Semi-Automatic Rapid Upper Limb Assessment (RULA) with Azure Kinect of assembly and disassembly tasks, and the related learning curve

Coruzzolo A.M.*, Rossini S. *, Alessandro Neri *, Lolli F. *, Gamberini R. *, Regattieri A. **

**Department of Sciences and Methods for Engineering, University of Modena and Reggio Emilia, Via Amendola 2, 42122– Reggio Emilia, Italy (antoniomaria.coruzzolo@unimore.it, salvatore.rossini3@unibo.it, 214017@studenti.unimore.it francesco.lolli@unimore.it, rita.gamberini@unimore.it)*

***Department of Industrial Engineering, University of Bologna, Viale del Risorgimento 2, 42122– Bologna, Italy (alberto.regattieri@unibo.it)*

Abstract: The correct use of a rapid upper limb assessment is fundamental to prevent musculoskeletal disorders. Motion Capture (MOCAP) technologies are now being investigated for ergonomic risk assessment. One of the most commonly used technologies is depth cameras, in particular Kinects. Using version 3 of Kinects (Azure Kinect), we developed an application, named AzKRULA, for ergonomic risk assessment using a Rapid Upper Limb Assessment (RULA) to carry out a video analysis on an assembly task. We analysed 140 videos of an operator performing assembly and disassembly tasks thus enabling us to identify both a short-term and a long-term learning effect. In addition, we found a negative correlation between the ergonomic risk and the learning curve which we believe should be investigated further.

Keywords: RULA, machine vision, ergonomic risk, learning

I. INTRODUCTION

Industry 4.0 has received considerable attention in the industrial production field [1] [2]. This revolution changed organizations and processes [3], as well as the way humans work [4]. Despite the continuous improvement in working conditions and robotization, human operators are still involved in various manual tasks since is difficult for robots to acquire soft skills and some specific competences [5]. In addition, more than a half of the tasks performed are short and repetitive [6], leading to work-related musculoskeletal disorders (WMSDs), i.e. “all musculoskeletal disorders that are induced or aggravated by work and the circumstances of its performance” [7]. As highlighted by the 6th European Working Conditions Survey, issues related to posture, involving repetitive hand and arm movements, are the most prevalent risks in Europe. Some 61% of workers have these issues, which play a key role in causing WMSDs [8]. In 2017, the US Bureau of Labor Statistics reported that in manufacturing 31.4% of time off work is caused by WMSDs [9]. In fact, WMSDs in the US have an estimated direct economic cost of USD 20 billion/year, and up to five times more for indirect costs (e.g. hiring and training of replacement workers [10]. To protect health and welfare of workers, policies are needed that minimize the risk of WMSDs [11]. The first step is to evaluate risk exposure to factor and plan any ergonomic interventions [12] (i.e. workplace redesign). There are basically three main methods to carry out this evaluation: self-reports, direct measurements and observational methods [13]. Self-reports are by nature subjective [14]. Direct methods entail attaching sensors to the worker’s body, and these sensors are usually expensive, highly intrusive, and imprecise. Consequently usage of the third approach - observational methods - has increased considerably since 2005 [15], as confirmed by a large survey on ergonomics practitioners [16]. The most common observational methods are: Rapid Upper Limb Assessment (RULA) [17], Rapid Entire Body Assessment (REBA) [18], the NIOSH lifting equation [19], the Strain Index [20], the OVAKO Working Posture Analysing System (OWAS) [21], and the Concise Exposure Index (OCRA) [22]. However, all these methods have the same drawback: they require an ergonomic practitioner to evaluate postures with a video analysis. This analysis is usually time-consuming, is not very accurate, and suffers from high intra-and-inter-observer variability [23]. To overcome these limitations, MOCAP technologies are now being use in ergonomic assessments (see Section 2). In this context, we exploited a new application for rapid upper limb assessment with Azure Kinect [24] in order to perform a video analysis of assembly tasks. Specifically, the analysis tried to find out whether there is a correlation between the ergonomic risk and the learning curve, i.e. whether the health risk decreases or increases with an increase in the learning curve obtained through repeating the same task many times. Importantly, we found that doing a task more efficiently actually increases the risk of health problems for the operator. The paper is structured as follows. Section 2 reviews MOCAP technologies in terms of ergonomic risk assessment. Section 3 outlines the theory on learning curves. Section 4 presents our experimental design, while Section 5 presents our results. In the final section we draw conclusions and suggest ways to further the research agenda.

II. Literature Review MOCAP

To eliminate the inherent weaknesses of observational methods, studies have integrated MOCAP technologies into ergonomic risk assessments (Manghisi *et al.*, 2017) [25] [26]. MOCAP technologies are essentially sensor-based or optical [27]. The main advantage of a sensor-based MOCAP is that, unlike an optical MOCAP, there are no occlusions. However, a sensor-based MOCAP is usually highly intrusive since it is attached to the worker's body and is not particularly accurate [28], leading to limited applications in industrial sites. In fact, there have been few studies related to sensor-based MOCAP technologies. In [29] the authors exploited inertial sensors to calculate RULA and OCRA in warehouse activities, Pepponi et al. [30] employed inertial sensors to assess the RULA and Strain Index. Hsu and Lin [31] calculated RULA in agricultural activities. There are also challenges due the discomfort for the worker [32], which goes against the main objective of a human centred design [33]. On the other hand, optical systems are less intrusive and provide a valid solution for an ergonomic risk assessment (Manghisi *et al.*, 2017). The most popular cameras are Kinects since they are a ready-to-use technology that provides a real time segmentation using the depth-RGB data that can be processed in real time using the software development kit provided. The current generation of Kinect - the third - is called Azure Kinect c. Many studies have used Kinects for ergonomic risk assessments. For example, Diego-Mas et al. [34] calculated OWAS using Kinect v. 1 in a sequence of images with different postures and found a good agreement with an expert evaluation. Manghisi et al. (2017) developed a software application that semi-automatically calculates RULA with a Kinect v. 2, which showed a good agreement with an expert, an optical motion capture system and with some commercial software based on Kinect v. 1 in the analysis of 15 static postures. Plantard et al. [35] calculated RULA from Kinect v. 2 data finding a substantial agreement with an expert evaluation in both the laboratory and a real working environment. Bortolini et al. (2018) utilized four Kinect v. 2 cameras, each connected to a dedicated personal computer to create a Motion Capture System (MAS) that captures segmentation data without one of the main drawbacks of depth cameras: the inaccuracy derived from occluded postures (Plantard *et al.*, 2015). This inaccuracy was demonstrated in [36] where Kinect v. 2 was tested against an optical marker-based system and IMU, revealing that the RULA provided by the Kinect is less stable than the other two systems, but it can be used for an ergonomic evaluation in a working environment without severe occlusions. These results were confirmed in a recent work [37], where Kinect v. 2 showed a fair to moderate agreement in the RULA score provided with respect to a reference MAS made up of eight Vicon cameras due mainly to occlusion issues. Finally, Coruzzolo et al. (2022) developed an Azure Kinect based application for RULA calculation (AzKRULA) and tested it in comparison with an ergonomic expert and a machine vision algorithm based on simple RGB videos: they found a substantial agreement between the three solutions. In this work, we exploited the new AzKRULA to carry out a video analysis of assembly and disassembly tasks. Specifically, for 7 working days an operator performed 10 assembly tasks and 10 disassembly tasks (on an IKEA bedside table) for a total of 140 videos recorded. We also modelled the learning effect of the operator with classical learning curves and tried to find a correlation between the ergonomic risk detected and the learning effect.

III. Learning Curves: models and applications

When an individual performs an activity, this leaves a mark on their memory. The German psychologist Hermann Ebbinghaus was the first to investigate this aspect in his work [38]. Since that time, the effects of learning and forgetting have been studied in medicine, neuroscience, psychology, engineering, and many others [39]. Wright investigated learning effects in aircraft manufacturers and created a mathematical model for manufacturing contexts [40]. He observed, in an aircraft manufacturing facility, that the cost per unit decreases by a constant percentage while doubling the outputs.

He quantified this decrease in the following log-linear model:

$$y(x)_m = y_1 * x^b \tag{1)}$$

He was the first to use the effects of learning and forgetting to analyse production and operations. In the Wright Learning Curve (WLC) formula, $y(x)_m$ represents the cumulative average time (cost) to produce the xth quantity, y_1 the time (cost) to perform the first unit, x is the xth quantity, and b represents the learning exponent:

$$b = \log(p)/\log 2, \quad b \in [-1; 0] \tag{2)}$$

where p is the Learning Rate (LR) and describes how the operator's performance improves while increasing repetitions. Despite being rather simplistic, this model has been widely used in different contexts [41], and several researchers have tried to correct the model's limits. Crawford identified the output of Wright's model not as an average value, but as the time, or cost, to produce the x^{th} unit. De Jong proposed the introduction of a machine factor M $(0 \leq M \leq 1)$ considering that a task's fraction is executed by machinery [42]. Stanford-B's model incorporated prior worker experience (B) and quantified it by considering the number of units already produced by the operator [43]. Based on Yelle's model and the Stanford-B's model, the S-curve model describes learning and forgetting effects when experience and machinery are part of the production [44]. The resulting formula maintained the original parameters of the previous model but added the machine contribution (M) and the experience of the worker (B):

$$y(x) = y_1[M + (1 - M)(x + B)^b] \quad 3)$$

One of the main limits of WLC is that when the quantities tend to infinity (or to a very large number), the time per unit (or cost per unit) tends to zero. To improve this aspect, we used Plateau's model, which entails inserting a constant parameter C that represents the minimum value in terms of cost or time to produce one unit [45]. According to Blancett [46], learning curves are the most useful mathematical model to predict the production rate in repetitive operations. In this study we decided to investigate the effects of learning and forgetting utilizing Wright's, Crawford's and Plateau's models, given that the operator has no experience and there is no machinery involved in the assembly and disassembly processes. Several studies have found that the learning rate can vary across different firms and different sectors [47] [48] [49], and depends on the characteristics of the operators on the complexity of the task. In order to fit Crawford, Wright and Plateau's models to the empirical data, we modified the LR in a classical regression. The mean square error (MSE) was then minimized to obtain the best fit between the models and the empirical data.

IV. Experiment Design

The experiment was carried out over a period of seven working days during which a volunteer (male, 24 years old, 180 cm, 80 Kg) performed 10 assembly and 10 disassembly operations per day to assemble and disassemble an IKEA bedside table. A total of 140 videos (375 minutes) were recorded by "Azure Kinect DK". In order to have a standard and fixed height (110 cm) in each recording, the depth camera was mounted on an aluminium support structure with an average distance of 220-250 cm from the subject. The camera was placed in order to capture the main part of the body that was the right one since the volunteer was right-handed. From now on we will refer to RULA as the RULA score of the right side of the body that was always visible to the camera and the most affected by repetitive movements. The Azure Kinect has been exploited with the following settings: Colour mode→ On 720p, Depth mode→ On NFOV 2x2 binned, No depth delays, Frames per second (fps)→15, IMU→ON, External sync→Standalone, Sync delay →0, Exposure→ Auto, Gain →Auto. In particular the NFOV 2x2 binned setting was used since was demonstrated to outperform previous version in terms of accuracy [50].

The operations were completed on a 150x90x80 cm wooden worktable, equipped with a storage panel including objects such as screwdrivers, that the worker needed to execute the tasks, thus reproducing in a realistic way an operator's workstation in an industrial field. The operations were performed in a controlled laboratory with a mean temperature of 23°C and a mean controlled illumination of 300 Lux.

The volunteer assembled and disassembled an IKEA bedside table, "Lixhult" model, made up of two brackets, two side panels, upper floor, lower floor, one internal shelf, and four legs. The item's components were placed on a shelf located 65cm in front of the workstation, as shown in figure below. Assembly and disassembly tasks were considered separately. The various processes consist of 12 phases each, where data were collected by Azure Kinect and processed with AzKRULA to extract the RULA evaluation at each frame, and then exported to Excel for processing and analysis to understand the learning curve.

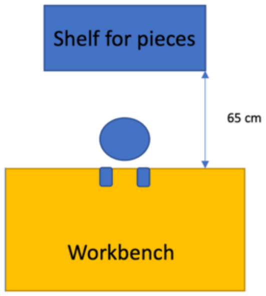

Fig. 1. Assembly station configuration.

V. Results

To investigate how the volunteer increased his productivity over time and through repetition, 10 repetitions per day were performed for each process. Simultaneously, the "Azure Kinect DK" recorded movements and postures. The results relating to the learning effect and the ergonomic risk are first presented separately and then analyzed together to investigate possible correlations.

A. *Performance Results*

During the tests, the volunteer carried out 12 tasks to complete the assembly, spending a time for the total assembly task in a range from 139 to 300 seconds with a mean value of 199 seconds and a standard deviation of 39.20 seconds. The minimum time was reached in the sixth repetition on the seventh day. The total disassembly time was much since was performed in 227 seconds in the worst case, and in 85 seconds at best, with a mean value of 135 seconds. Crawford's, Wright's and Plateau's models were fitted for each day by minimizing the mean squared error (MSE). Secondly, the mean average value was calculated every day in order to reveal the learning curve during the total period of the 10 days and eliminating any variability during individual days through the mean average value. On the first day of testing, the volunteer performed the assembly tasks in a range between 252 and 180 seconds, with an average time of 210.3. The highest value was achieved when performing the first assembly test, which took 19.83% more than the average time needed on the same day. Subsequently, predictions extrapolated from Wright's, Crawford's and Plateau's models were calculated and are shown in Figure 2.

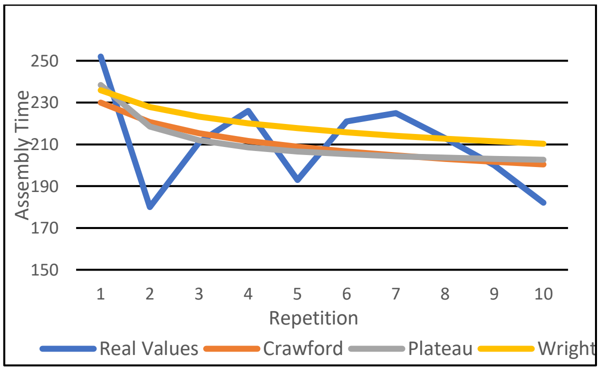

Fig. 2. Fitted Models for the assembly times in the first day

Plateau's and Crawford's models were the ones the fitted the data best. Plateau's model had the lowest MSE, as reported in Table 1 where the MSEs of all the models are reported for each day.

TABLE I
MSE FOR WRIGHT, PLATEAU AND CRAWFORD MODELS FOR THE ASSEMBLY DURING DAYS

	MSE: Wright	MSE: Plateau	MSE: Crawford
Day 1	342.65	335.54	367.05
Day 2	12,666.07	644.92	888.90
Day 3	1,222.25	1202.96	1202.96
Day 4	11292.76	826.80	5790.32
Day 5	686.84	670.74	715.02
Day 6	393.94	323.82	659.89
Day 7	452.42	383.02	383.89

As Table 1 shows the best model to fit the learning process in the assembly task in each day respect to MSE was always the Plateau's.

The results obtained by monitoring the assembly task times performed during the seven days could highlight some interesting aspects:

✓ For the whole period, completing the first assembly task took longer time than the last one on the same day. This reveals a "short-term" learning effect due to improved performance by the operator over the course of the day.

✓ The completion times for the first task of the day were longer than those recorded in the last test of the previous day. This indicates that although the worker improved during the course of a day, at the beginning of the next day this improvement had already been lost, i.e. the experience gained in completing the task on the previous day had already been forgotten in a forgetting phase between days.

✓ The average times recorded in the last three tests on each day were always shorter than both the average time for the first three tests and overall average time of reference day, reinforcing the intra-day learning

✓ The highest completion time was recorded for the first test on the second and on the fourth day, while the minimum value was recorded for the sixth test of the last test day. Despite the phases of forgetting, described at the second point, between several days, therefore, there also seems to be a "long-term" learning phase.

Figure 3 shows the Plateau models fitted for each day of testing, since this was the best model to fit the real data from all seven days. Figure 3 shows that the Plateau models for the last two days are significantly lower than the others thus indicating that there is long-term learning effect. Figure 3 also highlights the short-term learning effect in each day and the forgetting effect in subsequent days.

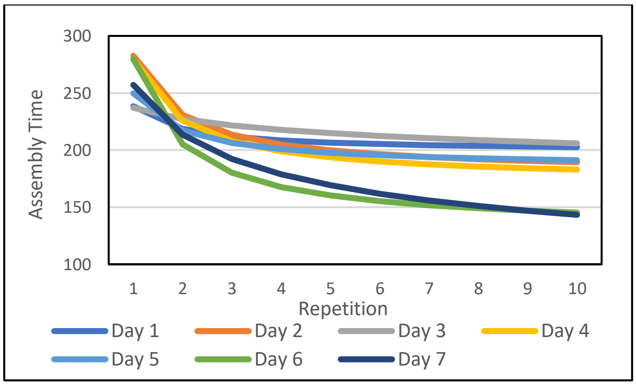

Fig. 3. Fitted Plateau models for the assembly during days

Very similar results were found for the disassembly phase. In fact, for the disassembly task the Plateau model was again the one that best fitted the data for each day and the same learning effect during the day, the forgetting between days and the long-term learning phase were detected.

B. Rula results

The ergonomic index, RULA, was calculated through AzKRULA an application developed and described in detail in our previous paper (Coruzzolo et al. 2022).

TABLE II
RISK LEVEL AND ACTION LEVEL FOR RULA

Score	Risk Level	Action Level
1-2	Negligible risk	The posture is acceptable provided that it is not maintained or repeated for long periods
3-4	Low risk	Further investigation is needed, and actions may be required
5-6	Medium risk	Investigation and changes are required soon.
7	High risk	Investigation and changes are required immediately.

The RULA score comes from an assessment grid which is filled in using joint angles. It separates the human body into two sections: Section A - upper arm, lower arm, and wrist; Section B - neck, trunk, and legs. For each joint in each section a series of principal factors, based on the joint angles, along with secondary factors (e.g., abduction or trunk twist) are evaluated and integrated into a score (Lynn and Corlett, 1993). The final RULA score ranges from 1 to 7. It is classified into four levels of actions required to reduce the risk of injury for an operator [17] as reported in Table 2.

Not all the retrieved joints were needed to calculate the angles for the RULA score. However, additional

processing was required on the retrieved joints to create the geometrical structures needed.

We followed the procedure developed by Manghisi et al. (2017) modifying it accordingly with the new joints provided by Azure Kinect (with respect to Kinect v. 2) exploiting the Azure Kinect SDK for retrieving joints. Then, AzKRULA calculates the RULA for each frame of each video analysed. RULA is semi-automatic since some manual inputs are needed. In fact, for the *leg score*, we carried out a manual evaluation like we had done for *muscle* and *force factors*. For all these manuals evaluated factors default values are used. However, with respect to the RULA calculation with Kinect v. 2 developed by Manghisi et al. (2017), who did a manual evaluation of the neck twist, our application calculates it automatically thanks to the new joints tracked by the Azure Kinect in the head area (Tölgyessy et al., 2021). The video was recorded in 15 fps, calculating the RULA score for each frame, and reporting a mean value for each second. The RULA scores in the first assembly day are reported in Figure 3. As Figure 4 shows all the cycles reach a plateau for a RULA score of 3, which corresponds to a low risk. However, there are some peaks, for example in the first day in cycles 6 and 1, where the RULA score has the maximum value possible, 7 (i.e. a risk that requires an immediate intervention). From the same data regarding the other seven assembly days, we calculated the mean RULA for each assembly repetition in each day. The results are shown in Figure 5.

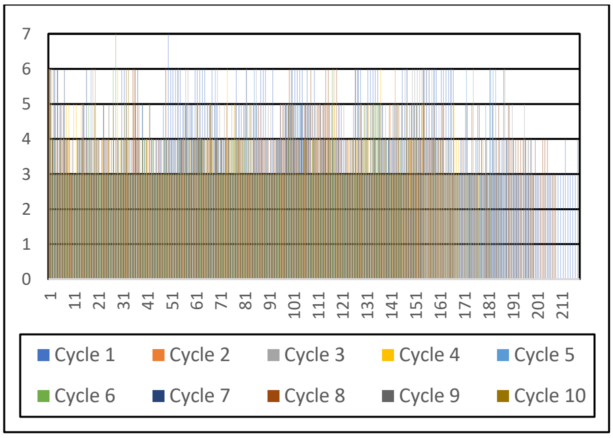

Fig. 4. RULA scores in the first assembly day

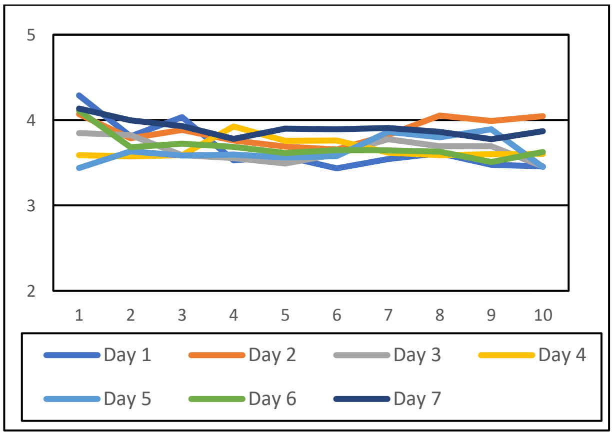

Fig. 5. Mean RULA scores in the assembly tasks for each repetition during days

The mean RULA score for the different repetitions in the various days seems to follow the same trend, with lower values in the intermediate repetitions. The same calculations were made for the disassembly, with very similar results which are not reported for the sake of brevity.

C. *Learning and RULA*

The last phase of our results analysis regards the relation between learning and RULA. Specifically, we investigated the correlation between the learning curve and the ergonomic risk in the assembly and disassembly tasks. We only considered the long-term learning curve by calculating the correlation between the mean assembly (disassembly) time per day with the mean RULA score in the same day during that task. The data with the mean assembly-disassembly time per day and the mean RULA in each of the task for each day are reported in Table 3. Table 3 shows that the long-term learning curve already detected since both the mean assembly and disassembly times follow a decreasing trend among days. We then calculated the coefficient of correlation between the mean assembly time and the mean RULA during this assembly task, which resulted in a negative correlation of -0.29, and was -0.31 for the disassembly. The correlation between the two factors was not strong (-0.30) and was very similar for the two cases.

This is an interesting result that highlights how by decreasing his performance time in the assembly and disassembly tasks (and thus increasing his performance) the volunteer actually increases the ergonomic risk to which he is subjected to.

TABLE III
MEAN ASSEMBLY AND DISASSEMBLY TIME AND RELATIVE MEAN RULA FOR EACH DAY

	Mean Assembly Time	Mean RULA Assembly	Mean Disassembly Time	Mean RULA Disassembly
Day 1	210.3	3.67	132.4	3.11
Day 2	209	3.95	139.9	3.84
Day 3	216.3	3.65	111.8	3.74
Day 4	208.8	3.59	113.4	3.43
Day 5	203.7	3.63	115.2	3.67
Day 6	174.1	3.68	102	3.91
Day 7	177	3.90	110.6	3.58

This effect can be explained by the fact that to increase his performance, the volunteer made more extreme movements both from a joint angle and frequency perspective. In addition, the fact that a very similar correlation was found between the ergonomic risk in both the assembly and disassembly, reinforces these findings.

VI. CONCLUSIONS

We have presented an experimental study where we exploited a MOCAP-based application for the semi-automatic evaluation of the RULA ergonomic risk index [24]. The experiment covered seven days of testing where in each day a volunteer performed ten assembly and ten disassembly tasks related to an IKEA bedside table at a workstation for a total time of 375 minutes. The first part of our analysis related to the learning curve and the second to the ergonomic risk. The results we found are the following:

➢ Short-term learning: we fitted three different models minimizing the MSE for each day and found that the Plateau learning curve was the one that best fit the short-term learning process during each day both for the disassembly and disassembly tasks.

➢ Long-term learning: we found a long-term learning effect through the course of the experiment, but which was hindered by a forgetting phase between days. This was demonstrated also by comparing the various plateau models through the days as shown in Figure 3.

➢ Ergonomic risk: for the RULA score we found a plateau value in each repetition was near to three and similar scores between the various days coupled with some peaks at the highest ergonomic risk possible.

In addition, we investigated a possible correlation between the ergonomic risk and the learning effect. We studied it in terms of long-term learning by calculating the correlation between the mean assembly (disassembly) time per day with the mean RULA score in the same day during that task. We found a negative correlation (around -0.30) between them which was very similar both for the assembly and disassembly tasks. This negative correlation highlights how by increasing his performance by reducing the task time the volunteer was subjected to higher ergonomic risks. This result is explained by the fact that to increase his performance the volunteer made more extreme movements from a joint-angle perspective.

Future extensions of our work could include the following aspects to confirm our findings:

➢ Extensive experiments with a panel of volunteers of different ages and physical characteristics.

➢ Different tasks with respect to assembly/disassembly and different ad hoc ergonomic risk indexes, e.g., picking and the NIOSH index.

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