Upper-Limb and Low-Back Load Analysis in Workers Performing an Actual Industrial Use-Case with and without a Dual-Arm Collaborative Robot

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Upper-Limb and Low-Back Load Analysis in Workers Performing an Actual Industrial Use-Case with and without a Dual-Arm Collaborative Robot

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Abstract: In the Industry 4.0 scenario, human–robot collaboration (HRC) plays a key role in factories to reduce costs, increase production, and help aged and/or sick workers maintain their job. The approaches of the ISO 11228 series commonly used for biomechanical risk assessments cannot be applied in Industry 4.0, as they do not involve interactions between workers and HRC technologies. The use of wearable sensor networks and software for biomechanical risk assessments could help us develop a more reliable idea about the effectiveness of collaborative robots (coBots) in reducing the biomechanical load for workers. The aim of the present study was to investigate some biomechanical parameters with the 3D Static Strength Prediction Program (3DSSPP) software v.7.1.3, on workers executing a practical manual material-handling task, by comparing a dual-arm coBot-assisted scenario with a no-coBot scenario. In this study, we calculated the mean and the standard deviation (SD) values from eleven participants for some 3DSSPP parameters. We considered the following parameters: the percentage of maximum voluntary contraction (%MVC), the maximum allowed static exertion time (MaxST), the low-back spine compression forces at the L4/L5 level (L4Ort), and the strength percent capable value (SPC). The advantages of introducing the coBot, according to our statistics, concerned trunk flexion (SPC from 85.8% without coBot to 95.2%; %MVC from 63.5% without coBot to 43.4%; MaxST from 33.9 s without coBot to 86.2 s), left shoulder abdo-adduction (%MVC from 46.1% without coBot to 32.6%; MaxST from 32.7 s without coBot to 65 s), and right shoulder abdo-adduction (%MVC from 43.9% without coBot to 30.0%; MaxST from 37.2 s without coBot to 70.7 s) in Phase 1, and right shoulder humeral rotation (%MVC from 68.4% without coBot to 7.4%; MaxST from 873.0 s without coBot to 125.2 s), right shoulder abdo-adduction (%MVC from 31.0% without coBot to 18.3%; MaxST from 60.3 s without coBot to 183.6 s), and right wrist flexion/extension rotation (%MVC from 50.2% without coBot to 3.0%; MaxST from 58.8 s without coBot to 1200.0 s) in Phase 2. Moreover, Phase 3, which consisted of another manual handling task, would be removed by using a coBot. In summary, using a coBot in this industrial scenario would reduce the biomechanical risk for workers, particularly for the trunk, both shoulders, and the right wrist. Finally, the 3DSSPP software could be an easy, fast, and costless tool for biomechanical risk assessments in an Industry 4.0 scenario where ISO 11228 series cannot be applied; it could be used by occupational medicine physicians and health and safety technicians, and could also help employers to justify a long-term investment.

Keywords: human–robot collaboration; motor coordination; manual material handling

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1. Introduction

With millions of workers affected, work-related musculoskeletal disorders (WMDs) of the neck, trunk, and upper limbs are a major cause of lost workdays. Lost workdays come at a high cost to companies and public health systems, amounting to billions of dollars [1]. It has been known for a long time that the onset and progression of these illnesses are influenced by biomechanical overload [2]. For example, during heavy lifting activities, if the compressive and shear forces stressing the lumbosacral junction exceed the tissue tolerance, damage can occur [3].

Industry 4.0 (https://www.bcg.com/publications/2015/engineered_products_project_business_industry_4_future_productivity_growth_manufacturing_industries.aspx last accessed on 31 July 2024) is the implementation of intelligent technologies to increase productivity and to reduce the associated biomechanical risks [4]. From a general point of view, the integration of ergonomic and human-factor requirements in human–robot collaborative (HRC) systems, such as collaborative robots (coBots), represents a new option for reducing the physical effort of workers during the execution of manual material-handling (MMH) activities, and for adopting new ergonomic interventions to prevent work-related musculoskeletal disorders (WMDs). In detail, the use of coBots in smart manufacturing environments provides a unique opportunity to design MMH activities executed by hybrid human–robot teams, thus reducing the physical exertion of the human member of the team [5].

As the use of coBots in manufacturing has recently increased considerably, all the potential benefits need to be investigated in depth and proven, especially in the MMH phases, where the physical interaction of the worker with the coBot takes place. Indeed, while the issue of safety in this new hybrid scenario is currently being widely investigated, the issue of health has been investigated very little [6]; also, considering the fact that the above-mentioned physical interaction was not foreseen by the methods listed in the International Ergonomics Standards Series [7–10], that presents also other limitations [11–13]. For this reason, it will be crucial to include the broadest knowledge of the biomechanics of the occupational tasks performed with the aid of coBots, within the new approaches that will be developed for biomechanical risk assessments [14–17]. On the other hand, the complexity of the problem requires the identification of the risk of WMDs in MMH activities, with a preference for instrumental-based and personalized analyses and models [16–20]. These include the need for assessing kinematic, kinetic, and muscular behaviors.

While the measurement of kinematic and muscular behaviors is nowadays easier thanks to wearable sensor networks consisting of inertial measurement units (IMUs) and surface electromyography sensors (sEMGs), the measurement of forces affecting the body districts of interest is more difficult. In fact, force platforms are not usable in the field and shoes or sensor insoles are not yet precise and accurate enough for measuring vector information [17].

As evidence of the above, and with regards to the kinematic analysis, the improvement to the physical ergonomics of MMH activities performed with the aid of coBots has been measured in a real-work scenario [6,15] through the application of the occupational repetitive action (OCRA) [21] and rapid upper limb assessment (RULA) [22] methods. With regards to the estimation of muscular activities, an experimental session carried out under the aegis of the SOPHIA (Socio-Physical Interaction Skills for Cooperative Human–Robot Systems in Agile Production, http://www.project-sophia.eu, accessed on 12 March 2024) project allowed for an evaluation of upper limb muscle coordination and activation by using a wearable sensor network in workers performing actual use-case MMH with and without the help of a dual-arm coBot, namely BAZAR [23]. The results of this study showed that, when MMH was carried out with BAZAR, both the upper limb and trunk muscular co-activations and activations were decreased, demonstrating that coBots have a positive impact on workers' motor strategies. For instance, with regards to the assessment of the forces acting on the spine, several studies have considered regression models based on the muscle activity or trunk posture [24,25], optimization procedures [26–29], the combination of sEMG measurements and data-driven musculoskeletal models [30–34], or video-based software such as the Static Strength Prediction Program (3DSSPP) [35,36].

Among the approaches for studying joint kinetics, the latter, designed by the University of Michigan, is a simple option for measuring compressive forces acting at the lumbo-sacral joint during the execution of hybrid worker–coBot MMH tasks, under the hypotheses that this interaction may reduce the L4–L5 and L5–S1 forces and enhance the maximum static holding time. In addition, the use of 3DSSPP becomes even more interesting when the analysis of human–coBot interactions includes an industrial use-case. The literature shows that the assessment of the kinetics of the lumbo-sacral joint indicates a robust correlation between the results obtained using 3DSSPP and those obtained using other methods. It can satisfactorily predict the L4–L5 interdiscal pressure, including low exposures, and detect similar patterns in the compressive forces [37–40]. Furthermore, 3DSSPP has been applied to assess the biomechanical risks in several workplaces, for several tasks, and under several conditions [13,41–55].

Hence, the aim of the present study was to compare kinetic variables in workers executing an actual industrial use-case performed with (wB) and without (woB) BAZAR. It was hypothesized that the load on the lumbosacral joints would be reduced in wB activities.

We also aimed to verify if the 3DSSPP software could be a useful tool for biomechanical risk assessments in an Industry 4.0 scenario, where ISO 11228 standards [7–9] cannot be applied by occupational medicine physicians and health and safety technicians, and if 3DSSPP can help employers justify a long-term investment in a coBot.

This study was performed as part of the SOPHIA project, funded by the European Union's Horizon 2020 Research and Innovation Programme under Grant Agreement No. 871237. The SOPHIA project has set an aim of providing a contribution to the development of new coBots to effectively mitigate the physical effort and reduce the WMDs associated with several MMH activities [56,57].

This paper is structured as follows: Section 2 presents the setup, the experimental protocol, and the conducted analysis. The results are illustrated in Section 3. Section 4 contains a discussion on the work, and finally, Section 5 contains the conclusions.

2. Materials and Methods

2.1. Participants

Eleven participants (five females and six males; age: 27.73 ± 5.99 years; height: 175.4 ± 7.7 cm; weight: 71.3 ± 15.2 kg; body mass index [BMI]: 23.06 ± 3.93 kg/m^2) took part in the study. This study was carried out at the University of Montpellier in accordance with the Helsinki Declaration and authorized by the University of Montpellier EuroMov's laboratory ethics committee (protocol number IRB-EM 2103A). An inability to give informed written consent; a history of musculoskeletal disorders, upper, lower limb, or trunk surgery, orthopedic or neurological diseases, vestibular system disorders, visual impairments, or back pain; a current pregnancy; current pharmacological treatment; and obesity were all exclusion criteria.

Each participant completed the task six times: three times wB and three times woB. We randomly ordered the two conditions (wB and woB) for each subject to avoid bias. Before the participant performed either condition for the first time, we instructed him/her by showing them a video of the task, and by letting him/her execute it once without recording.

The sample size (11) was as large as possible due to the complexity of the task and the limited time we had (one week); the study involved performing the work task twice, without and with the BAZAR robot. In this week, we recruited all the subjects who voluntarily decided to participate in the study and who met the inclusion criteria. We tried to acquire a sample as homogenous as possible under the point of view of anthropometric characteristics. In the algorithm that 3DDSSP applies, the anthropometry, particularly the weight, affects the orthogonal compression forces at the L4/L5 level. The sample had a near-average BMI because we wanted to minimize possible outlier data due to a high or low BMI, thus minimizing a remarkable bias.

2.2. Task Analysis

The experimental session was the same as that described in a previous article [23], so we recommend reading it for further information about the task analysis.

The differences between the two tasks were as follows:

- Phase I: subtask 3 wB (Figure 1(a1)) replaced subtask 4 woB (Figure 1(b1));
- Phase II: subtasks 7 and 8 wB (Figure 1(a2)) replaced subtasks 8, 9, and 10 woB (Figure 1(b2));
- Phase III: subtasks 9 and 10 wB (Figure 1(a3)) replaced subtask 11 woB (Figure 1(b3)).

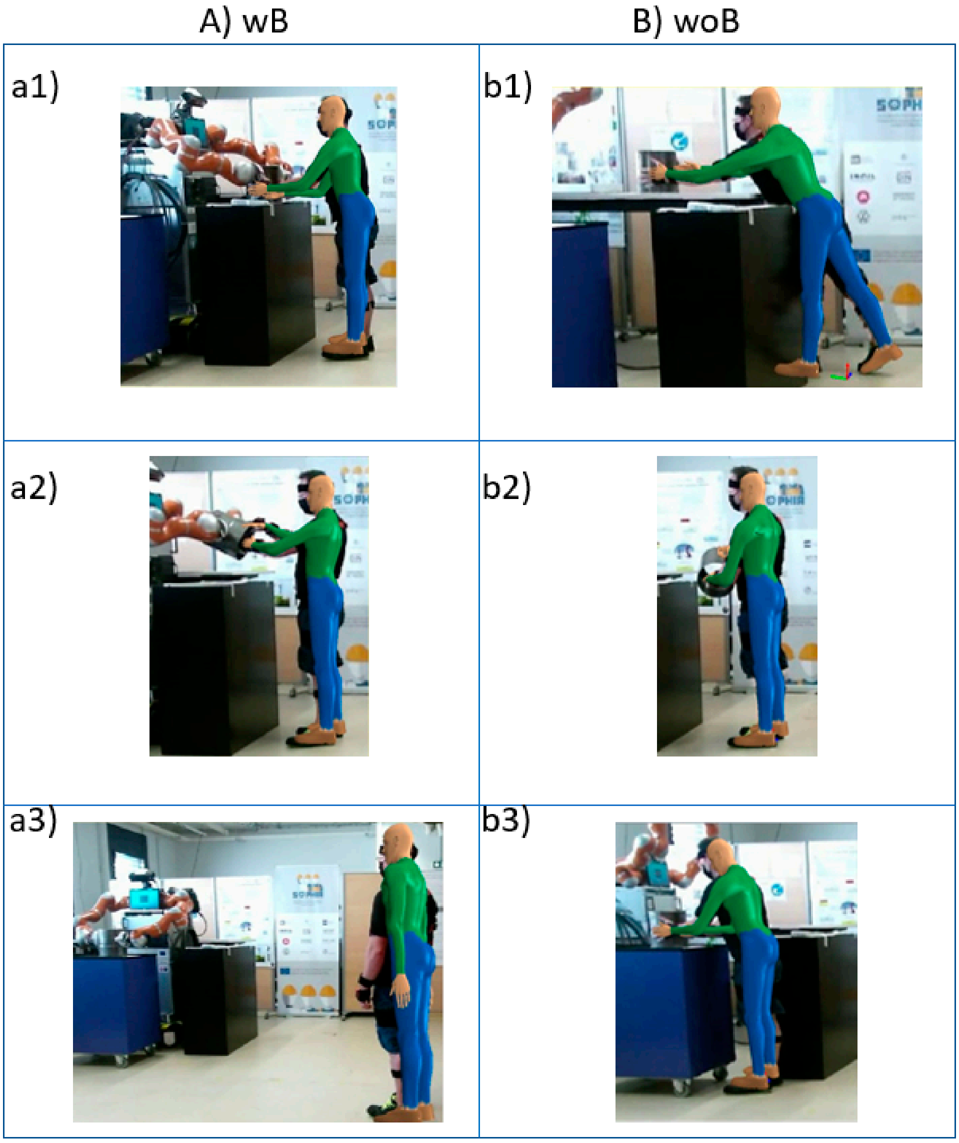

Figure 1. Some 3DSSPP reconstructions of the three subtasks analyzed: Phase 1 with (**a1**) and without (**b1**) the coBot; Phase 2 with (**a2**) and without (**b2**) the coBot; and Phase 3 with (**a3**) and without (**b3**) the coBot.

In this study, we considered these three phases for the tasks wB and woB.

The experiments are shown in the video available at the following link: https://www.youtube.com/watch?v=vul8iLO0Sdw, accessed on 12 March 2024.

2.3. 3D Static Strength Prediction Program (3DSSPP) v 7.1.3

Through 3DSSPP, it is possible to recreate a worker's posture by overlaying an avatar model on a selected frame [35,36]. The entry data that the software requires are the worker gender, height, and weight. These last two data items can be obtained from specific input data or through population percentiles (95th, 50th, and 5th). In this paper, we used the real data of the participants. The body segments of the avatar can be manipulated by clicking any joint and dragging it to a new location through an angle dialog. We used this software because it provides a good balance among the accuracy of the data, the costs of a biomechanical risk assessment for medium–small factories, and user friendliness. The common biomechanical risk assessment tools in the ISO standards [7–9] are cheaper, but they cannot be applied in an Industry 4.0 scenario; a posture analysis with optoelectronic systems or inertial measurement units (IMUs) is very accurate, but it is expensive and requires specialized skills. The reconstruction made with 3DSSPP suffers in accuracy because it depends on subjective eye visualization, but it can be used in our scenario, is easy to use, provides parameters that could be helpful for better understanding the biomechanical overload differences in our case scenario, and is cheaper than an instrumental assessment.

In this study, we calculated the mean and the standard deviation (SD) values for eleven participants for some 3DSSPP parameters. The 3DSSPP parameters that we considered useful for the investigated task were the following: the percentage of maximum voluntary contraction (%MVC), the maximum allowed static exertion time (MaxST), the low-back spine compression forces (L4Ort), and the strength percent capable value (SPC). All the values of the parameters considered were obtained from the reconstructions made with the software. For each participant, the best image was selected. The values represented the three identified phases, where the presence of the coBot significantly changed the execution.

2.3.1. Percentage of Maximum Voluntary Contraction (%MVC)

According to 3DSSPP, the percentage of maximum voluntary contraction (%MVC) is the required effort at each joint. Unlike what is performed by sEMGs, where the %MVC is determined for each individual muscle, in 3DSSPP, the values refer to a joint district, so several muscles can be part of the district for a selected population.

In the software, it is possible to choose the %MVC of a selected population corresponding to the 5th, 25th, or 50th percentile. These values represent workers who are very weak, weak, or with an average strength. In our study, we considered the %MVC bilaterally for the following:

- Wrist flexion/extension (wrist flex/ext), ulnar/radial deviation (wrist uln/rad), and rotation (wrist rot);
- Elbow flexion/extension (elbow flex/ext);
- Shoulder humeral rotation (shoulder hum rot), backward/forward rotation (shoulder bk/fw), and abduction/adduction (shoulder abd/add);
- Neck flexion/extension (neck flex/ext);
- Trunk flexion/extension (trunk flex/ext).

We considered these %MVC values because we wanted to analyze the most involved joints.

2.3.2. Maximum Allowed Static (Continuous) Exertion Time (MaxST)

This parameter refers to the maximum static exertion. ACGIH embedded a refitted curve from Potvin's data [58,59] in the ACGIH TLVs and BEIs [60] for localized fatigue of the upper limb and the trunk. The maximum static exertion duration time was 20 min (1200 s). The static duration is strictly correlated to the %MVC. Also, for the static duration, it is possible to select the population strength percentile and gender. As for the %MVC, we estimated the MaxST bilaterally for the most involved joints in the task:

- Wrist flexion/extension, ulnar/radial deviation, and rotation;
- Elbow flexion/extension;
- Shoulder humeral rotation, backward/forward rotation, and abduction/adduction;
- Neck flexion/extension;
- Trunk flexion/extension.

2.3.3. Low-Back Spine Compression Forces (L4Ort)

The software provides values for orthogonal forces acting on the spine. The biomechanical model is optimized for the L4/L5 level, but it also provides values at the L5/S1 level. 3DSSPP indicates the strength design limit (SDL) and the strength upper limit (SUL) corresponding to the NIOSH action limit (3400N) [61] and maximum permissible limit (6400N) [62]. The SDL designation was set at 99% for men and 75% for women. The SUL designation was set at 25% for men and 1% for women, as per the NIOSH. In this paper, we only used data from the compression forces at the L4/L5 level, since it is the most considered joint in biomechanics.

2.3.4. Strength Percent Capable (SPC) Parameter

The strength percent capable parameter analyzes the strength of the major joints (wrist, elbow, shoulder, trunk, hip, knee, and ankle). It indicates the percentage of the selected population capable of performing the analyzed task without injuries. In our study, we only considered the SPC values that were most relevant for our task (wrist, elbow, shoulder, and trunk).

2.4. Statistical Analysis

To check the differences between the two conditions (wB and woB), a statistical analysis was carried out using PASW Statistics 18. The Shapiro–Wilk test was used to verify the normality of the data distribution for each parameter. A paired-sample *t*-test was then used to evaluate whether the help of the coBot resulted in significant changes in each parameter. The significance level for all the statistical analyses was set at a p-value < 0.05.

3. Results

3.1. Phase 1

Figure 2 shows the mean results of the reconstructions of the 11 subjects in Phase 1 wB and woB.

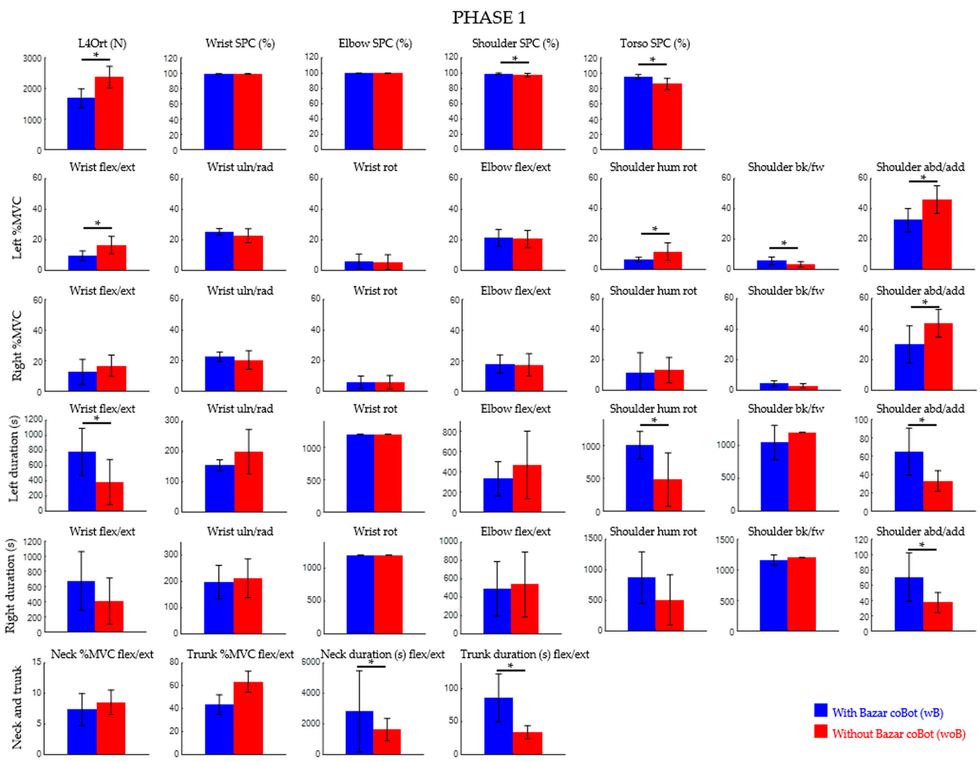

Figure 2. Mean and SD values for Phase 1, with Bazar (wB) in blue and without Bazar (woB) in red, for the investigated parameters (L4–L5 orthogonal forces, strength percent capable value, %MVC, and maximum holding time). An asterisk (*) over the bars shows statistical significance.

In this phase, the only parameter presenting a significant statistical difference in favor of not using the coBot was the left shoulder bk/fw movement (3.5% vs. 5.7%, $p = 0.028$).

Several parameters, meanwhile, showed statistically significant differences in support of coBot use. The results showed a statistically significant reduction in the orthogonal force at the L4/L5 level (1675.5 N vs. 2365 N, $p \leq 0.01$). A reduced risk for the trunk was also confirmed in the corresponding SPC parameter (95.2% vs. 85.8%, $p \leq 0.01$), trunk %MVC (43.4% vs. 63.5%, $p \leq 0.01$), and maximum static holding time (63.5 s vs. 43.4 s, $p \leq 0.01$). A further value of SPC in support of the use of the coBot was that for the shoulders (99.1% vs. 97.4%, $p = 0.0388$). With regards to the left arm, a statistically significant reduction in the %MVC was found for wrist flex/ext (9.5% vs. 16.6%, $p = 0.0018$), shoulder hum rot (6.5% vs. 11.8%, $p \leq 0.01$), and shoulder abd/add (32.6% vs. 46.1%, $p \leq 0.01$). The right arm had a statistically significant reduction only in shoulder abd/add (30% vs. 43.9%, $p \leq 0.01$).

The maximum allowed static continuous exertion time parameter was strongly related to the %MVC. The same %MVC results were statistically significant. The MaxST parameters of the left arm increased for wrist flex/ext (783 s vs. 384 s, $p \leq 0.01$), shoulder hum rot (1007.9 s vs. 481.3 s, $p \leq 0.01$), and shoulder abd/add (65 s vs. 32.7 s, $p \leq 0.01$). For the right arm, abd/add of the shoulder was the only statistically significant difference (70.7 s vs. 37.2 s, $p \leq 0.01$) in which MaxST increased.

3.2. Phase 2

Figure 3 shows the mean results of the reconstructions of the 11 subjects in Phase 2.

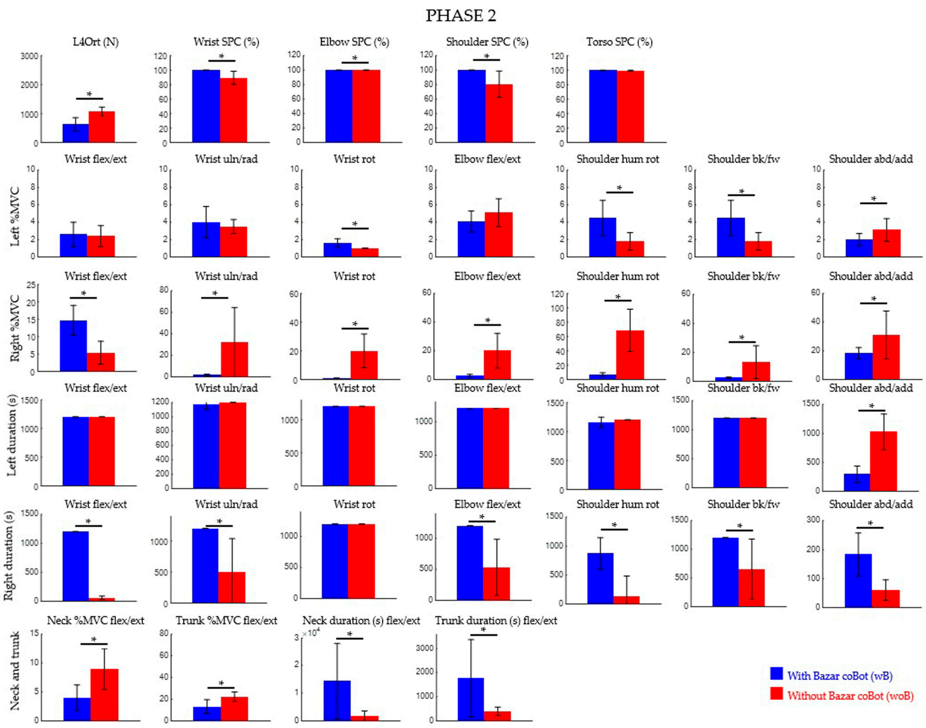

Figure 3. Mean and SD values for Phase 2, with Bazar (wB) in blue and without Bazar (woB) in red, for the investigated parameters (L4–L5 orthogonal forces, strength percent capable value, %MVC, and maximum holding time). An asterisk (*) over the bars shows statistical significance.

This phase reported, only for the left arm, three parameters that were unfavorable for the %MVC when using the coBot and one parameter for the maximum holding time. For the %MVC, there was a drawback in the use of the coBot for wrist rot (1.6% vs. 1.0%, $p \leq 0.01$), shoulder hum rot (4.5% vs. 1.8%, $p \leq 0.01$), and shoulder abd/add (14.7% vs. 5.4%, $p \leq 0.01$); for the maximum holding time, the drawback in the use of the coBot was only for left shoulder abd/add (294 s vs. 1025.6 s, $p \leq 0.01$).

Many parameters argue in favor of using the coBot. Statistically significant differences can be seen in the orthogonal force at the L4/L5 level (628.5 N vs. 1066.6 N, $p \leq 0.01$) and in the SPC for the wrist (100% vs. 89.3%, $p \leq 0.01$), elbow (100% vs. 99.6%, $p = 0.0171$), and shoulder (100% vs. 80.4%, $p \leq 0.01$). The %MVC parameter was unfavorable only for the left shoulder bk/fw (2.0% vs. 3.1%, $p = 0.0226$). All the %MVC parameters for the right arm were statistically significant in favor of coBot use: wrist flex/ext (3.0% vs. 50.2%, $p \leq 0.01$), wrist uln/rad (1.7% vs. 31.9%, $p = \leq 0.01$), wrist rot (1.0% vs. 20.0%, $p = \leq 0.01$), elbow flex/ext (2.6% vs. 20.1%, $p \leq 0.01$), shoulder hum rot (7.4% vs. 68.4%, $p \leq 0.01$), shoulder bk/fw (2.4% vs. 13.2%, $p = \leq 0.01$), and shoulder abd/add (18.3% vs. 31.0%, $p = 0.0235$). Favorable statistically significant differences also emerged for the neck (4.0% vs. 8.9%, $p \leq 0.01$) and trunk (13% vs. 22.2%, $p \leq 0.01$) %MVCs.

Statistically significant differences in the maximum holding time were found only for the right upper arm for the following parameters: wrist flex/ext (1200 s vs. 58.8 s, $p \leq 0.01$), wrist uln/rad (1200 s vs. 494.7 s, $p \leq 0.01$), elbow flex/ext (1200 s vs. 531.5 s, $p = 0.00009$), shoulder hum rot (873 s vs. 125.2 s, $p \leq 0.01$), and shoulder bk/fw (1200 s vs. 656.9 s, $p \leq 0.01$).

Lastly, the neck's maximum holding time also proved to be statistically significant (13,282.7 s vs. 1803.4 s, $p = 0.0109$).

3.3. Phase 3

Figure 4 shows the mean results of the reconstructions of the 11 subjects in Phase 3. This figure only shows the values of the task performed without the coBot, since this phase was eliminated with the coBot.

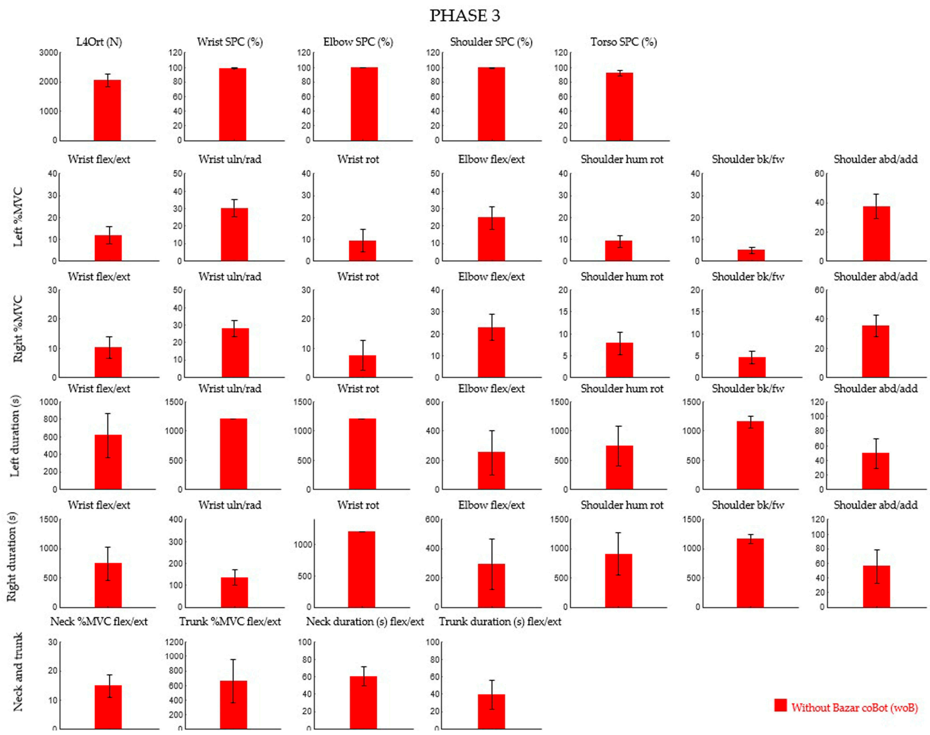

Figure 4. Mean and SD values for Phase 3 without Bazar (woB) in red, for the investigated parameters (L4–L5 orthogonal forces, strength percent capable value, %MVC, and maximum holding time). When using the Bazar coBot, this phase would be totally automatized, so we do not have values with the Bazar (wB).

4. Discussion

The 3DSSPP software was developed by the University of Michigan based on studies and research that lasted for over 40 years in the field of biomechanics [35,36]. This software is a useful tool in both proactive and reactive ergonomics, for designing and assessing workplaces and work tasks and for showing the effectiveness of an ergonomic intervention.

In our study, unskilled participants performed a real work task, which we replicated in the laboratory. We assessed, through the 3DSSPP software, the different biomechanical loads when executing the task with and without a coBot. Introducing the coBot involved changes in task execution. The main differences were a change in lifting (Phase 1), support during workpiece cleaning (Phase 2), and the removal, with the coBot, of further lifting (Phase 3). From 3DSSPP, we obtained various parameters that can help us perform a biomechanical risk assessment. The percentage of maximum voluntary contraction (%MVC) is the required effort at each joint, and it is a parameter that can be helpful when estimating workers' muscle activity without using surface electromyography, which is a more objective tool for quantifying muscle activity but is not as cheap or easy to use as 3DSSPP [63]. The maximum allowed static (continuous) exertion time (MaxST) is a parameter that helps us to know for how long a worker can assume an analyzed posture before fatigue appears; also, this parameter can be estimated through a surface electromyography analysis. However, in our lab simulation, the task was performed for only a few minutes and sEMGs could not provide fatigue data after so short a time. The low-back spine compression forces (L4Ort) is a parameter that helps us to quantify the reduction in the orthogonal forces acting on the low back. It is well known that low-back compression and shear force are among the most relevant causes of lower-back MSDs [3]. The strength percent capable (SPC) parameter indicates the percentage of the selected population capable of performing the analyzed task without injuries for several joints of the body; this parameter could be helpful to employers in quantifying the reduction in lost days due to MSDs and helping them justify a long-term investment such as acquiring a coBot.

The possibility of estimating the direct involvement of the variables described above in the generation of damage with a video-based approach is particularly relevant. In fact, this would allow a worker to be monitored, even during his interaction with coBots, without altering his natural motor strategy and without interfering with his work. Currently, when analyzing occupational tasks, marker-/sensor-based approaches are largely used. A further strength of this study relates to it being a use-case, simulated in the lab in the same way as it is executed in the workplace, since the task is an actual industrial case. Our experimental data helped the factory to justify a long-term investment in coBots for this task.

With regards to the downsides, in Phase 1, the statistically significant increase in the %MVC of the left shoulder back/forward (5.7% vs. 3.5%, $p = 0.028$, Figure 2) did not correspond to a statistically significant decrease in the maximum holding time (1049.1 s vs. 1200 s, $p = 0.0689$, Figure 2). In addition to this, we must consider the effective duration of the task (about 180s), which is well below the maximum holding time allowed by the algorithm of the software, meaning that these negative data are negligible. The same conclusions apply in Phase 2 for the left wrist rot (1.6% vs. 1.0%, $p \leq 0.01$, Figure 3) and for the left shoulder hum rot (4.5% vs. 1.8%, $p \leq 0.01$, Figure 3), which did not match statistically significantly with the maximum holding time (1200 s vs. 1200 s, left wrist rot, $p = 1$, Figure 3; 1200 s vs. 1160.2 s, left shoulder hum rot, $p = 0.1536$, Figure 3). The only movement showing a statistical significance against coBot use for both the %MVC and the maximum holding time was left shoulder abd/add (5.7% vs. 14.7%, $p \leq 0.01$, Figure 3; 1025.6 s vs. 294 s, $p \leq 0.01$, Figure 3). For Phase 1 as well, the maximum holding time, based on 3DSSPP data, was higher than the effective task duration.

Remarks analogous to the negative aspects can also be made about the positive ones. Although largely within the thresholds proposed by Jager [64], there was a statistically significant reduction in the L4/L5 orthogonal force in all phases. In detail, these reductions were 2365 N vs. 1675.5 N in Phase 1 ($p \leq 0.01$, Figure 2) and 1066.6 N vs. 628.5 N in Phase 2 ($p \leq 0.01$, Figure 3); in Phase 3, the 2046.1 N mean (Figure 4) was eliminated, since the task was fully performed by the coBot. Therefore, in these phases, there was a reduction in the biomechanical effort when the coBot was used. These results could be attributed to the fact that the coBot helps the worker in the analyzed phases reduce his/her biomechanical risk without obstructing him/her. Indeed, the coBot works in a synchronized manner with the worker and does not hinder him from working.

Notable statistically significant reductions in the SPC parameter involved the trunk in Phase 1 (95.2% vs. 85.8%, $p \leq 0.01$, Figure 2) and the shoulders in Phase 2 (100% vs. 80.4%, $p \leq 0.01$, Figure 3).

As for the %MVC, most of the relevant results in Phase 1 concerned the reduction in the abdo-adduction values for both the shoulders and for the trunk (Figure 2). Contextually, we found an increase in the maximum exposure times from 32.7 s to 65 s for the left shoulder, from 37.2 s to 70.7 s for the right shoulder, and from 33.9 s to 86.2 s for trunk flexion (Figure 2). Although the lifting in Phase 1 only lasts a few seconds, relative to the overall length of the task, the maximum exposure time is about double, leading to a reduction in the biomechanical risk for the worker when the task is executed with a coBot. The risk is reduced in this phase because the worker, through the coBot, performs the lifting with a reduced trunk flexion and shoulder extension as the coBot helps move the load/gear closer to the worker than the usual position without the coBot (Figure 1(a1,b1)).

In Phase 2, the most notable results concerned the flexion/extension of the right wrist and the humeral rotation of the right shoulder. The %MVC of the wrist decreased from 50.2% to 3.0% and that of the shoulder decreased from 68.4% to 7.4% (Figure 3). The contemporary maximum exposure times increased from 58.8 s to 1200 s for the wrist and from 125.2 s to 873.0 s for the shoulder (Figure 3). In this phase, the worker cleans the load/gear and its weight, unassisted by the coBot, and is fully sustained by his/her right limb. Together with the hooking grip that the workers use, it is possible to better understand how much this task overloads the shoulder and wrist joints (Figure 1(a2)). By using the coBot, the load/gear would be completely supported by it. The worker would only locate the load/gear in the most correct position for his/her anthropometric characteristics without holding it (Figure 1(b2)).

As mentioned previously, by using the coBot, there would not be a Phase 3. In this phase, the lifting of the load/gear inside the packaging would be fully automated (Figure 1(a3,b3)).

A few remarks should also be made concerning this paper. A limitation of the study is the small sample size. This was due to the lengthy and intricate nature of the experimental session, which entailed performing the work task twice, once with and once without the BAZAR robot. Moreover, the experiments were only feasible for a brief period, during which two research groups collaborated and shared technologies and knowledge at the University of Montpellier as part of the EU's Horizon 2020 SOPHIA project (refer to the "Funding" section for more information). Larger sample sizes in subsequent research will be helpful in validating the findings of this investigation.

Regarding the methodology, a recent article [65] reported that the output of the 3DSSPP software did not accurately correlate with the estimated linear arm strength values and percent capable values in females for the range of conditions tested, likely due to the overly simplified assumptions made to estimate the triaxial shoulder strength. The data affected relate to the shoulder results, and not to those of the trunk and wrist. With regards to Phase 1, our data were mediated by a mixed sample of men and women, resulting in a narrow margin of error. As far as Phase 2 data are concerned, however, the difference observed was sufficiently wide to overcome the method error margins shown by Hall. Moreover, in contrast to these considerations, there are findings in another article [66] stating that static models underestimate joint loads and that, therefore, the risk under real, dynamic working conditions could be potentially higher than in our results. Finally, the reconstructions were not as accurate as they could have been with optoelectronic and IMU systems, and they suffered from the subjective perception of the person who performed the reconstructions. We tried to minimize this bias by making two different reconstructions of the same picture from two different authors in a double-blind manner. At the end, all the authors discussed all the reconstructions together, trying to reduce subjective perception.

5. Conclusions

The data presented last year by the President of Italian Workers' Compensation Authority [67] to the Italian Parliament demonstrate that Italian occupational illnesses caused by work-related musculoskeletal disorders (WR-MSDs) have increased continuously since 2011, in both absolute terms and percentage terms [67]. The most recent data show that WR-MSDs represent, with 41.960 reports in 2022, 69.17% of all the occupational illnesses reported to the institute. Due to the exponential increasing trend of WR-MSDs in the last decade, INAIL promotes the research of Industry 4.0 technologies, such as exoskeletons, coBots, and robots, to mitigate the occurrence of WR-MSDs in work environments.

A long-term investment in Industry 4.0 technologies is justified because introducing coBots can lead to a decrease in the cost associated with sick leave, rehabilitation, and health insurance premiums for the factory. Moreover, coBots can improve the production quality and reduce the waste of resources [68,69].

In our study, we used the 3DSSPP software to assess the biomechanical risk in an actual scenario by analyzing some parameters without and with the use of a coBot. The parameters we investigated with 3DSSPP did not have a correlation with injury except for the 3DSSPP strength percent capable value, which is correlated only with the reconstructed posture, not considering other additional risk factors. This is because work-related musculoskeletal disorders have a multifactorial etiology that includes not only physical stressors, but also psychosocial risk factors, such as job strain, social support at work, and job dissatisfaction [2,70].

The results of our study showed that, for some occupational tasks, collaboration with coBots allows for a decrease in joint loads. Furthermore, the use of easy and cheap risk assessment tools such as the 3DSSPP software allows for a complete biomechanical risk assessment in Industry 4.0. Future developments of the present study could be aimed at developing an in-depth correlation of the extracted parameters with sEMG-based indexes. Our paper shows that, for biomechanical risk assessments in Industry 4.0, where it is not possible to use the common standardized protocols of the standard ISO 11228 series [7–9], is it possible, in our scenario, to use easy and cheaper risk assessment tools, such as the 3DSSPP software, rather than sEMGs, IMUs, or optoelectronic systems [63].

In conclusion, we can claim that using a coBot in this industrial scenario would reduce the biomechanical risk for workers. The advantages in Phase 1 concern trunk flexion and the abdo-adduction of both shoulders, since the coBot helps the workers reduce their horizontal distance during manual handling; the advantages in Phase 2 concern the reduced humeral rotation of the right shoulder and the reduced flexion/extension of the right wrist, since the coBot helps the workers hold the workpiece in the cleaning task, allowing for a better posture. The advantages in Phase 3 consist of removing another task of manual handling, which is totally automated, giving the worker a well-deserved rest.

As shown in several previous papers, the use of coBots is a promising way to reduce the biomechanical load of workers during MMH activities in industrial settings.

In the future, it would be useful to integrate artificial intelligence algorithms into marker-less motion analyses to investigate motion in real work environments, also through smartphone-based tools [71], as they do not interfere with worker movement in the real work environment and they provide accurate feedback stimuli. These tools are still in an early stage, but over the coming years, they could provide useful and objective information on workers' biomechanical risk in real time with more accuracy than 3DSSPP, which suffers from subjective perception.

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