Empowering Social Sustainability Through Human centered HRC

Joan Lario[1,2](✉), Francisco Fraile[2], Iveta Eimontaite[3] and Sarah Fletcher[3]
[1] Departamento de Organización de Empresas, Universitat Politècnica de València (UPV), 46022 Valencia, Spain
[2] Research Centre on Production Management and Engineering (CIGIP), Universitat Politècnica de València (UPV), 46022 Valencia, Spain. joalafe@upv.es
[3] Centre for Robotics and Assembly, Cranfield University, Cranfield, United Kingdom

Abstract

The integration of Human-Robot Collaboration in manufacturing processes signifies a transformative shift towards safer, more efficient, and worker-centric production. Driven by the need for adaptable manufacturing, advanced technologies like machine vision algorithms and sensors have enhanced the accuracy and safety of robotic systems, transitioning from isolated robots to collaborative coworkers. The presented case studies in furniture, electronics, food and beverages, and printed circuit boards underscore the tangible benefits of Human-Robot Collaboration, including reduced manual labor, minimized exposure to hazards, and enhanced ergonomics. Five pilot cases were analyzed in terms of key human factors involved in the associated process illustrating the aspects of physical comfort, safety, and mental fatigue needed to be met to achieve social sustainability objectives. This approach represents a significant stride towards a more sustainable and harmonious coexistence between humans and robots in manufacturing which would allow the development of technology self-efficacy and worker upskilling/reskilling.

Keywords

Sustainability, Human-Robot Collaborative, human factors; HRC

1. Introduction

Conventional automatic manufacturing cells, composed of robotics arms, have been isolated from human access due to safety issues [1]. In other scenarios, if the amount of production or level of complexity is too high, the assembly or reassembly tasks have been performed by manual labour. In order to improve the European industrial scenario, new challenges have been raised in the past decade, requiring flexible and easily programmable control systems for robotics systems in a safe environment for human workers' cooperation [2]. The accuracy and safety of automatic robotic systems have been enhanced thanks to the development of advanced technologies, such as machine vision algorithms and RGB optical and Laser Imaging Detection and Ranging (LIDAR) sensors, which have successfully integrated into Robotic Operative Systems (ROS). Automatic manufacturing cells, whether industrial or collaborative, robot arms are evolving into flexible coworkers, expected to assist humans with intricate or physically demanding work in dynamic and partially unknown environments [3]. Motion planning adjusts robot motion in advance to optimize performance, considering collision avoidance and working efficiency.

Collaboration involves joint goal-oriented activities, sharing capabilities, competencies, and resources [4]. Human-Robot Collaboration (HRC) working environments or production cells involve three main design factors: safety, optimized task distribution, environment interaction, and human-robot interaction/adaptive control, compared to traditional isolated robotic cells. Ensuring human safety in an open or fenceless workspace is a mandatory safety requirement that should be covered to deploy HRC production cells. Integrating several types of sensors (scanners, cameras, etc.) and artificial intelligence algorithms is required to automatically assess the robot's movements to avoid collision risk [1].

The production capabilities that present the robotic systems (power, velocity, precision, repeatability, etc.) can be combined with the flexibility of humans in a collaborative production

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joalafe@upv.es (J. Lario); ffraile@cigip.upv.es (F. Fraile); iveta.eimontaite@cranfield.ac.uk (I. Eimontaite); s.fletcher@cranfield.ac.uk (S. Fletcher)
0000-0003-4843-3334 (J. Lario); 0000-0002-3275-7740 (F. Fraile); 0000-0002-8622-937X (I. Eimontaite); 0000-0001-6606-7556 (S. Fletcher)

environment. Collaborative robotic manipulators, designed for safe coexistence with humans, offer opportunities to enhance manufacturing line flexibility. Repetitive and monotonous movements with light-weight tools, common in manual industries, can lead to work-related musculoskeletal disorders. A new production scenario may arise from these synergies where manual labour tasks are reduced, operator working conditions are improved, and operational costs are reduced [4], [5].

Furthermore, integration of collaborative systems can improve workers physical and psychological wellbeing, however, the desired impact depends on worker acceptance and engagement with the introduced changes [6]. Early consultation with the workers, co-creation throughout the development is essential for the acceptance of the proposed technological changes as well as yielding deeper insights allowing to understand the process and assembly steps [7]. Therefore, to achieve social sustainability, human factors need to be considered at the early stage of design process and needs to be co-created with the end-users.

The industrial pilot focuses on multimodal communication, real-time sensor integration, and AI-PRISM solutions for context awareness and adaptive control. AI-PRISM improves working conditions, allowing workers to delegate heavy or repetitive tasks and decreasing the probability of work-related musculoskeletal disorders. All this is achieved working closely with the workers and technology developers. The HRC production environments where AI-PRISM solutions are integrated foster the development of sustainable worker conditions, transforming manufacturing through a more efficient, safe, and collaborative scenario.

2. Social Sustainability Objectives for HRC

2.1. Furniture

The furniture painting process involves multiple stages: loading, background coating, painting, sanding, and final coating. Depending on the furniture piece that is going to be produced, different processes are required, with some needing multiple layers of painting or specific sanding. Conventional furniture industrial production is intensive in human labour since several operations include sanding, painting, upholstery and assembly. These tasks involve repetitive and monotonous movements with tools that can lead to muscle fatigue and work-related musculoskeletal disorders.

Table 1: Furniture pilot social sustainability objectives

KPI	Description	Assessment method
Painting comfort and satisfaction KPI	Comfort and Satisfaction, with which to measure the perception of reached wellness in workers, since the incorporation of the collaborative robot. **Unit of measure:** Self report tools/questionnaires changes between baseline and technology validation time points.	Work-related body-part discomfort scale [8] triangulated with heart rate and adapted physical exertion scale [9]. System Usability Scale [10] the 68% of the scale indicating above average usability (expected result to be above 80%). Occupational self-efficacy [11].
Painting engagement KPI	Positive engagement and attitudes toward the new developed process. **Unit of measure:** Self report tools/questionnaires changes between baseline and technology validation time points	Technology acceptance model 3 [12] and Trust in industrial HRC [13].

The current AI-PRISM project aims to address this: autonomous collaborative robots integration into painting production cells to reduce manual labour and improve worker conditions. The industrial pilot focuses on developing symbiotic HRC to improve manufacturing performance and ergonomics. The goal is for operators to teach robots specific tasks, reducing the workload and physical strain on humans. In this collaborative scenario, humans and robots share their capabilities, competencies, and resources. Operators primarily handle quality inspections and assurance and teach robots new programs by programming per demonstration, while robots perform painting tasks efficiently due to their repeatability.

The collaboration between humans and robots in the furniture painting process reduces manual labour and exposition to chemical agents employed for painting. The working area can be shared without physical separation, enhancing safety and providing symbiotic collaboration, significantly reducing risks and costs compared to manual operations. This innovative approach combines the flexibility of humans with the efficiency of robots, creating a more streamlined and ergonomic production process.

2.2. Electronics

The chip manufacturing process involves precise positioning and glueing semiconductors to wires, with a repeatability range between 0.01-0.005mm. Customizing chips usually relies on small batches, which makes them more economically inefficient and complicates the automation process. Manual assembly and glueing of chips to wires in semiconductor processing lines depend highly on operator skills. Frequent manual turning of screws for positioning at high speeds can lead to finger-related occupational diseases. The cycle times are a function of the operator's experience and skills, and their main tasks are controlling the microscope and positioning the chip. Eye strain is a significant human factor due to working with small parts and the need for a microscope.

The human-centric objectives involve reducing physical discomfort, decreasing mental fatigue, and increasing cognitive engagement with perceived self-efficacy. The proposed solution includes a motorized XY stage with position repeatability of 0.001 mm and wax replacement with low-adhesive tape or a vacuum suction cup. A high-resolution camera for pattern recognition, unchanged glue and wires, and an AI algorithm learned by the operator are essential. The AI will assist in vision positioning, motion control, defect detection, and material recognition. The AI-PRISM project aims to improve work quality and adapt the shop floor to Industry 5.0. The chosen process serves as a perfect use case for enhancing physical comfort and reducing mental fatigue, as AI algorithms support operators in positioning, replacing manual XY stages with robotic solutions. The vision by demonstrations module is particularly effective for high-mixed volume production where traditional automation falls short, decreasing screen time and minimizing the risk of eye diseases.

Table 2. Electronics pilot social sustainability objectives

KPI	Description	Assessment method
Chips physical comfort KPI	Physical comfort (eye strain, long time in sitting position) **Unit of measure:** Percentage of time looking at the screen and self-report tool/questionnaire changes between baseline and technology validation time points	30% reduction of time spent on looking on screen as well as lower scores on Work-related body-part discomfort scale [8].
Chips metal fatigue KPI	Mental fatigue – wellness improvement **Unit of measure:** Brain activity in the prefrontal cortex in terms of oxy- and deoxyhemoglobin concentration and self-report tool/questionnaire changes between baseline and technology validation time points.	30% reduction of mental fatigue and mental demand as measured by NASA TLX [14] and triangulated with physiological data capture (fNIRS)

2.3. Food and Beverages

In the brewing infrastructure and processing, a crucial component is the filtration system utilizing hazardous chemical compounds in powder form. These chemicals are introduced into the system at an average rate of three sacks per minute. An operator depalletize and load 22.7 kg powder sacks to conveyor system and releasing them for processing. To alleviate operator physical strain, a vacuum lifter is employed to load the sacks on the conveyor belt. One potential risk during sacks manipulation a powder leakage can occurred, due to it hazardous nature inhalation can precipitate significant health consequences. Also, the use of Personal Protective Equipment required to manipulate hazardous materials increase the mental workload of the operators. Introducing a collaborative robot solution bifurcates responsibilities, with the operator overseeing the system and the cobot handling sack transportation. This upgrade enhances ergonomics, safety and efficiency in the process, as the cobot interprets recipe data, engages the vacuum lifter, and ensures the sacks supply onto the conveyor.

Automatic inspection vision and sorting systems of the returned bottles for re-utilization must be deployed to enhance the brewing industry's sustainability. Currently, the process pilot has automized the crate supply by depalletizing and loading the crates onto the conveyor, and the second robotic system extracts the bottles from the crates. The identification and sorting of different model bottles are visually inspected and manually moved by operators. This operation potentially has health and safety issues related to handling glass bottles with some remaining liquid. Integrating collaborative robots equipped with artificial vision capabilities for bottle identification and sorting will reduce mental and physical workers' fatigue. Integrating two collaborative robot systems for filtration material sack manipulation and bottle sorting will reduce the physical activities that operators should perform during the shift, reducing the probability of developing musculoskeletal disorders due to the repetitive and strenuous actions involved. From the human factors point of view, the HRC will improve and increase psychological comfort, decrease physical discomfort and increase job satisfaction and organizational commitment.

Table 3. Food and Beverages pilot social sustainability objectives

KPI	Description	Assessment method
Beverages Worker's safety KPI	Improvement of workers safety and wellbeing **Unit of measure:** self-report tool/questionnaire changes between baseline and technology validation time points and physiological data in terms of Heart Rate Variability (HRV)	Reduction by 30% in number of workers working in heavy tasks and high-risk areas (Baseline 20-30 persons) 1. Decrease physical discomfort by 30% as measured by Work-related body-part discomfort scale [8], adapted Borg physical exertion scale [9] and triangulated with the heart rate variability data 2. Increase of satisfaction and organization commitment with Organizational commitment and motivational scale [15]. 3. System Usability Score [10] above 80% and TAM scores regarding perceived safety and satisfaction indicating acceptance of the new technology.

2.4. Printed Circuit Boards

The current use case is based on the supply, separation, visual inspection, mounting and testing of the printed circuit boards (PCBs) produced with the surface mount technology production line. The repetitive nature of PCB testing, with an elevated turnaround rate, emphasises the potential for increased operator mental fatigue. The current AI-PRISM project aims to deploy robot assistance systems into the previously mentioned production steps. These robotics systems will work in a collaborative environment; by deploying artificial vision systems, they will be capable of recognising, manipulating, and handling different PCBs in production.

Two main robotic systems will be developed in this industrial use case; the first solution will be oriented to help the operators on the Automated Guided Vehicle (AGV) to assist the operator in supplying PCBs materials. The second robotic system will perform the test on PCBs. This second solution will be equipped with vision sensors to identify and grasp various PCB types, precisely inserting them into a testing adapter. Successfully tested PCBs are organised in a predefined pattern in a box, while those with failures are segregated for further processing. A human co-worker configures the robot's perception system for detection and grasping using suggested modalities, aiming to develop an interactive GUI for enhanced human-system collaboration. This integration allows continuous improvement by considering feedback and refining the system's workplace understanding.

Table 4: PCB handling and testing process

Name	Description	Assessment method
PCB physical comfort KPI	A Mobile AGV following and assisting the user **Unit of measure:** self-report tool/questionnaire changes between baseline and technology validation time points	Improved acceptance of the new interfaces (System usability scale [10] 80% acceptance; Technology acceptance model 3 questionnaire [12]; Occupational self-efficacy [11]; Technology Readiness Scale [16]).
PCB metal fatigue KPI	The mental load experienced during training phase. **Unit of measure:** time in hours to develop knowledge and confidence to work on the process and self-report/questionnaire changes	20% decrease in time needed to be trained on the new process and 10% decrease in mental and temporal demands during the initial stages of working on the new system (as measured by NASA TLX [14]).

3. Conclusions

The integration of HRC in manufacturing processes presents a paradigm shift from conventional automated systems, emphasizing safety, efficiency, and worker well-being. This shift has been driven by the need of more flexible, safe, and adaptable manufacturing processes. The use of advanced technologies, such as machine vision algorithms and sensors, has significantly contributed to the accuracy and safety of automatic robotic systems, marking a transition from traditional isolated robotics to collaborative and flexible coworkers enabling increase social sustainability and workforce upskilling and better integration within the manufacturing sector.

The case studies in furniture, electronics, food and beverages, and printed circuit boards further illustrate the tangible benefits of HRC in enhancing worker conditions. The reduction of manual labor, exposure to hazardous materials, and improvement of ergonomics showcase the positive impact of collaborative robots on the manufacturing process. The defined KPIs for each pilot, ranging from physical comfort, safety and mental fatigue reduction, allow the improvement and further development of the more complex needs such as technology self-efficacy and upskilling/reskilling. Taking everything into account the approach discussed in this paper provides a comprehensive framework for assessing the success of social sustainability objectives.

In conclusion, the integration of HRC, guided by well-defined KPIs and a focus on social sustainability, represents a transformative force in the manufacturing landscape. Meaningful integration of HRC with the aims of both greater manufacturing flexibility but also improved worker psychological safety contributes to a more sustainable and collaborative future in manufacturing.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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