for a complex, long-cycle repetitive task, and across working conditions differing in pace and production process.

The temporal organisation of work was changed by altering both pace and production process. Our data confirmed that across the implemented changes resulted in assembly work that was performed at three different speeds (range 44.5s–47.3s), and which resulted in different mean exposure levels (mean trapezius amplitude range: 100.7–122.1 %RVE; mean upper arm elevation angle range: 51.2–52.8°). The changes in temporal organisation also resulted in different average sizes of MV for several of the MV metrics. Together these data confirm that the implemented changes altered the task sufficiently, and that work was performed differently.

All metrics showed a variance between days, indicating subjects performed the assembly work differently, to some degree, on different days; however, this variance was relatively small compared to the variance between subjects, particularly for EMG metrics. A markedly larger between-subjects variability is in line with previous findings from
our research group during a highly standardized short-cycle task (pipetting) (Sandlund et al., 2017) as well as other studies where both within- and between-subjects variability have been considered (Luger et al., 2017; Perez and Nussbaum, 2006; Zare et al., 2018), and it further emphasizes that the extent of MV may, to a considerable extent, be a personal trait.

In this study, we considered MV metrics which we believed relevant and accessible to clinicians and researchers alike. Additional MV metrics have also been proposed in previous studies of occupational tasks, including more complex analyses, such as, principal components analysis, entropy, and goal equivalent manifold methods (Samani et al., 2015; Sedigi and Nussbaum, 2019). While these metrics require more complex calculations and (often difficult) interpretation, they may convey additional MV information not accessible with the metrics used in the current study, for example, aspects of motor control strategies in the brain. Future research investigating MV via such metrics may offer additional evidence on individual MV traits and their relevance to MSDs. Additional research is also required to determine how MV magnitude relates to key health outcomes, for example, MSD risk. Further, research is required to consider the clinical relevance of suggesting a specific MV cut-off to explicitly categorize individuals into low (‘repeater’) and high (‘replacer’) MV groups, or whether these terms should be used only as relative descriptors to illustrate that subjects differ in MV, just like the terms ‘strong’ and ‘weak’ are used for subjects varying in muscle strength, but with no absolute definition of ‘strong’ and ‘weak’.

Participants in our study showed increased pace resulted in either increased MV (EMGVSD of means, EMGVSD of SDs, and UAEMVSD of SDs), or no obvious change in MV. This was in contrast to the findings of Srinivasan et al. (2015a,b) for participants performing a short-cycle, simple pipetting task, who found a decrease in MV at faster paces. However, our findings were comparable to the findings of Bosch et al. (2011) who also studied a more complex assembly task and found increased pace led to either increased variability (extensor digitorum EMG and wrist kinematic variables) or no change in variability (trapezius EMG) (Bosch et al., 2011). Bosch et al. also reported increased numbers of errors at the higher work pace. While we did not quantitatively assess this attribute, anecdotal, it was clear that participants required greater focus, made more errors, and found the 120 MTM condition markedly more difficult than the 110 MTM or self-paced work conditions. It is possible that the differing levels of complexity may contribute to the opposing findings, where variability decreases at faster paces for simple individual movements, but increases with more complex tasks involving multiple chained movements.

It is also possible that the increased variability seen at 120 MTM stemmed from the unique temporal organisation of the 120 MTM pacing condition. We designed all 110- and 120-MTM work pace conditions to maintain a consistent level of productivity; to do so, we inserted a 15 s break after each set of 6 assembly cycles during the 120 MTM work pace. Thus, unlike all other pacing conditions, the 120 MTM condition comprised both work and forced break components (NB - only data from the assembly cycles were included in the MV metric computations). Participants were not instructed on how they should use the break time, that is, we did not enforce either passive or active behaviours. We found break behaviours varied both between and within participants, however, the time was often spent actively, tidying the workspace, stretching, adjusting work position, or performing myriad other small activities. Previous research has shown that active pauses can increase the variability of trapezius EMG patterns during continuous computer mouse work (Samani et al., 2009). Thus, the inclusion of pauses and the self-selected active pause behaviours may, in addition to the effect of pace, explain the increased MV in the 120-MTM condition; however, further research is required to determine the unique impacts of pace and breaks on MV. That the motor variability metrics for the line-120 MTM condition differed from the batch-110 MTM condition but not the

![Fig. 3](image-url). Magnitude of MV by subject for each work condition for one representative EMG and kinematic MV metric. (A) EMGMean of SDs (B) UAEMMean of SDs. Individual subjects presented on the x-axis in ascending ordering of mean metric value.

Table 4

<table>
<thead>
<tr>
<th>Metric</th>
<th>Mean</th>
<th>S^2^ss</th>
<th>(95% CI)</th>
<th>S^2^ws</th>
<th>(95% CI)</th>
<th>CVss</th>
<th>CVws</th>
</tr>
</thead>
<tbody>
<tr>
<td>EMGMean of means</td>
<td>109.4</td>
<td>441.00</td>
<td>(1090.51-7375.50)</td>
<td>433.56</td>
<td>(320.65-619.03)</td>
<td>0.61</td>
<td>0.19</td>
</tr>
<tr>
<td>EMGMean of SDs</td>
<td>55.8</td>
<td>1745.34</td>
<td>(440.75-3049.93)</td>
<td>94.24</td>
<td>(69.70-134.55)</td>
<td>0.60</td>
<td>0.33</td>
</tr>
<tr>
<td>EMGD of means</td>
<td>7.7</td>
<td>21.07</td>
<td>(4.70-37.49)</td>
<td>6.47</td>
<td>(4.79-9.24)</td>
<td>0.75</td>
<td>0.17</td>
</tr>
<tr>
<td>EMGD of SDs</td>
<td>5.0</td>
<td>10.50</td>
<td>(2.47-18.53)</td>
<td>2.01</td>
<td>(1.49-2.87)</td>
<td>0.65</td>
<td>0.28</td>
</tr>
<tr>
<td>UAEMMean of means</td>
<td>51.8</td>
<td>42.79</td>
<td>(10.13-75.45)</td>
<td>7.73</td>
<td>(5.70-11.11)</td>
<td>0.13</td>
<td>0.05</td>
</tr>
<tr>
<td>UAEMMean of SDs</td>
<td>11.0</td>
<td>4.91</td>
<td>(1.19-8.63)</td>
<td>0.63</td>
<td>(0.47-0.91)</td>
<td>0.13</td>
<td>0.18</td>
</tr>
<tr>
<td>UAEMMean of means</td>
<td>1.6</td>
<td>0.04</td>
<td>(-0.90-1.08)</td>
<td>0.08</td>
<td>(0.06-0.12)</td>
<td>0.20</td>
<td>0.07</td>
</tr>
<tr>
<td>UAEMMean of SDs</td>
<td>1.1</td>
<td>0.14</td>
<td>(0.02-0.26)</td>
<td>0.13</td>
<td>(0.02-0.09)</td>
<td>0.34</td>
<td>0.33</td>
</tr>
<tr>
<td>UAEMMean of PP-SDs</td>
<td>8.3</td>
<td>1.48</td>
<td>(0.27-2.69)</td>
<td>0.90</td>
<td>(0.15-1.29)</td>
<td>0.15</td>
<td>0.11</td>
</tr>
</tbody>
</table>
line-110 MTM work may be a result of the surprisingly lower temporal variability seen in the batch work compared with the line work, as previously reported (Dempsey et al., 2010).

In designing the four conditions, we altered aspects of temporal organisation by adjusting both work pace and using two production processes, namely, batch and line type assembly conditions. No difference was found in terms of variability between the batch- and line-type work performed at 110-MTM, suggesting the two production processes we considered did not strongly affect motor variability. Differences were, however, seen in motor variability metrics between the batch-110 MTM and line-120 MTM conditions. This may suggest that a combination of pace and temporal organisation changes are required to elicit differences in motor variability.

The long-cycle assembly task used in this study was, by design, more complex and longer than many of the tasks previously used to examine MV consistency, for example, pick and place movements (Lager et al., 2019, 2017), pipetting (Sandlund et al., 2017; Srinivasan et al., 2015b) and single walking strides (Konig et al., 2014). The task was selected to closely represent an actual assembly task one might encounter in a real work setting, and thus to be of better ecological validity than, for example, a simple pick-and-place task. To reduce possibility for the occurrence of task variability which could confound our measures of MV, we fixed the location of all components relative to the workstation, and adjusted the height of the workstation and chair to the same relative position for each participant. Further all participants completed three paid days of training and had demonstrated task proficiency at 120 MTM. However, in leaving autonomy for the participants in how they used the workstation (for example, relocating components from the fixed bins to the table beside the jig) it is possible that some of the changes in UAE and EMG muscle activity are due to differences in the task itself and not only due to MV across repetitions of a strictly controlled task. An additional limitation is that we only repeated measurements across days for the line-110 and self-paced working conditions, and thus we implicitly assumed that the between-days within-subject variance was consistent across the four conditions.

While the exact physiological mechanisms underlying MSDs are not yet known, there is a consensus in the literature that sustained muscle activity is a primary cause (Visser and Van Dieen, 2006). This is particularly true for type-1 muscle fibres due to their selective recruitment and risk for overuse, as described in the Cinderella hypothesis (Hagg, 1991). It is, therefore, reasonable that the trapezius EMG MV metrics explored in the current study may be mechanistically more closely related to injury risk than the upper arm elevation MV metrics and, further, that EMG variability metrics may be of greater importance when considering risk factors for MSDs. The evidence of consistent individual MV traits in this study was stronger among EMG MV metrics than kinematic metrics, as seen by the substantially larger proportion of the total variance accounted for by the variance between subjects compared with the within-subject variance between days, which further supports the proposition that individual MV traits in EMG metrics may have a better predictive ability in determining MSD risk than kinematic MV metrics. However, we only considered upper arm elevation, and examination of postural MV metrics for other body angles may be warranted in the context of MSD risk.

Our data support the notion of MV as a personal trait. However, this does not preclude the possibility of altering MV via ergonomic intervention. As has been commonly shown, our data indicate that if variability exist (in one class (ex. kinematic) of MV metrics), then variability will also increase in the other class (ex. EMG) of MV metrics. One could theoretically exploit this apparent correlation between kinematic and EMG metrics of MV to increase muscle activity variability via deliberate alteration of kinematic patterns during work, a finding that may prove useful for ergonomists aiming to alter muscle loading patterns. However, any increase in kinematic variability must be done within a limited range so as to not negatively impact production. Kinematic metrics may be preferential if the focus of a study is on production rather than musculoskeletal health.

In this study we confirmed consistent individual MV traits in healthy female workers ages 18–45 performing a cyclic assembly task under different working conditions of temporal organisation. This finding supports the notion that individual MV traits could be an important determinant of MSD risk, and indicates further research is required to elucidate the role of MV in MSDs. A natural progression would be to determine whether consistent individual MV strategies are still evident in workers performing tasks that differ to a greater extent than those investigated in the present study. In addition, research is required to determine whether individual traits are still present when introducing other elements that may influence MV, for example, when learning novel tasks (Lager et al., 2019). Since it is known that motor patterns are influenced by health (pain) status (Madeleine et al., 2008a), gender (Cid et al., 2019), and age (Christou and Carlton, 2002), investigation of MV in other populations is required to determine the extent to which the present findings are generalizable. While differences in physiological responses are well established between individuals performing a same task (ex. (de Looze et al., 2009; Mathiassen and Winkel, 1996)), to establish a direct linkage between MV and risk of MSD, an association of MV to relevant indicators of MSDs must also be established. For example, it is possible that metabolic accumulates will differ between individuals performing repetitive work in a very repeatable way versus those demonstrating more variable MV traits, thus resulting in lower times to fatigue among ‘repeaters’ than ‘replacers’, as exemplified by the findings of van Dieen et al. (1993) (van Dieen et al., 1993).

5. Conclusion

Consistent motor control traits were observed in females performing repetitive assembly work under four working conditions that differed in terms of autonomy in pace and work organisation. Thus, individuals with high MV at one condition also had high MV when working at other paces and under other production processes. These results lend support to the notion of consistent individual MV traits and consistent differences between subjects, and thus are in line with the hypothesis that ‘repeater’ and ‘replacer’ type individuals may exist. Additional research is required to determine whether MV traits are consistent across markedly different tasks, and whether individual MV traits influence a worker’s risk for MSD development.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.japergo.2020.103046.


