Human Workload and Ergonomics during Human-Robot Collaborative Electronic Waste Disassembly

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2022 IEEE 3rd International Conference on Human-Machine Systems (ICHMS) | 978-1-6654-5238-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICHMS56717.2022.9980828

***Abstract*—A rapid rise in the recycling and remanufacturing of end-of-use electronic waste (e-waste) has been observed due to multiple factors including our increased dependence on electronic products and the lack of resources to meet the demand. E-waste disassembly, which is the operation of extracting valuable components for recycling purposes, has received ever increasing attention as it can serve both the economy and the environment. Traditionally, e-waste disassembly is labor intensive with significant occupational hazards. To reduce labor costs and enhance working efficiency, collaborative robots (cobots) might be a viable option and the feasibility of deploying cobots in high-risk or low value-added e-waste disassembly operations is of tremendous significance to be investigated. Therefore, the major objective of this study was to evaluate the effects of working with a cobot during e-waste disassembly processes on human workload and ergonomics through a human subject experiment. Statistical results revealed that using a cobot to assist participants with the desktop disassembly task reduced the sum of the NASA-TLX scores significantly compared to disassembling by themselves (p = 0.001). With regard to ergonomics, a significant reduction was observed in participants' mean L5/S1 flexion angle as well as mean shoulder flexion angle on both sides when working with the cobot (p < 0.001). However, participants took a significantly longer time to accomplish the disassembly task when working with the cobot (p < 0.001), indicating a trade-off of deploying cobot in the e-waste disassembly process. Results from this study could advance the knowledge of how human workers would behave and react during human-robot collaborative e-waste disassembly tasks and shed light on the design of better HRC for this specific context.**

Keywords—human-robot collaboration, electronic waste disassembly, human workload and ergonomics

I. Introduction

Electronic gadgets are now a part of every aspect of our lives because of technological advancement. Although the intention of these technologies is to improve and simplify our lives, as our reliance on electronic products grows, the amount of electronic waste (e-waste) being produced each year when we discard or replace these devices has been rising. According to the Global E-waste Monitor 2020 [1], global e-waste production reached a record 53.6 million tonnes in 2019, increasing 21% in just five years. At the same time, there has been an increased interest in end-of-use product recovery and e-waste management [2]–[4]. To promote greener and more resource friendly productions, e-waste disassembly is a necessary step to extract valuable materials and components from end-of-use electronics.

While e-waste disassembly could increase the number of materials and components available for recovery and reuse, the process is one of the most expensive steps in e-waste management and may introduce various safety risks [5]. Given that most e-wastes are currently manually dismantled, the labor-intensive nature and high exposure to hazardous substances pose serious occupational hazards to human workers [6], [7]. To reduce labor costs and enhance efficiency, a new robot architecture: the collaborative robot, or cobot, has been developed. In contrast to traditional autonomous industrial robots which must be isolated from people for safety reasons, cobots are intended for direct physical interaction with human workers in close proximity [8], [9]. In compliance with the upcoming Industry 5.0 paradigm, leveraging the strength and intelligence of cobots to promote more efficient and sustainable productions is receiving growing attention [10].

A large body of literature put focuses on human-robot collaboration (HRC) during the disassembly process. For example, Axenopoulos et al. [11] have discussed a novel framework for e-waste recycling. A hybrid HRC approach was proposed for device classification, disassembly, and component sorting. Gerbers et al. (2018) researched and implemented 3D safety sensors based intuitive programming environment for HRC in the disassembly of Lithium-Ion Batteries [12]. However, enabling safe and seamless collaboration between human workers and robot assistants in a shared workspace is a non-trivial problem that calls for not only recent advances in robotics, such as human-aware obstacle avoidance [13], [14] and real-time object detection [15], [16], but also a thorough understanding of how humans will physically and psychologically respond to this new working mode [17], [18].

This investigation was made possible by Award No. 2026276 from the National Science Foundation.

978-1-6654-5238-0/22/$31.00 ©2022 IEEE

As far as the authors are aware, earlier research efforts that took into account human workload and ergonomics during human-robot collaborative e-waste disassembly were mostly from the viewpoints of workplace design [19], [20] and task planning [21], [22]. Therefore, the major objective of this study was to quantitatively evaluate the effects of working with a cobot during the e-waste disassembly process on human workload and ergonomics through a high fidelity human-in-the-loop experiment. Based on the results from our pilot tests, we hypothesized that: compared to the working alone condition, working with a robot assistant 1) reduces the overall human workload; and 2) lessens the physical stress that the task puts on the human workers.

II. Methods

A. *Participants*

Ten male participants were recruited from the university student population to participate in this study. Their mean (SD) age, height, and body weight were 24.5 (2.5) years, 178.6 (8.7) cm, and 74.0 (24.9) kg. All participants reported themselves to be in good health, able to stand for periods of at least 5 minutes, have a negative COVID-19 test result with the official report within 2 weeks, and free from any musculoskeletal injuries that required medical treatment in the past 6 months. Nine out of 10 participants claimed to be right-handed, with the remaining one claiming to be ambidextrous. Before any data collection, participants completed informed consent and the experiment protocol was approved by the University of Florida Institutional Review Board (IRB202200211).

B. *Instrumentation*

For data collection, an inertial measurement unit (IMU) based motion capture system (MVN Awinda, Xsens Technologies BV, Enschede, The Netherlands) consisting of 17 inertial sensors attached to different parts of the participant's body according to manufacturer's instructions (Fig. 1). Each sensor contained 3D gyroscopes, 3D accelerometers, and 3D magnetometers [23], [24]. The sampling frequency of the system was set at 60 Hz throughout the study. The data was wirelessly transmitted via Bluetooth to a computer running the MVN Analyze software which allows the motion data to be observed, recorded, and analyzed.

Fig. 1. Pictures showing the motion capture sensors setup.

The robot assistant used in the study was the UR5 robot manipulator (Universal Robots, Odense, Denmark). The robot is 18.4 kg in weight and it has 6-degree-of-freedom on articulated joints. It is designed to automate tasks with a weight of up to 5 kg with a working radius of 850 mm. A Robotiq 2-finger adaptive gripper 85 (Robotiq, Levis, Canada) was mounted and integrated with the robot manipulator (Fig. 2), serving as the end effector to enable grasping. The robot was programmed using the software provided by The Universal Robots Company that allows intuitive programming with 3D visualization.

Fig. 2. The robot assistant and its end effector used in the study.

To simulate the e-waste disassembly process, a Dell Optiplex 9020 desktop computer (Dell Inc., Round Rock, USA) was randomly selected. As shown in Fig. 3, five components were targeted to be taken apart in a pre-defined fixed sequence, i.e., 1 - an optical disc drive, 2 - a hard drive, 3 - a fan shroud, 4 - a heat sink, and 5 - a RAM. The disassembly sequence was determined mainly due to the physical constraint. For example, the heat sink can only be removed after the fan shroud to gain access.

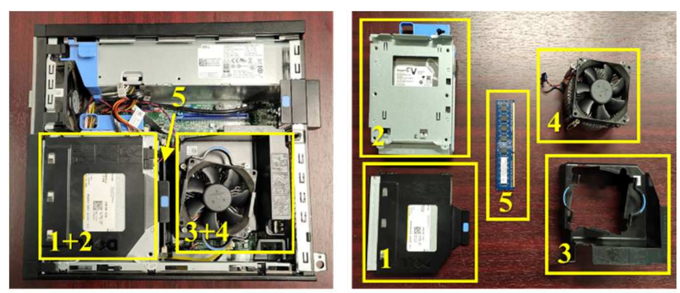

Fig. 3. The desktop computer used in the study and components selected for disassembly.

C. *Experimental Design*

A one-way, repeated measure experiment was adopted to evaluate the effects of working with a cobot during the e-waste disassembly process on human workload and ergonomics. Two working modes were tested in the experiment: 1) performing the disassembly task alone (no robot) and 2) performing the disassembly task with the cobot's assistance (with robot). Each participant completed 2 repetitions of each working mode. Table I shows the required tasks and sequence in order to accomplish one simulated disassembly trial. In "no robot" mode, participants were asked to perform all the tasks by themselves. The cobot, on the other hand, assisted the participant with some of the activities based on the robot's capabilities in "with robot" mode (Fig. 4 & Fig. 5). The order of experimental trials was counterbalanced. NASA-TLX and joint angles (mean L5/S1 flexion angle as well as mean shoulder flexion angle on both sides) were the main dependent variables. Additionally, participant's task completion time for each trial was recorded.

TABLE I. REQUIRED DISASSEMBLY TASKS AND SEQUENCE.

Task No.	Task Description	Tool Required
Task 1	Move the desktop computer from the cart to the disassembly station.	None
Task 2	Disconnect the data cable from the optical drive.	None
Task 3	Disconnect the power cable from the optical drive.	None
Task 4	Lift the tab and slide the optical drive out.	None
Task 5	Move the optical drive to the desired bin.	None
Task 6	Disconnect the data cable from the hard drive.	None
Task 7	Disconnect the power cable from the hard drive.	None
Task 8	Slide the blue drive-cage handle toward unlock position.	None
Task 9	Lift the hard drive and move it to the desired bin.	None
Task 10	Using both hands, push away the two release handles while lifting the fan shroud upward and off the computer	None
Task 11	Move the fan shroud to the desired bin.	None
Task 12	Disconnect the fan cable (with clip) from the system board.	None
Task 13	Loosen the captive screws (x4).	Screwdriver × 1
Task 14	Lift the heat sink assembly and move it to the desired bin.	None
Task 15	Press down on the memory retaining tabs on each side of the memory module.	None
Task 16	Lift the memory module out of the connectors and move it to the desired bin.	None
Task 17	Move the desktop to the disassembly station.	None

Fig. 4. A photograph of the participant performing the disassembly task with the cobot's assistance.

D. Procedures

Upon arrival, participants were first asked to read and sign the informed consent form. Demographic information including age, gender, weight, and height was then collected. Next, the researcher demonstrated to participants how to complete the required disassembly tasks and the fixed disassembly sequence. At least two practice trials of each mode were given to participants until they felt comfortable with the process. Following that, the motion capture sensors were attached and the system was then calibrated according to manufacturer's instructions. Subsequently, participants completed the simulated disassembly trials. There were 2 repetitions for each working mode and the test order was counterbalanced. After each trial, a sheet of NASA-TLX was collected followed by a minimum 2-minute rest period.

E. Statistical Analysis

To test our hypotheses, one-way repeated measures analyses of variance (ANOVA) were performed on dependent variables. The assumptions of normality and homogeneity of the ANOVA model residuals were verified using the Shapiro-Wilk test and Levene's test. Each repetition was treated as a single observation with 'participant' being the blocking variable. All analyses were conducted using R studio version 4.2.1, with statistical significance achieved when $p < 0.05$. Partial Eta squared η_p^2 was used to determine the effect size.

III. Results

A total of 40 trials (10 participants × 2 working modes × 2 repetitions) were collected in this study. NASA-TLX scores

Fig. 5. Task allocation when the participant performed the disassembly process with the robot assistant.

were manually organized and entered into an Excel worksheet by two researchers independently. Joint angles, including L5/S1 flexion angle, left shoulder flexion angle, and right shoulder flexion angle, were calculated and exported using MVN Analyze software. Task completion time of each trial was determined by the duration of the trial recorded by MVN Analyze software as well. Table II summarizes the statistical analysis results including sum of NASA-TLX scores, joint angles, and task completion time.

A. NASA-TLX

NASA-TLX was analyzed to assess participants' perceived workload. The sum of scores reveals that participant's overall workload was significantly affected by the working mode (F (1,29) = 15.31, p = 0.001, η_p^2 = 0.35). More specifically, the sum of NASA-TLX scores is 96.75 (52.70) for "with robot" working mode, which is significantly lower than 165.60 (106.52) for "no robot" mode.

B. Joint Angle

As shown in Table II and Fig. 6, the working mode had a significant influence on participant's L5/S1 flexion angle and shoulder flexion angle on both sides. Compared to the baseline "no robot" working mode, participant's mean L5/S1 flexion angle decreased significantly from 12.55° (2.94°) to 8.87° (3.94°) in the "with robot" mode (F (1,29) = 83.26, p < 0.001, η_p^2 = 0.74). A similar impact was observed in mean shoulder flexion angle. Compared to "no robot" working mode, working with the cobot significantly reduced participant's mean shoulder flexion angle on both the right side (from 61.85° (12.96°) to 41.52° (8.13°), F (1,29) = 149.95, p < 0.001, η_p^2 = 0.84) and the left side (from 56.10° (13.19°) to 40.09° (7.10°), F (1,29) = 69.47, p < 0.001, η_p^2 = 0.71).

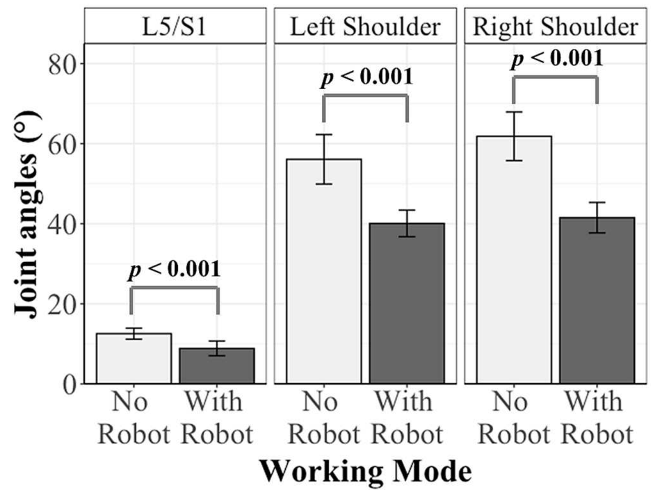

Fig. 6. Participants' mean joint angles in two working modes. The error bars represent the 95% confidence intervals.

C. Task Completion Time

In addition to NASA-TLX and joint angles, task completion time was shown to be significantly impacted by the working mode (F (1,29) = 105.35, p = 0.001, η_p^2 = 0.83). While participants spent an average of 105.35 (18.38) seconds to complete the disassembly process in "no robot" working mode, they took significantly longer time, i.e., an average of 159.05 (22.68) seconds, with cobot's assistance.

IV. DISCUSSION

The major objective of this study is to quantitatively evaluate the effects of working with a cobot during the e-waste disassembly process on human workload and ergonomics. To this end, NASA-TLX, a commonly used subjective workload measurement during HRC [18], [25], was adopted to assess participants' perceived workload during the experiment. Motion data, including L5/S1 flexion angle, left shoulder flexion angle, and right shoulder flexion angle, were selected to assess ergonomics due to the prevalence of low back pain and shoulder disorders among manufacturing workers [26]–[28]. In addition, task completion time was recorded and compared across working modes to evaluate the efficiency of the HRC design.

TABLE II. REQUIRED DISASSEMBLY TASKS AND SEQUENCE

Dependent Variable	**Mean (SD)**		***F*-value**	***p*-value**	**Effect Size η_p^2**
	No Robot	**With Robot**			
NASA-TLX (sum of scores)	165.60 (106.52)	96.75 (52.70)	15.31	**0.001**	0.35
Mean L5/S1 flexion (°)	12.55 (2.94)	8.87 (3.94)	83.26	**< 0.001**	0.74
Mean shoulder flexion – right side (°)	61.85 (12.96)	41.52 (8.13)	149.95	**< 0.001**	0.84
Mean shoulder flexion – left side (°)	56.10 (13.19)	40.09 (7.10)	69.47	**< 0.001**	0.71
Task completion time (s)	105.35 (18.38)	159.05 (22.68)	144.54	**< 0.001**	0.83

A. NASA-TLX

NASA-TLX is made up of six subscales: mental demand, physical demand, temporal demand, frustration, effort, and performance. It is assumed that the combination of these factors will likely represent the workload experienced by most people performing most tasks [29]. In this study, the ratings were simply added to get an estimate of the overall workload [30]. Statistical analysis revealed that working mode had a significant effect on the sum of scores ($p = 0.001$), indicating a significant reduction in workload when working with a cobot to complete the disassembly process. Despite being encouraging, the finding contradicts our earlier research [18], [31], which revealed that sharing the workspace with an autonomous mobile robot increased human workload. We argue that the conflicting results were mostly caused by inherent job characteristics. In [18], [31], participants were asked to conduct order picking and assembly tasks while a mobile robot mimicked pallet moving tasks in the same shared workplace. Since no direct collaboration was intended, the introduction of the robot agent did not reduce the amount of effort required of participants. Furthermore, participants had to allocate extra mental resources to situation awareness in order to ensure their safety when interacting with the robot in close proximity. This may explain the negative impact of working alongside the robot on participants' perceived workload. However, in this study the cobot took over nearly half of the required tasks from participants, including tasks 1 and 17, which required the most force exertion to complete. Moreover, the motion of the cobot was programmed to be secure and consistent throughout the trials, making it simple for participants to become accustomed to the robot's movements after adequate practice. Therefore, a significant reduction in perceived workload was observed when performing the disassembly task with the cobot's assistance.

B. Joint Angle

Low back pain is the most common musculoskeletal problem globally [32]. According to previous research [33], performing certain bending exercises can contribute toward low back pain. In this study, participants' mean L5/S1 flexion angle significantly decreased when working with the cobot compared to working alone ($p < 0.001$). The less the flexion angle, the less compression and shear force on the low back, indicating improved ergonomics introduced by the "with robot" working mode. Similarly, significant reductions in shoulder flexion angle on both sides ($p < 0.001$) revealed a lower risk of shoulder disorders when working with the cobot. Literature has revealed that shoulder disorders are associated with severe shoulder flexion [28]. The reductions in joint angles are attributed to fewer reaching activities being required in "with robot" working mode. As seen in Fig. 5, the cobot complements human workers on the majority of bending and reaching duties, e.g., moving the dismantled component to the desired bin that was far from the participant's location, so that participants could focus on the tasks that are more precision and flexibility demanding but didn't need making too many ergonomic compromises. Given the promising results, it is fair to assume that the ergonomics of human workers, particularly the risk of low back pain and shoulder disorders, might be improved by integrating the cobot assistant into the disassembly process.

C. Task Completion Time

While the results supported all of our original hypotheses, the negative impact of introducing the cobot system shouldn't be overlooked. Results showed that the working mode had a significant effect on task completion time ($p < 0.001$), which was unexpected yet found to be true. More specifically, the disassembly process was completed far more slowly by the human worker and cobot team than it was by the human worker alone. In line with previous research [34], the finding demonstrated a trade-off between job efficiency loss and gains in human workload and ergonomics. However, the current issue can be largely solved with an improved scheduling or HRC optimization process. During the experiment, there was a substantial amount of idle time on both the cobot and human worker sides. This resulted from the pairing of one human worker with one cobot on a single disassembly operation. An optimization problem might be hence generated by considering multiple human workers, multiple cobots, multiple ongoing tasks, or a mix of them.

D. Limitations and Future Work

The study was limited by the small sample size ($n = 10$), and only male participants were recruited. In order to investigate more detailed responses (i.e., sub-scales of the NASA-TLX), a larger sample size would be necessary. Objective workload measurement, such as surface electromyography and eye tracking, would be beneficial to complement subjective workload assessment using NASA-TLX. As for ergonomics, in addition to mean L5/S1 and shoulder flexion angles, a comprehensive full body kinematics analysis will be carried out to better understand human physical responses to the cobot.

V. CONCLUSIONS

In conclusion, results from the study supported the original hypotheses, i.e., compared to the working alone condition, working with the cobot reduced the overall human workload and the physical stress that the disassembly task placed on participants. This study confirmed that integrating HRC into e-waste disassembly processes could decrease human workload and improve ergonomics compared to traditional manual only disassembly. However, the task completion time was found to be negatively impacted when working with the cobot, indicating a trade-off between job efficiency loss and gains in human workload and ergonomics.

ACKNOWLEDGMENT

This investigation was made possible by Award No. 2026276 from the National Science Foundation (NSF). Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the NSF.

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