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# A Novel Diagnostic Tool for Human-Centric Quality Monitoring in Human-Robot Collaboration Manufacturing

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#### 25 ABSTRACT

26 The manufacturing industry is currently facing an increasing demand for customized products, leading to a

27 shift from mass production to mass customization. As a result, operators are required to produce multiple

- 28 product variants with varying complexity levels while maintaining high-quality standards. Further, in line
- 29 with the human-centered paradigm of Industry 5.0, ensuring the well-being of workers is equally important
- 30 as production quality. This paper proposes a novel tool, the "Human-Robot Collaboration Quality and Well-
- 31 Being Assessment Tool" (HRC-QWAT), which combines the analysis of overall defects generated during
- 32 product variant manufacturing with the evaluation of human well-being in terms of stress response. The
- 33 HRC-QWAT enables the evaluation and monitoring of human-robot collaboration systems during product

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34 variant production from a broader standpoint. A case study of collaborative human-robot assembly is used 35 to demonstrate the applicability of the proposed approach. The results suggest that the HRC-QWAT can 36 evaluate both production quality and human well-being, providing a useful tool for companies to monitor 37 and improve their manufacturing processes. Overall, this paper contributes to developing a human-centric 38 approach to quality monitoring in the context of human-robot collaborative manufacturing.

39

#### 40 **1. INTRODUCTION**

41 Mass production has long been the standard in manufacturing, allowing efficient 42 use of available resources and a corresponding reduction in production costs. In recent 43 years, however, there has been a shift towards mass customization, an approach to 44 production that allows products to be individually tailored to meet each customer's specific needs and preferences [1]. Several factors have driven this shift, including 45 46 technological advances, increased demand for customized products, and growing 47 awareness of mass production's environmental and social impacts [2]. As a result, 48 manufacturers are increasingly turning to mass customization as a way to remain 49 competitive in the marketplace and meet the evolving needs of their customers, thus 50 representing a significant paradigm shift in how goods are produced and consumed.

51 While greater product variety can increase market share and sales volumes, it also 52 increases product complexity and costs [1]. As a result, mass customization requires a 53 flexible production system that can adapt to product volume and type variations. An 54 effective approach to mass customization is the use of collaborative robots (also called 55 cobots) in what is known as Human-Robot Collaboration (HRC) [3]. This approach 56 combines the flexibility and versatility of human operators with the precision of cobots, 57 creating a flexible system capable of assembling different product variants in the same58 workstation [4].

59 Interest in HRC has grown with the development of Industry 4.0 and is becoming 60 increasingly important with the emergence of Industry 5.0. Indeed, the main goal of 61 Industry 5.0 is to put human well-being at the center of production systems in order to 62 provide sustainable prosperity for long-term development [5–7]. The technologies and 63 processes used in Industry 5.0 are designed to enhance the capabilities of human 64 operators, as in the case of cobots. This approach departs from traditional production methods, which prioritize efficiency and automation over the satisfaction of human 65 workers. This shift towards human-centred production should lead to improved 66 productivity, greater job satisfaction and a more sustainable manufacturing sector 67 68 towards mass customization.

While the benefits of HRC are clear, there is a lack of comprehensive tools that can assess and monitor the quality and well-being aspects of these systems. Therefore, a need exists for an evaluation tool that not only considers production quality but also considers the well-being of the human operator. With the growing emphasis on humancentered production in Industry 5.0, such an assessment tool becomes increasingly crucial.

To address the lack of comprehensive tools for assessing and monitoring HRC systems taking into account both process performance and human-centered performance for highly customized product variants, this research aims to answer the following research question: How can a diagnostic tool be developed to assess the 79 performance of HRC systems considering the specificities of highly customized product 80 variants?

81 In response to this research question, this paper introduces a novel tool, the 82 "Human-Robot Collaboration Quality and Well-Being Assessment Tool" (HRC-QWAT). This 83 tool integrates two indicators, a product and process quality indicator and a human stress 84 response indicator, to assess and monitor the quality of an HRC system, specifically 85 tailored to accommodate the unique challenges and variations associated with highly customized product variants. Unlike previous studies that focused on individual 86 measurements and indicators, the HRC-QWAT incorporates multiple dimensions of 87 88 evaluation, encompassing product and process quality as well as human well-being. This 89 comprehensive approach enables a holistic assessment of the collaborative assembly 90 process, capturing the interplay between quality outcomes and the well-being of human 91 operators.

The versatility and adaptability of the HRC-QWAT are demonstrated by its applicability to single-variant and small-batch variant production scenarios, catering to diverse production contexts. Thus, the HRC-QWAT fills a critical gap in assessing and monitoring HRC systems, providing practitioners and researchers with a valuable tool for evaluating, diagnosing, and optimizing HRC systems in the context of diverse and customized product variants.

98 To show the practical implementation of the HRC-QWAT, a real-life case study was 99 conducted involving the assembly of electronic board variants using a human-robot 100 collaborative assembly system. The methodology consists of two main phases: (1) the 101 realization phase, in which the HRC-QWAT is constructed by collecting historical 102 experimental data and developing a model that relates the two performance measures, 103 i.e. total defects (cobot-related and human-related errors) and human stress response, to 104 represent the overall quality of the system; and (2) the use phase, in which the HRC-QWAT 105 is used as a reference for predicting future products/batches and identifying critical 106 products in terms of defects and human stress response. The HRC-QWAT can be used to 107 identify critical production scenarios and implement necessary corrective actions to 108 maintain the desired quality level while taking into account the well-being of human 109 operators, thus advancing human-centered production practices within the framework of 110 Industry 5.0.

111 The remaining paper is structured as follows. Section 2 summarizes the main 112 studies in the field of quality in HRC. Section 3 presents the HRC assembly system used as 113 a case study. Section 4 illustrates the complexity assessment of the product HRC 114 assemblies. Section 5 presents the data collected on product and process quality and their 115 relationship with assembly complexity. Section 6 illustrates data on human well-being and 116 discusses the relationship with assembly complexity of product variants. Section 7 117 presents the novel diagnostic tool called HRC-QWAT, which shows the potential for single 118 variant and small-batch production. Finally, Section 8 concludes the paper.

119

120 **2. LITERATURE REVIEW** 

HRC is a rapidly developing field with promising applications in service, social, and industrial contexts. When designing and implementing an HRC system, evaluating its quality is crucial to ensure that the system meets individual, collective, and production

124 needs or objectives. From an engineering point of view, quality refers to the degree to 125 which a system, product, service, or process conforms to specified requirements and 126 conditions [6]. Quality models, such as conceptual or definition models, are commonly used in engineering to support, evaluate, and manage quality [8]. These models outline a 127 128 set of quality attributes and their potential interrelationships and serve as a guide for 129 selecting relevant factors for experimental validation of applications, services or systems. 130 However, efforts to identify and classify factors, measures and metrics that describe quality in the HRC field are still rare, especially from a human-centred 131 132 perspective [6,9]. The industrial perspective can be categorized into two interests: 133 performance-centred and human-centred. The former considers robots as a means to 134 optimize the production process, often involving full automation and substituting human 135 workers with machines, while the latter aims to improve human well-being by respecting their role, needs, job, talents, and rights [10-12]. Consequently, there is a trade-off 136 137 between optimising the production process and optimising the well-being of the 138 operators, which requires the use of performance measures specific to the collaborative 139 environment.

According to [6], performance measures for HRC are variables that can be obtained from physical measurements or an aggregate of facts to assess the current or final state of the human, robot, process, or interaction. These measures can be grouped into four categories:

Time behavior measures indicate the response and processing times required to
 perform functions or complete tasks.

146	• Process measures are an aggregation of facts related to task completion,
147	workspace design, safety, or product quality.
148	• Physiological measures are obtained from body measures, such as heart rate, to
149	understand the current state of the human.
150	• Human-Robot physical measures are obtained from sensors that indicate the
151	current state of the interaction, such as the distance between the human and the
152	robot.
153	Moreover, performance metrics for HRC can be defined as a combination of direct
154	measures used to express a rate, average or input/output relationship [6]. Efficiency and
155	effectiveness are considered the main attributes used to evaluate such performance.
156	Efficiency metrics assess the use of resources, i.e. the input/output ratio. On the other
157	hand, effectiveness metrics assess the accuracy and completeness of the achievement of
158	specific objectives, measuring the relationship between actual and expected results.
159	These metrics assess whether HRC systems are "doing things right" and "doing the right
160	things", respectively.

As far as the human-centred perspective is concerned, quality factors that have received more attention in the robotics literature are safety [13], trust [14], attitudes and acceptance [15], mental and physical workload [16,17], situation awareness and mental models [18,19], emotional responses [20,21] and anxiety [22].

Additionally, the review paper [6] identifies seven emergent research topics that could have a significant impact on future Industry 5.0 applications, including (i) noninvasive monitoring and online analysis of human factors, (ii) individualized HRC, (iii) transparent robotic systems, (iv) fluency, (v) adaptive workload systems, (vi) privacy in
data-driven HRC, and (vii) benchmarks.

170 Regarding point (i), the Industry 5.0 paradigm aims to optimize human well-being through human-centred smart environments. However, most tools for assessing human 171 factors in HRC require offline or intrusive techniques. Creating accurate, non-invasive, and 172 173 online ergonomic assessment tools that require short preparation represents a relevant 174 challenge in HRC for manufacturing settings [23,24]. One of the most widely used tools 175 for this purpose is the digital twin, which allows the human comfort and flexibility of the cobot to be improved in a non-intrusive way [25]. Several DT applications have already 176 177 been implemented in the area of collaborative assembly and disassembly [26].

178 Concerning point (ii), applications enabling collaborations between humans and 179 robots are generally short and static for practical reasons [27]. However, individualized machine collaboration is essential for Industry 5.0. Nowadays, various technologies have 180 181 been identified that enable machine collaboration, such as human action recognition, 182 intention prediction, augmented, virtual or mixed reality, exoskeletons, and collaborative 183 robots. Personalized HRI systems can continuously collect and process personal and 184 physiological data, adapt to individuals' needs and preferences, and maintain long-term 185 interactions [27,28]. Hedonics factors, which mostly focus on individual goals, require 186 more research attention on applications for Industry 5.0 [29]. Additionally, human-187 centred initiatives need to consider technologies enabling job satisfaction, work-life 188 balance, and up-skilling and re-skilling of workers [12].

189 Regarding point (iii), Industry 4.0 applications use black-box AI to enhance 190 autonomy, while Industry 5.0 requires transparent AI that interacts with humans. In HRC, 191 this transparency includes predictability, legibility, and explainability. Legibility enables 192 observers to quickly infer correct goals, while predictability matches expectations. 193 Creating legible trajectories is a broad open issue. Multimodal systems for anticipating 194 human actions face high-dimensional data, which dimensionality reduction techniques 195 can address. AI aims to explain robot behavior to users and improve trust and situational 196 awareness, but challenges include creating methods for generating explanations and 197 evaluating their effectiveness [30,31].

198 With regard to point (iv), fluency is not considered a metric but rather a quality of 199 interaction in HRC, as described in [32]. In HRC environment, fluency refers to the 200 seamless interaction between humans and robots. It involves a high level of coordination, well-synchronized joint activities with precise and efficient timing, and dynamic 201 202 adaptation of plans and actions. However, fluency is still a relatively new concept in HRC 203 research, and proposed metrics for fluency are often task-specific [32]. Recent studies, 204 such as those of Hoffman [32], have categorized fluency metrics as subjective or objective. 205 However, due to the somewhat vague and ephemeral nature of fluency, it remains a topic 206 of discussion in the robotics community, with further research needed to fully understand 207 the factors affecting fluency and to design metrics that can assess it in various 208 collaborative settings.

209 Concerning point (v), real-time workload assessment algorithms using 210 physiological measures, such as heart rate, electrodermal activity and skin temperature, can accurately estimate optimal workload levels in humans [17,33]. This information can
be used to improve task performance, reduce errors, and prevent accidents by changing
interaction mediums, level of autonomy, and reallocating tasks and responsibilities
between humans and robots [33]. Such systems are called adaptive workload or adaptive
teaming systems [17]. The use of these algorithms in various human-robot teaming
scenarios remains an open challenge [34].

217 Regarding point (vi), data-driven technologies like big data, machine learning, cloud computing, and IoT can enhance production performance and human working 218 219 conditions. However, Industry 4.0 has largely overlooked the human factor and the 220 privacy issues arising from the collection, storage and processing of personal data that 221 these technologies entail [35,36]. In human-centred manufacturing, privacy efforts must 222 focus on protecting workers' personal information and ensuring data security [35]. Cybersecurity assessment criteria for HRI in automobile manufacturing have been 223 224 proposed [37], but comprehensive metrics are needed for HRI and HRC [37].

225 Finally, with respect to point (vii), international robotics competitions have 226 become a valuable tool for evaluating the performance of robotics systems, providing a 227 form of reproducibility and enabling the evaluation of non-competing systems. Although 228 the scoring mechanism tends to hide the underlying characteristics of the system, 229 competitions allow systems to be compared by linking relevant metrics to the score and 230 explaining which aspects influenced the score and in what way. Typically, the score is 231 based on objective task completion (e.g., image classification accuracy), with few 232 competitions evaluating safety in HRI. However, there is a shift towards more human233 centred objective evaluations, exemplified by the safety score in the Future Convenience

234 Store Challenge [38,39].

235 Based on the literature review, it is evident that many approaches proposed in the field of HRC have a performance-centred perspective, which fails to consider the full 236 potential of HRC applications. Towards a human-centred society and industry, HRC 237 238 researchers should broaden their perspective beyond mere task fulfilment and adopt 239 holistic approaches that enable robotic systems to achieve both collective and individual goals. In line with this viewpoint and to help address the challenges identified in the seven 240 emerging research topics, the "Human-Robot Collaboration Quality and Well-Being 241 Assessment Tool" (HRC-QWAT) has been proposed. In detail, the proposed tool can 242 243 respond to the challenges mentioned above as follows:

(i) Non-invasive monitoring and online analysis of human factors: HRC-QWAT allows for
real-time, non-invasive monitoring of human operators' stress levels and well-being
through the integration of wearable devices and sensors. This real-time evaluation
ensures a prompt intervention to reduce stress levels, fostering a more efficient and
balanced working environment.

(ii) Individualized HRC: The tool offers the possibility of individualized HRC by considering
the unique physiological responses of each worker. This personalized approach promotes
a more efficient and harmonious human-robot interaction, potentially leading to
improved productivity and well-being.

(iii) Transparent robotic systems: Transparency is facilitated as the tool evaluates thecollaborative process based on clear performance indicators and stress responses. These

evaluations can be shared with human operators, fostering an understanding of the robot

- 256 function and promoting trust and collaboration.
- 257 (iv) Fluency: By measuring the quality of the collaboration through multiple performance
- 258 indicators, the HRC-QWAT contributes to assessing the fluency of the human-robot
- 259 interaction and collaboration. This analysis promotes the optimization of joint actions and
- 260 the creation of more fluid and synchronized interactions.
- 261 (v) Adaptive workload systems: The HRC-QWAT real-time monitoring of human stress
- 262 responses can inform adaptive systems. By detecting stress or overwork, the system can
- automatically adjust the workload distribution between human and robot, improving
- 264 efficiency and reducing the risk of human error or health implications.
- (vi) Privacy in data-driven HRC: While HRC-QWAT uses data-driven methods for evaluation, it is designed with the utmost respect for privacy standards. Personal and sensitive data are strictly used for the intended purpose of enhancing human-robot interaction and are safeguarded according to the highest security protocols.
- (vii) Benchmarks: The proposed tool also serves as a benchmarking instrument for HRC in
   different scenarios. By providing comprehensive metrics on both the performance of the
   collaborative process and the well-being of the human operator, the HRC-QWAT offers a
- valuable standard against which different collaboration setups can be compared.
- Accordingly, the HRC-QWAT serves as a comprehensive tool, specifically addressing the identified challenges in HRC, thereby offering a strategic instrument for human-centered Industry 5.0.
- 276

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#### **3. HRC ASSEMBLY SYSTEM**

An experimental campaign is conducted to assemble six different variants of electronic boards (from variant V1 to variant V6) using the ARDUINO UNO starter kit (ARDUINO®). The choice of electronic boards is based on the fact that, by using the same components, highly customized products with varying levels of complexity can be assembled (as will be discussed in the next Section 4). Moreover, these boards allow realtime verification of the correct functioning of the products, i.e., their proper assembly.

284 The ARDUINO UNO starter kit is composed of: (i) the components that are 285 assembled to make up the various boards listed in Table 1 (e.g., the jumper wires that 286 carry current between the various components); (ii) the microcontroller, i.e., a small 287 computer that enables the circuits to function; and (iii) the breadboard, i.e., a board on 288 which the actual circuit can be built. The breadboard consists of rows and columns of holes that conduct electricity through thin metal connectors under the plastic screen, 289 290 allowing the circuit components to be connected. The ARDUINO UNO Breadboard is 291 defined as 'seamless' as the components do not need to be welded but simply inserted 292 into the holes. Fig. 1(a) shows an example of an assembled electronic board (variant V3), while Fig. 1(b) displays the product circuit diagram. 293

Each of the selected products has a varying number of components, which are connected to the breadboard. As outlined in Section 4, the six electronic boards were chosen to span a broad range of assembly complexity. Table 1 indicates the type and number of components required for each of the six electronic board variants (V1 – V6). 298 The assembly of the six electronic board variants was conducted using a Universal 299 Robots<sup>™</sup> UR3e cobot, as depicted in Fig. 2. The boards were assembled using an 300 OnRobot<sup>™</sup> RG6 gripper, a versatile gripper capable of handling small objects and a range 301 of other objects. Six skilled operators, proficient in electronics and electrical engineering, 302 were involved in the assembly process of all six electronic boards, following a random 303 order to prevent any learning effects. During the preliminary stages, each operator 304 underwent training sessions to ensure consistent proficiency among the participants and 305 minimize the potential impact of varying skill levels on the results. These training sessions 306 were carefully designed to familiarize the operators with the assembly process and 307 equipment, allowing them to develop a solid understanding of the tasks involved in the 308 HRC assembly. Table 2 provides an overview of the participants' characteristics, including 309 relevant information such as age, gender, domain knowledge of HRC, and domain knowledge of assembly tasks. The inclusion of skilled operators with expertise in 310 311 electronics and electrical engineering helped ensure that the participants were familiar 312 with the intricacies of electronic board assembly and could contribute effectively to the 313 HRC trials.

In the assembly phase, the cobot handed over the required components to the operator, who assembled the electronic boards in a predetermined order, defined based on circuit theory [40]. The operator completely controlled the logistic tasks by activating the cobot using a button. After the assembly was completed, an experienced external operator (who was not involved in the assembly) conducted an offline quality control check to identify any defects in the final product. Data on overall assembly defects (cobotrelated and human-related errors) were collected during the trials, as described in Section
5. Additionally, data on the operators' stress response during the assembly phase were
collected, as per Section 6.

323

#### **4. COMPLEXITY ANALYSIS**

325 In scientific literature, complexity is typically used as a metric to predict 326 production performance, including production times and defects. Indeed, it is often found 327 that a reduction in complexity is associated with a significant performance improvement 328 [41–43]. In this study, the structural complexity model, first introduced by Sinha et al. [44] 329 and later adapted by Alkan and Harrison [45] and Verna et al. [43,46], serves as the 330 foundation for assessing the assembly complexity of selected ARDUINO products. This 331 model, originally developed for manual and fully automated assembly, is extended to the 332 HRC assembly of the present case study, where the robot primarily performs 333 organizational and logistical tasks, such as selecting components to be assembled in a 334 predetermined sequence and delivering them to the human assembler. Adapting and 335 integrating the structural complexity model to the domain of HRC assembly for highly customized product variants represents an innovative aspect of this study. This enables a 336 337 quantitative assessment of assembly complexity within the context of mass customization. 338

The six product variants were selected to cover a wide range of assembly complexity. In the case study, each hole on the breadboard was modelled as a single component. This assumption allows multiple connections between the components and the board to be modelled and distinguished from single connections. For example, pushbuttons, i.e., the components that close a circuit when pressed, consist of four different pins that need to be connected to the board. As this type of connection is more complex than connecting a single-pin component, it was necessary to model the individual holes on the board to distinguish these different cases.

The structural complexity model used to model the HRC assembly complexity is based on Huckel's molecular theory [47] and defines the structural complexity of any network-based engineering system as a function of the complexity of individual components ( $C_1$ ), the pairwise interaction between connected components ( $C_2$ ), and the effects of the overall system topology ( $C_3$ ). The structural complexity, represented as C, is a combination of these factors and can be expressed as:

$$C = C_1 + C_2 \cdot C_3. \tag{1}$$

In Eq. (1),  $C_1$  represents the complexity of managing and interacting with the individual components of a product when they are considered separately, i.e., the handling complexity of the product.  $C_1$  can be defined as follows:

$$C_1 = \sum_{p=1}^{N} h_p \tag{2}$$

where *N* is the total number of product components and  $h_p$  is the handling complexity of component *p*. One of the most widely accepted models for calculating a handling complexity index of individual components is the Lucas method [45], based on Design For Assembly (DFA). This method uses a point scale that provides a relative measure of assembly difficulty (a normalized handling complexity index) based on the size, weight, handling difficulty and orientation (alpha and beta symmetry) of individual components (see Table 3). Using the Lucas method, each component can be assigned a different handling complexity index (see Table 5). The higher the value of  $h_p$ , the more difficult the component is to handle and place on the board. These values are obtained as follows:

$$h_{p} = \frac{d_{h}^{A} + \sum_{1}^{N_{B}} d_{h}^{B} + d_{h}^{C} + d_{h}^{D}}{h_{max}}$$
(3)

where  $d_h^{i \in \{A,B,C,D\}}$  is the handling difficulty of attribute *i*,  $N_B$  is the number of applicable handling difficulties related to attribute B, and  $h_{\max}$  is the theoretical maximum value for the handling index (i.e., 6.9, according to Table 3).

368 In Eq. (1),  $C_2$  is the complexity of connections and liaisons between components, 369 calculated as the sum of the complexities of the pairwise connections present in the 370 product structure, according to Eq. (4):

$$C_2 = \sum_{p=1}^{N-1} \sum_{r=p+1}^{N} c_{pr} \cdot e_{pr}$$
(4)

371 where  $c_{pr}$  is the complexity in achieving a connection between components p and r, and 372  $e_{pr}$  is the  $(p,r)^{\text{th}}$  entry of the binary adjacency matrix (**AM**) of the product. It has to be 373 noted that in this specific case study, given that all components are connected to the 374 breadboard, the *r*-th component is always the breadboard.

The complexity  $c_{pr}$  can be evaluated by the Lucas Method [45], by using the difficulty of connection attributes reported in Table 4, and is obtained as follows: Copyright © 2023 bASME Journal of Manufacturing Science and Engineering

$$c_{pr} = \frac{d_c^E + d_c^F + d_c^G + d_c^H + d_c^I + d_c^J + d_c^K}{c_{\max}}$$
(5)

where d<sub>c</sub><sup>j ∈ {E,F,G,H,I,J,K}</sup> is the connection difficulty of attribute *j*, and c<sub>max</sub> is the theoretical
maximum value for the connection index (i.e., 13.1, according to Table 4).
Thus, the Lucas method provides a normalized assembly index that penalizes the
physical attributes (e.g. component positioning and fastening, assembly direction,
visibility, alignment and resistance to insertion) that affect assembly difficulty.

382 In Eq. (4),  $e_{pr}$  is defined by using the symmetric **AM** matrix of the product (see Fig.

383 3). It can take two different values:

$$e_{pr} = \begin{cases} 1, & \text{if there is a connection between } p \text{ and } r \\ 0, & \text{otherwise} \end{cases}$$
(6)

Each entry in the *AM* matrix indicates the presence of an assembly connection between the component and the breadboard. As an example, Fig. 3 shows the *AM* matrix of product variant V3.

As shown in Table 5, the connection complexity of each component with the breadboard ( $c_{pr}$ ) in the six electronic board variants (V1-V6) can take different values depending on multiple factors. For example, the connection complexity of long wires to the breadboard ranges from 3.7 to 6.3, depending on how the component is inserted into the breadboard and what other components are already connected. A complexity score of 5.3, for instance, is given if the wire needs to be bent to make the connection, and 6.3 if the connection is made with reduced visibility. Finally, in Eq. (1),  $C_3$  represents the topological complexity, i.e., the complexity associated with the product architecture pattern, which is defined as follows:

$$C_3 = \frac{E_{AM}}{N} = \frac{\sum_{q=1}^N \delta_q}{N},\tag{7}$$

396 where  $E_{AM}$  is the matrix energy of **AM**, i.e. the sum of the singular values  $\delta_q$  of **AM** [43]. 397 It increases as the system topology shifts from centralized to more distributed 398 architectures [44].

According to the increasing total assembly complexity *C*, Table 6 lists the complexities  $C_1$ ,  $C_2$  and  $C_3$  of the selected product variants. It is worth noting that an increase in complexity does not always imply an increase in the number of components. In fact, although variant V5 has more components than variant V6, the total complexity of variant V6 is higher than that of variant V5. This is due to the different nature of the components that compose the different products, the nature of the connections and the architecture of the final assembly.

406

#### 407 **5. PRODUCT AND PROCESS QUALITY ANALYSIS**

In this section, complexity measures are integrated into the analysis of product and process quality, providing a novel perspective on the relationship between assembly complexity and the occurrence of defects in collaborative assembly processes for customized products.

412 During the manufacturing process, quality data on the overall defectiveness of 413 product and process were collected to assess the quality of the HRC system (see Table 7). 414 Specifically, for each product variant assembly, the total number of defects (both in-415 process defects occurring during assembly – referred to as D1 - and offline defects 416 detected during offline quality control – referred to as D2) was recorded. A classification 417 was made for both types of defects, D1 and D2 (see Table 8). During the manufacturing 418 process, the assembly operators and the quality control operator filled Table 8, indicating 419 the number of defects found in each category for each assembled board. Certain defect 420 categories, such as "Unpicked Component" and "Slipped Component," specifically relate 421 to errors made by the cobot during the assembly phase. These categories reflect instances where the cobot failed to pick up a component or where a component slipped during the 422 423 cobot handling. It is important to highlight that these defect categories capture cobot-424 related errors occurring during the assembly phase. Furthermore, it should be noted that 425 the defects recorded in the in-process and offline phases reflect a combination of both cobot-related and human-related errors. This means that the defect data collected 426 427 encompasses the performance of both the cobot and the human operators involved in 428 the assembly process. To achieve a holistic view of the quality of the system, the total 429 number of assembly defects  $D_{tot}$  (i.e., the sum of in-process and offline defects) were considered and analyzed (see Table 7). 430

The exclusion rule used was the Modified Interquartile Range Method, which is widely recognized as a practical and effective method for identifying outliers, taking into account the sample size [48]. The relationship between the total number of defects recorded by the six operators for each of the six variants of electronic boards and the complexity of the assembly (calculated as described in Section 4) was then analyzed. The 436 "operator factor" was not considered in the analysis after checking its non-significance at 437 95% confidence level using a two-way ANOVA (p-value of 0.290). The Poisson regression 438 model was used for the analysis, as total defects are count data [49]. The logarithm and 439 square root link functions were considered, and different models were compared up to 440 the third order of the predictor (i.e., assembly complexity C). The selection of the best 441 model was made based on Akaike's Corrected Information Criterion (AICc) and Bayesian 442 Information Criterion (BIC), goodness-of-fit tests (Deviance and Pearson tests), and 443 deviance residual plots [49,50]. The Deviance and Pearson tests assessed whether the 444 predicted number of events deviated from the observed number in a way that was not 445 predicted by the Poisson distribution. If the p-value was less than the significance level, the null hypothesis that the Poisson distribution provided a good fit could be rejected 446 447 [49,50].

According to the results, the most appropriate Poisson model to describe the relationship between defects and complexity was the one using the square root link function, represented as:

$$D_{tot} = (k_1 \cdot C)^2, \tag{8}$$

451 where  $D_{tot}$  is the total number of defects (in-process and offline), *C* is assembly 452 complexity evaluated according to Eq. (1), and  $k_1$  is the regression coefficient. The results 453 of the Poisson regression analysis, reported in Table 9, showed that the relationship 454 between  $D_{tot}$  and *C* was statistically significant. In addition, the analysis of the deviance 455 residuals and the goodness-of-fit tests of Deviance and Pearson (where *p*-values are 456 higher than the significance level of 0.05) indicated that the model fitted the data well. In 457 addition, a very high value of the deviance  $R^2$  was obtained.

458 Fig. 4(a) shows the total defects recorded during the experiment and the predicted curve obtained by Poisson regression with 95% confidence and prediction intervals are 459 460 represented. Moreover, Fig. 4(b) shows the deviance residual plots, where the residuals 461 appear satisfactory overall. Also using the Anderson-Darling test, the hypothesis of 462 normality of the residual distribution cannot be rejected at the 95% confidence level (p-463 value = 0.194, which is higher than the significance level of 5%). The results obtained for 464 product and process quality show that the increase in assembly complexity of the variants leads to an increase in the total number of defects, following a non-linear trend. 465

466

#### 467 6. HUMAN WELL-BEING ANALYSIS

In this section, existing methodologies for assessing human well-being are integrated and adapted to capture the impact of assembly complexity on the human stress response in the context of mass customization, showcasing the originality of the proposed approach.

Physiological measures can be used to assess the state of human well-being during production, providing an objective measure compared to self-report tools, which may suffer from retrospective post-task bias [51]. Electrodermal activity (EDA) data is used in this study as a measure of human well-being, as it is commonly used as an indicator of the human stress response [52]. The Empatica E4 wristband (see Fig. 5(a)), a non-invasive biosensor that records EDA information at 4 Hz, was used to collect the EDA data. In 478 addition to EDA, the Empatica E4 also records information on pulsed blood volume (BVP),

479 operator pulse motion (ACC), heart rate variability (HRV) and temperature (TMP). Fig. 5(b)

480 shows an example of the raw output provided by the Empatica E4.

481 For each test performed by the operators, this raw signal was recorded and then 482 analyzed using the EDA Explorer software [53]. This software removes any external noise 483 from the raw signal and decomposes the EDA signal into two types of signals: the tonic 484 signal and the phasic signal. The tonic signal refers to the long-term fluctuations of the 485 EDA signal that are not explicitly triggered by external stimuli. Changes in Skin 486 Conductance Level (SCL) are the best indicator of tonic activity. On the other hand, phasic 487 activity refers to transient changes in EDA that are triggered by typically perceived and 488 externally delivered stimuli. It is best characterized by Skin Conductance Response (SCR) 489 changes. Accordingly, the SCR can be defined as a change in the amplitude of the EDA 490 signal from the SCL to a peak in the response [52].

491 According to its widespread use [51,52], the average value of the SCR peak 492 amplitude was used as a stress indicator for each assembly worker in this study. The peak 493 amplitude values were then normalized in the formulation of the final stress indicator to 494 remove individual differences between individuals. As a result, the human stress response 495  $(H_s)$  indicator for each operator can be defined as:

$$H_{S} = \left[\frac{\frac{\sum_{w=1}^{N_{P}} a_{w}}{N_{P}} - a_{min}}{a_{max} - a_{min}}\right] \cdot 100,$$
(9)

496 where  $a_w$  is the amplitude of the *w*-th SCR peak,  $N_P$  is the total number of SCR peaks 497 during the assembly of a given product variant,  $a_{min}$  is the minimum amplitude of the 498 SRC peaks and  $a_{max}$  is the maximum amplitude of the SRC peaks (both related to each 499 operator).

The human stress response data obtained during the 36 assembly processes (i.e., the 6 product variant assemblies performed by the 6 operators) are reported in Table 7. The  $H_S$  value of each operator is related to the assembly complexity (as per Section 4) in order to model the function that captures their relationship. The "operator factor" was not considered in the analysis after checking its non-significance at 95% confidence level using a two-way ANOVA (*p*-value of 0.999). Fig. 6 shows the two-term power curve fitting relating human stress response and product variant assembly complexity, in the form:

$$H_S = k_2 \cdot C^{k_3}, \tag{10}$$

507 where  $H_S$  is the human stress response, *C* is the assembly complexity evaluated according 508 to Eq. (1), and  $k_2$  and  $k_3$  are the regression coefficients.

509 This model was the best-fitting model compared to various linear and non-linear 510 models, considering the goodness-of-fit statistics and residual analysis [54]. The statistical 511 significance of the parameter estimate is confirmed by checking that the 95% confidence 512 intervals for the parameters, calculated from the corresponding Standard Errors (SE) 513 reported in Table 10, exclude the zero [55,56]. The S-value, i.e., the standard error of the 514 regression, is a measure of the goodness of fit of the model under consideration instead 515 of the R<sup>2</sup> for non-linear models [56]. The residual plots in Fig. 6(b) appear satisfactory 516 overall and, using the Anderson-Darling test, the hypothesis of normality of the residual 517 distribution cannot be rejected at the 95% confidence level. It should be noted that, 518 according to the result obtained, non-linear regression is preferable to linear quadratic 519 regression, as linearizing the function to perform linear regression can lead to bias in the 520 predictions [57]. According to the results shown in Table 10 and Fig. 6, there is a super-521 linear relationship between human stress response and the complexity of product variant 522 assembly. This result, which is one of the first attempts to study the relationship between 523 assembly complexity and human stress response, shows that as the complexity of the 524 product assembly increases, the assembly process becomes more challenging and entails 525 a higher degree of mental workload and cognitive effort, leading to a more than 526 proportional increase in human stress response.

527

#### 528 **7. HRC-QWAT**

This section introduces the "Human-Robot Collaboration Quality and Well-Being 529 Assessment Tool" (HRC-QWAT), a tool designed to synthesize previous analyses of quality 530 531 and human well-being, by directly relating  $H_S$  and  $D_{tot}$ , regardless of the complexity of 532 the product assembled. The selection of total defects and human stress response in the 533 HRC-QWAT tool was based on their significant impact on evaluating the performance of 534 the HRC system, including both product quality and human well-being. The tool 535 establishes a direct relationship between human stress response and total defects, 536 enabling a comprehensive assessment of system performance within the context of 537 single-variant and small-batch variant production. This design is specifically tailored to address the distinct challenges and demands posed by customized production scenarios, 538 539 where the adaptability of the production process and the individuality of each assembly 540 play pivotal roles.

541 Two typologies of HRC-QWAT are proposed. The first typology is intended for 542 single variant production of highly customized products produced one by one in the HRC 543 system, even if repeated over time. This type of production involves the manufacture of 544 a single product variant at a time, typically in response to specific customer orders or 545 market demand. The production process is adapted as required for each variant, which 546 can result in longer lead times and higher production costs. In this scenario, the company 547 is interested in monitoring the performance of each individual product variant assembly in terms of quality and human well-being. On the other hand, the second typology of HRC-548 549 QWAT is proposed to provide companies with a diagnostic method for products of the same variant manufactured in small batches, after each of such productions. This type of 550 551 production involves the manufacture of small batches of the same product variant, 552 typically in response to forecasted demand or market trends. The production process is 553 adapted for each batch, allowing a product variant to be produced more efficiently and 554 cost-effectively than in the single variant scenario. The choice between single variant production and small-batch variant production generally depends on factors such as 555 556 demand variability, lead time requirements, and production costs. Single variant 557 production is best suited for highly customized products with low demand, while variant 558 batch production is more efficient for producing a range of products with moderate to high demand. 559

The use phase of the proposed tool is the same for practitioners in both cases,while the difference lies in the realization phase of the HRC-QWAT.

562 In both typologies, the HRC-QWAT allows for the assessment of quality and human 563 well-being in the collaborative assembly process, taking into account the unique 564 characteristics and requirements of each production scenario. This tool offers a comprehensive evaluation of the HRC system's performance, considering the relationship 565 566 between human stress response  $(H_S)$ , total defects  $(D_{tot})$ , and the complexity of the 567 assembly process. Although the complexity indicator is not explicitly included as a 568 separate metric in the HRC-QWAT, its influence on the performance measures is implicitly accounted for in the evaluation. As discussed in the previous sections, assembly 569 570 complexity plays a crucial role in affecting performance metrics, particularly in highly 571 customized and personalized product assemblies within the same product family [58–60]. 572 Although the HRC-QWAT does not directly measure complexity, it considers its impact on 573 the overall performance of the collaborative process. By capturing the relationship between human stress response, total defects, and the intricate nature of the assembly, 574 575 the tool indirectly accounts for the effects of assembly complexity on the HRC system's 576 performance.

To construct the HRC-QWAT, the following operational steps should be taken. First, a set of historical experimental data representative of the production must be collected. In the case of the HRC-QWAT for single variant production, a reasonable number of products (at least about thirty, for robust regression parameter estimation [61]) should be produced, and quality and human stress responses should be measured (according to Section 5 and 6, respectively). On the other hand, for the HRC-QWAT for small batches, an adequate number of production units should be collected for each batch (at least about fifteen units for each product type, if possible [61]) and the average
performance measures should be obtained for each batch. As mentioned in Section 5 and
6, it is advisable to perform preliminary data analysis using conventional statistical
techniques to detect and filter outliers [62].

588 Second, the model relating the two performance measures should be developed 589 to represent the overall quality of the systems, in terms of product/process quality and 590 human well-being. Considering the case study, the combination of the models in Eq. (8) and (10) leads to a linear model. Such a linear model is the best fit when considering single 591 592 variant production, as also confirmed by the goodness-of-fit statistics and residual analysis [54]. Fig. 7(a) depicts the prediction model relating human stress response  $H_S$  to 593 594 total defects  $D_{tot}$  and Fig. 7(b) shows the residual plots. The output of the regression is 595 shown in Table 11.

When considering small batches of products of the same variant, average values of human stress response ( $\overline{H_S}$ ) and total defects ( $\overline{D_{tot}}$ ) should be obtained for each variant. Then, the prediction model should be derived using these averages. In the case study, six small batches are considered, one for each product variant (V1-V6), each consisting of six products.

601 Referring to the case study data, Fig. 8 illustrates the best fitting model, i.e., a 602 linear regression model, with the residual plots, and the main output of the regression is 603 reported in Table 11.

604 The HRC-QWAT diagnostic tool (see Fig. 9) uses the model as a reference for 605 prediction and takes into account the associated uncertainty range. Specifically, the two 606 prediction limits (Lower Prediction Limit LPL and Upper Prediction Limit UPL) derived from 607 the regression models shown in Fig. 7 and 8, serve as thresholds for identifying critical 608 products and small batches, respectively. Products and small batches are classified as 609 critical in terms of both defects and human stress response when a special source of variation i.e., a source not inherent to the process, occurs [61]. It should be noted that 610 611 the negative values of LPL are set equal to zero, as this is not physically possible. As a 612 result, for some products or batches, the prediction interval may not be symmetrical with respect to the predicted regression value, as shown in Fig. 9. 613

614 The two prediction limits can be calculated as follows:

$$LPL = \widehat{H_S} - t_{1 - \frac{\alpha}{2}, \gamma} \sqrt{[SE(Fit)]^2 + S^2}$$

$$UPL = \widehat{H_S} + t_{1 - \frac{\alpha}{2}, \gamma} \sqrt{[SE(Fit)]^2 + S^2}$$
(11)

where  $\widehat{H_S}$  is the predicted value of the regression curve,  $t_{1-\frac{\alpha}{2},\gamma}$  is the value of the Student's t distribution with  $\gamma$  degrees of freedom (i.e., number of observations minus 1) and significance level  $\alpha$ , SE(Fit) is the standard error of the fit, and S is the standard error of the regression [61].

In the use phase, when new single products or small batches of products are produced, the observed values  $(D_{tot}, H_S)$  or  $(\overline{D_{tot}}, \overline{H_S})$  are compared with the corresponding prediction limits from the HRC-QWAT for single variant or small-batch production, respectively. Accordingly:

a) If the observed  $(D_{tot}, H_S)$  or  $(\overline{D_{tot}}, \overline{H_S})$  value falls within the prediction range (*LPL*, *UPL*), the product or batch is considered non-critical.

b) If the observed $(D_{tot}, H_S)$ or $(\overline{D_{tot}}, \overline{H_S})$ value is higher than the upper
prediction limit (UPL) (area A in Fig. 9) or lower than the lower prediction limit (LPL)
(area B in Fig. 9), it indicates a mismatch between the human stress response and the
total defects, and an abnormal situation exists, resulting in the product or batch being
signaled as critical. Specifically, products or batches located in area A of Fig. 9 are
reported as critical due to the high level of stress response experienced by operators
compared to the number of total defects detected. On the other hand, products or
batches lying in area B are characterized by abnormal defectiveness compared to the
level of human stress response.
Table 12 reports an example of critical product production and an example of
small-batch production detected as critical using the HRC-QWAT and possible root causes.
The proposed diagnostic tool has been developed with a dual objective. Firstly, it
aims to accurately position products or small batches on the HRC-QWAT, thereby
providing a clear understanding of their relative position compared to other products.
This information can be valuable in making informed quality control decisions and
identifying areas for improvement. Secondly, the diagnostic tool is designed to detect
unusual production scenarios and identify critical out-of-control situations. By
continuously monitoring production processes, the tool can identify any deviations from
established normal operating conditions, allowing corrective action to be taken in a timely
manner. This feature of the diagnostic tool acts as an in-process control mechanism,
ensuring that the quality of the overall system (product/process and human) remains
consistently high throughout the production process.

647 In conclusion, the proposed diagnostic tool represents a significant step forward
648 in quality control and monitoring, providing manufacturers with a powerful tool to ensure
649 consistent product quality and to detect and correct quality deviations in real-time.

650

#### 651 **8. DISCUSSION**

652 The novelty of the HRC-QWAT lies in its comprehensive assessment of quality 653 systems, encompassing both technical aspects of production quality and the human 654 factor of worker well-being. While previous studies have focused on individual 655 measurements and indicators in HRC systems, the HRC-QWAT combines multiple 656 dimensions of evaluation to provide a more holistic understanding of the collaborative assembly process. By integrating indicators related to total defects and human stress 657 658 response, the tool offers a more nuanced evaluation of the performance of HRC systems. Moreover, the HRC-QWAT's versatility and adaptability contribute to its novelty. 659 It can be applied to both single variant and small-batch production scenarios, 660 accommodating different production environments and collaboration settings. Whether 661 the work is predominantly performed by a robot or in a high-intensity human work 662 663 environment, the HRC-QWAT assesses production quality and worker stress response, 664 ensuring an optimized collaborative process. The tool's adaptability allows it to be fine-665 tuned to the unique parameters of various production environments and collaboration 666 scenarios, making it not only a quality and well-being assessment tool but also a strategic tool for comparing and contrasting different collaboration scenarios. 667

668 The potential for generalization is another key aspect of the HRC-QWAT's novelty. 669 Although the case study focused on electronic board assembly, the design and 670 methodology of the HRC-QWAT were conceived with a broader application in mind. Its adaptability allows it to be utilized in a wide range of production scenarios, even when a 671 672 robot performs the majority of the work and the role of the human operator is minimal 673 or focused on labor-intensive tasks. It should be noted, however, that the generalizability 674 of the HRC-QWAT depends on careful adaptation and refinement of the model 675 parameters. This will allow the tool to accurately reflect the interaction dynamics and 676 associated stress responses in different HRC settings. The possibility of extending the use 677 of the HRC-QWAT to more diverse and nuanced collaboration scenarios represent a promising avenue for future research and development in the field of HRC. 678

679

#### 680 **9. CONCLUSIONS**

The aim of the present research was to propose a novel tool, called the HRC-681 QWAT, which combines two indicators to evaluate and monitor the quality of a 682 683 production system: the total number of defects generated during the production of 684 product variants, and the stress response of workers. This innovative tool addresses a significant gap in the field of human-robot collaboration assessment, providing a unique 685 686 approach to evaluating both the production quality and the well-being of human operators. The methodology used a collaborative human-robot assembly system as a case 687 688 study to demonstrate the feasibility of the HRC-QWAT approach. The methodology 689 consists of two main phases: (1) the realization phase, in which the HRC-QWAT is 690 constructed by collecting historical experimental data and developing a model relating 691 the two performance measures (total defects and human stress response) that represent 692 the overall quality of the system; and (2) the use phase, in which the HRC-QWAT is used 693 as a reference for predicting future products/batches and identifying critical products in 694 terms of defects and human stress response. The diagnostic tool uses the model to 695 compare observed performance measures with corresponding prediction limits and 696 detect abnormal production scenarios.

The HRC-QWAT introduces a novel approach to the evaluation of quality systems 697 698 in HRC. Unlike previous studies that focused on individual metrics, this tool 699 comprehensively assesses both technical production quality and worker well-being 700 factors. Its adaptability and versatility make it suitable for single variant or small-batch 701 production, and for different environments and collaborative settings. In addition, although in this study the HRC-QWAT was applied to electronic boards assembly, its 702 703 adaptable design allows for a broader application, opening doors for future research in 704 the evaluation and development of human-robot collaboration.

A limitation of the proposed approach is the use of a structural complexity model, which was originally designed for manual and fully automated processes. While such a model serves as a good first approximation for collaborative human-robot contexts, as the cobot mainly performs logistical and organizational support tasks, a more refined complexity model will be required for a more accurate evaluation. Another limitation of the study is that the comparison in the HRC-QWAT is based on only two indicators, total defects and human stress response. In such measures, the performance of the cobot is not directly evaluated, although it is implicitly reflected in the total number of defects.
Furthermore, additional performance measures, such as workload, are not directly
addressed. Recognizing these limitations, it is important to consider that the proposed
approach has the flexibility to be extended to include additional indicators, including
cobot performance and workload, as well as encompass process sustainability and
economic impact measures.

718 Future research efforts will aim to overcome (at least some of) the above 719 limitations. Particular attention will be paid to refining the complexity model by including 720 factors related to HRC and performing a validation of the proposed approach using 721 different products to quantitatively assess its efficiency. In addition, the study could be 722 extended to include other cobot performance measures, including efficiency metrics (cycle time, throughput), accuracy and reliability metrics, safety metrics, and 723 724 environmental/economic sustainability indicators, such as equivalent carbon dioxide 725 emissions and life cycle costs.

726

#### 727 NOMENCLATURE

#### 728

HRC

С

Human-Robot Collaboration

HRC-QWAT Tool

- Assembly complexity
- C<sub>1</sub> Handling complexity

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Ν	Total number of product components
$h_p$	Handling complexity of component $p$
$d_h^{i\in\{A,B,C,D\}}$	Handling difficulty of attribute <i>i</i>
$h_{\max}$	Theoretical maximum value for the handling index
$N_B$	Number of applicable handling difficulties related to attribute B
<i>C</i> <sub>2</sub>	Complexity of connections and liaisons
C <sub>pr</sub>	Complexity in achieving a connection between components $p$ and $r$
АМ	Binary adjacency matrix of the product
e <sub>pr</sub>	( <i>p</i> , <i>r</i> ) <sup>th</sup> entry of the <b>AM</b> matrix of the product
$d_c^{j\in\{E,F,G,H,I,J,K\}}$	Connection difficulty of attribute <i>j</i>
<i>c</i> <sub>max</sub>	Theoretical maximum value for the connection index
e <sub>pr</sub>	$e_{pr} = \begin{cases} 1, & \text{if there is a connection between } p \text{ and } r \\ 0, & \text{otherwise} \end{cases}$
<i>C</i> <sub>3</sub>	Topological complexity
E <sub>AM</sub>	Matrix energy of <b>AM</b>
$\delta_q$	Singular values of <b>AM</b>
D1	In-process defects
D2	Offline defects
D <sub>tot</sub>	Total number of defects

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$k_1$	Regression coefficient of the model $D_{tot}$ vs C
EDA	Electrodermal activity
SCR	Skin Conductance Response
H <sub>S</sub>	Human stress response
$a_w$	Amplitude of the <i>w</i> -th SCR peak
$N_P$	Total number of SCR peaks
a <sub>min</sub>	Minimum amplitude of the SRC peaks
a <sub>max</sub>	Maximum amplitude of the SRC peaks
<i>k</i> <sub>2</sub>	Regression coefficient of the model $H_S$ vs C
<i>k</i> <sub>3</sub>	Regression coefficient of the model $H_S$ vs C
CI	Confidence Interval
SE	Standard Error
<i>R</i> <sup>2</sup>	Coefficient of determination
S	Standard error of the regression
$\overline{H_S}$	Average value of human stress response
$\overline{D_{tot}}$	Average value of total defects
k4	Regression coefficient of the model $H_S$ vs $D_{tot}$
PI	Prediction Interval
LPL	Lower Prediction Limit and

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	UP	L	Upper Prediction Limit								
	$\widehat{H_S}$		Predicted $H_S$ value of the regression curve								
	t <sub>1-</sub>	$\frac{\alpha}{2},\gamma$	Value of the Student's <i>t</i> distribution with $\gamma$ degrees of freedom and								
	SE	(Fit)	Standard error of the fit								
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17		Figure Captions List
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![](_page_46_Picture_1.jpeg)

- 926 927 928
- Fig. 2 Collaborative assembly workstation showing (a) the single-armed UR3e cobot equipped with the OnRobot RG6 gripper and (b) product components

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SW1	PZ	LW1	SW2	B1	SW3	R1	B2	SW4	R2	<b>B</b> 3	SW5	R3	B4	LW2	R4	BB	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	SW1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	PZ
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	LW1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	SW2
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	B1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	SW3
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	R1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	B2
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	SW4
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	R2
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	B3
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	SW5
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	R3
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	B4
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	LW2
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	R4
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	BB
	SW1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	SW1       PZ         0       0         0       0         0       0         0       0         0       0         0       0         0       0         0       0         0       0         0       0         0       0         0       0         0       0         0       0         0       0         0       0         0       0         0       0         1       1	SW1     PZ     LW1       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       1     1     1	SW1       PZ       LW1       SW2         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         0       0       0       0         1       1       1       1	SW1     PZ     LW1     SW2     BI       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       0     0     0     0     0       1     1     1     1     1	SW1         PZ         LW1         SW2         B1         SW3           0         0         0         0         0         0         0           0         0         0         0         0         0         0           0         0         0         0         0         0         0           0         0         0         0         0         0         0           0         0         0         0         0         0         0           0         0         0         0         0         0         0           0         0         0         0         0         0         0           0         0         0         0         0         0         0           0         0         0         0         0         0         0           0         0         0         0         0         0         0           0         0         0         0         0         0         0           0         0         0         0         0         0         0           0         0         0 <td< td=""><td>SW1       PZ       LW1       SW2       BI       SW3       RI         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0</td><td>SW1         PZ         LW1         SW2         B1         SW3         R1         B2           0         &lt;</td><td>SW1         PZ         LW1         SW2         B1         SW3         R1         B2         SW4           0</td><td>SW1         PZ         LW1         SW2         BI         SW3         RI         B2         SW4         R2           0</td><td>SW1       PZ       LW1       SW2       B1       SW3       R1       B2       SW4       R2       B3         0</td><td>SW1       PZ       LW1       SW2       BI       SW3       RI       BE       SW4       R2       BI       SW3         0</td><td>SV1         PZ         LV1         SV2         B1         SV3         R1         B2         SV4         R2         B3         SV5         R3           0</td><td>SW1       FX2       LW1       SW2       B1       SW3       R1       B2       SW4       R2       B3       SW5       R3       B4         0<!--</td--><td>SW1         FX2         LM1         SW2         R1         SW3         R1         R2         SW4         R2         R3         SW5         R3         R4         LW2           0</td></td></td<> <td>SN1         FZ         LM1         SN2         BI         SN3         RI         B2         SN4         R2         B3         SN5         R3         R4         LN2         R4           0<td>SM1         FZ         LM1         SM2         BI         SM3         RI         B2         SM4         R2         B3         SM5         R1         D0         0</td></td>	SW1       PZ       LW1       SW2       BI       SW3       RI         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0       0       0       0       0       0       0       0         0	SW1         PZ         LW1         SW2         B1         SW3         R1         B2           0         <	SW1         PZ         LW1         SW2         B1         SW3         R1         B2         SW4           0	SW1         PZ         LW1         SW2         BI         SW3         RI         B2         SW4         R2           0	SW1       PZ       LW1       SW2       B1       SW3       R1       B2       SW4       R2       B3         0	SW1       PZ       LW1       SW2       BI       SW3       RI       BE       SW4       R2       BI       SW3         0	SV1         PZ         LV1         SV2         B1         SV3         R1         B2         SV4         R2         B3         SV5         R3           0	SW1       FX2       LW1       SW2       B1       SW3       R1       B2       SW4       R2       B3       SW5       R3       B4         0 </td <td>SW1         FX2         LM1         SW2         R1         SW3         R1         R2         SW4         R2         R3         SW5         R3         R4         LW2           0</td>	SW1         FX2         LM1         SW2         R1         SW3         R1         R2         SW4         R2         R3         SW5         R3         R4         LW2           0	SN1         FZ         LM1         SN2         BI         SN3         RI         B2         SN4         R2         B3         SN5         R3         R4         LN2         R4           0 <td>SM1         FZ         LM1         SM2         BI         SM3         RI         B2         SM4         R2         B3         SM5         R1         D0         0</td>	SM1         FZ         LM1         SM2         BI         SM3         RI         B2         SM4         R2         B3         SM5         R1         D0         0

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![](_page_48_Figure_2.jpeg)

![](_page_48_Figure_3.jpeg)

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![](_page_49_Figure_1.jpeg)

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![](_page_50_Figure_2.jpeg)

940 Fig. 6 Human stress response  $(H_S)$  vs assembly complexity (C): (a) non-linear regression 941 model, and (b) residual plots 40%

Acceled Manufaction

![](_page_50_Figure_4.jpeg)

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![](_page_51_Figure_2.jpeg)

944 Fig. 7 Human stress response  $(H_S)$  vs total defects  $(D_{tot})$  for single variant production: sidu sidu (a) linear regression model, and (b) residual plots 945

![](_page_51_Figure_4.jpeg)

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![](_page_52_Figure_2.jpeg)

batches of product variant: (a) linear regression model, and (b) residual plots

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![](_page_52_Figure_4.jpeg)

![](_page_52_Figure_5.jpeg)

![](_page_53_Figure_1.jpeg)

951 952 Fig. 9 HRC-QWAT for (a) single variant production and (b) small-batch variant production 953

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#### Table 1 Components of the six electronic board variants (V1-V6)

V2 1 1 3 1 2 1 - - - - 9	V3 1 2 5 4 4 - - 1 - 1 - - 17	V4 1 8 3 6 - 1 3 - - - 22	V5 1 9 6 2 - - 1 1 1 1 1 24	V6 1 13 4 2 1 - - 1 - - 1 - - 23
1 1 3 1 2 1 - - - - - - 9	1 2 5 4 4 - - 1 - 1 - 17	1 8 3 6 - 1 3 - - - 22	1 9 6 2 - - 1 - 1 1 1 1 2 4	1 13 4 2 1 - - - - 23
1 3 1 - - - - - 9	2 5 4 - - 1 - - - 1 7	8 3 6 - 1 3 - - - 22	9 6 2 - - 1 1 1 1 24	13 4 2 1 - 1 - 1 - 23
3 1 2 1 - - - - 9	5 4 - - 1 - - - 17	3 6 - 1 3 - - - 22	6 2 - - 1 - 1 1 1 1 24	4 2 1 - 1 - 23
1 2 1 - - - - 9	4 - - 1 - - - - 17	6 - 1 3 - - - 22	2 2 - 1 - 1 1 1 1 24	2 1 - 1 - 1 - 23
2 1 - - - - 9	4 1 1	- 1 3 - - - 22	2 - 1 - 1 1 1 1 24	1 - - - - - - - - - - - - -
1 - - - - 9	- - - - - - - - - - - - - - - - - - -	1 3 - - 2 22	- 1 - 1 1 1 1 24	- 1 - - 23
- - - - 9	- 1 - - - - 17	3	- 1 - 1 1 1 1 24	- 1 - - - 23
- - - - 9	- 1 - - - 17	-	1 - - 1 1 1 1 24	1 - - - 23
- - - 9	1 - - - 17	-	- 1 1 1 24	1 - - 23
- - - 9	- - - 17	22	- 1 1 1 24	1 - - 23
- - 9	- - 17	22	1 1 1 24	23
- - 9	17	22	1 1 24	- - 23
9	<u> </u>	22	1 24	- 23
9	17	22	24	23
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	Participant	Age	Gender	Domain knowledge of HRC	Domain knowledge of electronic board assembly
	P1	21	Female	Intermediate	Intermediate
	P2	21	Male	Intermediate	Expert
	P3	22	Male	Expert	Expert
	P4	21	Male	Intermediate	Expert
	P5	27	Male	Intermediate	Expert
	P6	23	Male	Intermediate	Intermediate
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#### Table 2 Participants' characteristics

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- Size and weight (One of the following)	Very small - requires handling aids Easy - requires one hand only Large and/or heavy - requires more than one hand or aid	1.5
- Size and weight (One of the following)	Easy - requires one hand only Large and/or heavy - requires more than one hand or aid	1
- Size and weight (One of the following)	Large and/or heavy - requires more than one hand or aid	0
		1.5
	Large and/or heavy- requires hoist or more than one person	2
	Delicate	0.4
	Flexible	0.6
	Sticky	0.5
B - Handling difficulty	Tangible	0.8
(All that apply)	Severely nest	0.7
	Sharp/abrasive	0.3
	Untouchable Criania a rank law (cliana ar	0.5
	Automatic handling - no difficulty	0.2
	Symmetrical - no orientation required	0
C - Alpha Symmetry	Easy to orient - end to end	0.1
(One of the following)	Difficult to orient - end to end	0.5
D Bota Symmotry	Rotational orientation is not required	0
(One of the following)	Easy to orient - end to end	0.2
	Difficult to orient - end to end	0.4

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#### Table 3 Difficulty of component handling attributes. Adapted from [63]

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#### Table 4 Difficulty of component connection attributes. Adapted from [63]

Attributo i	Description	Connection difficulty
Attribute j	Description	$d_c$
E - Component placing	Self-holding	1
(One of the following)	Holding down required	2
	Self-securing	1.3
	Screwing	4
F – Component	Riveting	4
Tastening	Bending	4
(One of the following)	Mechanical deformation	4
	Soldering or welding	6
	Adhesive	5
	Straight line from above	0
G – Direction	Straight line not from above	0.1
(One of the following)	Not straight line and/or bending is required	1.6
II lecontion	Single	0
H = Insertion	Multiple	0.7
(One of the following)	Simultaneous multiple insertions	1.2
I – Restricted vision	Visible	0
(One of the following)	Not visible	1
J – Difficult to align	No	0
(One of the following)	Yes	0.7
K – Resistance to	No	0
(One of the following)	Yes	0.6

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968Table 5 Handling complexity  $(h_p)$  of components and connection complexity  $(c_{pr})$  of969components with the breadboard in the six electronic board variants (V1-V6)

Component	$h_p$	$c_{pr}$	
Breadboard (BB)	1.7	-	
Long wires (LW)	1.8	3.7, 5.3, 6.3	
Short wires (SW)	2.3	3.7, 5.3	
Resistors (R)	1.8	3.8	
Pushbuttons (PB)	1.9	4.2	
	19	4.2	
Phototransistor (F)	1 0	1.2	
Priototransistor (I)	1.5	4.2 E 0	
	1.7	5.0 2.7	
	1./	3.7	
LCD (LCD)	3.0	6.4	
Battery snap (BS)	1.8	3.7	
DC Motor (M)	1.8	3.7	
H-bridge (HB)	1.9	4.2	

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Table 6 Complexities of the six electronic boards (V1-V6)

		V1	V2	V3	V4	V5	V6
	$C_1$	1.64	3.12	5.35	6.59	7.49	6.97
	$C_2$	2.90	5.89	10.03	13.39	15.83	18.24
	<i>C</i> <sub>3</sub>	0.75	0.57	0.45	0.40	0.37	0.39
074	С	3.80	6.50	9.83	11.95	13.37	14.12
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995Table 7 Experimental values of total defects  $(D_{tot})$  and human stress response  $(H_S)$ 996recorded in each trial

Participant	Variant	С	D <sub>tot</sub>	H <sub>S</sub>
1	V4	11.95	3	8.97
1	V6	14.12	7	34.87
1	V1	3.8	0	0.00
1	V5	13.37	5	10.00
1	V3	9.83	3	4.02
1	V2	6.5	1	3.13
2	V5	13.37	4	12.70
2	V4	11.95	3	16.65
2	V3	9.83	3	8.46
2	V6	14.12	5	20.45
2	V2	6.5	0	0.33
2	V1	3.8	0	0.00
3	V3	9.83	0	8.95
3	V6	14.12	6	23.27
3	V1	3.8	0	0.00
3	V4	11.95	3	12.16
3	V2	6.5	2	2.23
3	V5	13.37	3	11.30
4	V2	6.5	2	7.35
4	V4	11.95	3	14.90
4	V1	3.8	0	0.00
4	V3	9.83	0	6.35
4	V6	14.12	4	19.84
4	V5	13.37	6	11.45
5	V1	3.8	0	0.00
5	V3	9.83	2	11.12
5	V5	13.37	3	9.21
5	V6	14.12	5	22.01
5	V4	11.95	0	11.55
5	V2	6.5	1	5.00
6	V6	14.12	6	27.88
6	V2	6.5	0	1.04
6	V5	13.37	1	17.31
6	V3	9.83	1	8.75
6	V1	3.8	0	0.00
6	V4	11.95	2	7.75

# 998Table 8 Number of defects classified into in-process (D1) and offline (D2) defects for the999six assembled products

	Inco Comp	rrect onent	Misp Comp	laced onent	Unpicked Component	Slipped Component	Defe Comp	ective oonent	Impro Inse Comr	operly erted onent
Variant	D1	D2	D1	D2	D1	D1	D1	D2	D1	D2
V1	0	0	0	0	0	0	0	0	0	0
V2	0	0	1	1	3	0	0	0	0	1
V3	0	0	5	2	3	0	0	0	0	1
V4	0	0	4	3	4	0	0	0	3	0
V5	0	0	6	3	11	2	0	0	0	0
V6	0	0	11	11	10	0	0	0	1	0
Total	0	0	27	20	31	2	0	0	4	2
						C				

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1002	Table 9 Poisson regression output for total defects ( $D_{tot}$ ) vs assembly complexity (C).
1003	Model is in the form $D_{tot} = (k_1 \cdot C)^2$

$k_1$	$SE(k_1)$	Coefficient <i>p</i> -value	Deviance <i>R</i> <sup>2</sup>	Goodness-of-Fit Te	ests
0.144	0.008	<0.0005	99.29%	Deviance Test <i>p</i> -value Pearson Test <i>p</i> -value	0.557
					0

# 1006Table 10 Non-linear regression output for human stress response $(H_S)$ vs assembly1007complexity (C). Model is in the form $H_S = k_2 \cdot C^{k_3}$

	ka	$SE(k_2)$	95% CI for $k_2$	k2	$SE(k_2)$	95% CI for $k_2$	S
	0.004	0.006	$(4 \cdot 10^{-5}, 0.076)$	3.222	0.594	(2.086, 5.025)	4.284
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# 1010Table 11 Linear regression output for human stress response vs total defects for single1011variant production and small-batch variant production

	Model	$k_4$	$SE(k_4)$	Coefficient <i>p</i> -value	<i>R</i> <sup>2</sup>	R <sup>2</sup> pred.	S
Single variant production	$H_S = k_4 \cdot D_{tot}$	3.821	0.278	<0.0005	84.38%	82.99%	5.243
Small-batch variant production	$\overline{H_S} = k_4 \cdot \overline{D_{tot}}$	4.257	0.294	<0.0005	97.67%	95.64%	2.127

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1013	Table 12 Examples of critical situations detected by the HRC-QWAT		
	HRC-QWAT	Observed values	Possible root cause
	Single variant production	( <i>D<sub>tot</sub></i> , <i>H<sub>S</sub></i> )=(2,35) Area A (cf. Fig. 9(a))	Abnormal stress experienced by the operator
	Small-batch variant production	$(\overline{D_{tot}}, \overline{H_S})$ =(6,10) Area B (cf. Fig. 9(b))	Wrong/faulty components undetected by the operator during the production process
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