

Exploring the effects of perceived complexity criteria on performance measures of human-robot collaborative assembly

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1 **Exploring the effects of perceived**
2 **complexity criteria on performance**
3 **measures of human-robot collaborative**
4 **assembly**
5

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28 **ABSTRACT**

29 *The use of Human-Robot Collaboration (HRC) in assembly tasks has gained increasing attention in*
30 *recent years as it allows for the combination of the flexibility and dexterity of human operators with the*
31 *repeatability of robots, thus meeting the demands of the current market. However, the performance of these*
32 *collaborative systems is known to be influenced by various factors, including the complexity perceived by*
33 *operators. This study aimed to investigate the effects of perceived complexity on the performance measures*
34 *of HRC assembly. An experimental campaign was conducted in which a sample of skilled operators was*
35 *instructed to perform six different variants of electronic boards and express a complexity assessment based*
36 *on a set of assembly complexity criteria. Performance measures such as assembly time, in-process defects,*
37 *quality control times, offline defects, total defects, and human stress response were monitored. The results*
38 *of the study showed that the perceived complexity had a significant effect on assembly time, in-process and*
39 *total defects, and human stress response, while no significant effect was found for offline defects and quality*
40 *control times. Specifically, product variants perceived as more complex resulted in lower performance*
41 *measures compared to products perceived as less complex. These findings hold important implications for*
42 *the design and implementation of HRC assembly systems and suggest that perceived complexity should be*
43 *taken into consideration to increase HRC performance.*

44

45 **1. INTRODUCTION**

46 In today's market, manufacturers are required to produce high-value-added
47 products that meet customer demands at a competitive price, while also complying with
48 sustainability requirements related to environmental and social aspects. As a result,
49 manufacturers must offer a wide range of continuously improved products at competitive
50 prices in order to maintain and increase their market share. Accordingly, balancing high
51 levels of customer adaptation and cost efficiency is crucial in achieving this goal. Research

52 has shown that an increase in product variety can lead to a higher market share and sales
53 volume, but also increases product complexity and cost [1–3] and requires a flexible
54 manufacturing system that can adapt to changes in product volumes and types [4]. This
55 is especially relevant in the automotive and electronic industries, where frequent changes
56 and an increased number of product variants with more features and functionality are
57 required to meet customer expectations. Managing a large product assortment and
58 assembly conditions can be challenging for manufacturers, however, effectively
59 navigating this complexity can result in a competitive advantage in the industry [5,6].

60 One approach to achieving mass customization is the use of a traditional manual
61 assembly system, which allows human operators to perform all assembly tasks. However,
62 this approach may result in a decrease in productivity and an increase in costs [7]. On the
63 other hand, automatic assembly systems offer high production rates and cost savings, but
64 they may not be suitable for mass customization [8]. Flexible assembly systems using
65 collaborative robots, or cobots, offer a solution by combining the flexibility of human
66 operators with the precision and accuracy of robots, typically resulting in increased
67 productivity and cost savings [4,9].

68 The collaboration between humans and cobots, known as human-robot
69 collaboration (HRC), has garnered significant attention in recent years due to the potential
70 benefits and challenges associated with this approach [10]. Previous research in the
71 manual assembly field has shown that assembly complexity and its perception can
72 significantly affect human and process performance [1,11,12]. However, there has been

73 limited research on the impact of perceived assembly complexity on the performance of
74 human-robot collaboration in assembly tasks. Building on these findings, the present
75 research aims to extend the investigation by examining the effects of varying product
76 complexity on perceived complexity and assembly performance measures in the context
77 of HRC assembly. This research allows for an understanding of how the perceived
78 complexity of human operators in HRC tasks is influenced by the complexity of the
79 product being assembled.

80 The main innovative contribution to the field provided by this research is to
81 examine the impact of perceived complexity on several HRC performance measures that
82 encompass the entire manufacturing process. These measures, which include
83 characteristics of the assembly process, the quality control process, and human aspects,
84 are (i) assembly times, (ii) quality control times carried out after the assembly, (iii) in-
85 process defects (catering for errors due to both human and collaborative robots), (iv)
86 offline product defects (i.e. defects detected during offline inspection), (v) total
87 defectiveness (i.e. sum of in-process and offline defects) and (vi) human stress response
88 during assembly. By considering both process performance and human factors, this
89 approach provides valuable insights into the relationship between performance measures
90 and perceived complexity in HRC assembly tasks.

91 In order to investigate the effects of perceived complexity on HRC performance
92 measures, the study involved the assembly of six variants of electronic boards with
93 different levels of complexity. Skilled operators, assisted by cobots, performed the

94 assembly tasks in a collaborative setup where both humans and cobots worked together
95 in the same workspace [13]. This collaborative configuration is commonly observed in
96 manufacturing environments and facilitates the combination of human dexterity and
97 adaptability with the precision and repeatability of cobots. The adoption of this
98 collaborative mode aimed to investigate the impact of perceived complexity on the
99 performance measures of human-robot collaborative assembly in a real-world context.
100 To ensure a comprehensive analysis of the effects of perceived complexity, a product-
101 centred approach was adopted. The product itself was modified to create different
102 assemblies with varying levels of complexity. This approach is often used in the
103 manufacture of highly customized product variants, where collaboration modes and
104 parameters remain consistent. By focusing on the product and its complexity variations,
105 the study aimed to capture the practical implications of perceived complexity on human-
106 robot collaborative assembly performance measures in an industry-relevant context.

107 The study's results provide insights into the association between performance
108 measures of human-robot collaboration in assembly tasks and perceived complexity and
109 offer practical implications for designing and implementing high-performing collaborative
110 systems. Furthermore, by considering both process performance and human-related
111 factors, the proposed approach aligns with the goals of sustainable, high-quality, resilient
112 and human-centric HRC systems within the context of the Industry 5.0 paradigm.

113 The remainder of the paper is organized as follows. In Section 2, the most recent
114 research studies on human-robot collaboration are reviewed. Section 3 presents the

115 experimental details and methods adopted in the present study. In Section 4, results are
116 presented and discussed, and the conclusions and future work are outlined in Section 5.

117

118 **2. LITERATURE REVIEW**

119 In recent years, there has been a growing interest in the field of Human-Robot
120 Collaboration (HRC), resulting in a significant increase in research activities and
121 publications. HRC involves the collaboration between humans and robots working
122 together in a shared workspace to perform a task, with each partner contributing their
123 specific skills and abilities [14,15].

124 The literature on HRC emphasizes the importance of providing technologies that
125 facilitate natural and smooth interactions between humans and robots. Wang et al. [16]
126 highlighted the importance of the communicative interface between robots and humans,
127 to achieve a symbiotic HRC. Inkulu et al. [17] highlighted the prospects and major
128 challenges of HRC, pointing out that human-robot communication modes, such as
129 gestures and speech, enable fluent and immediate interaction, although they still need to
130 be explored in depth.

131 To date, most research on HRC has focused on safety, communication, and
132 human-robot interaction. Much attention has been given to safety concerns and the
133 development of effective safety measures to support HRC. Indeed, safety is a major
134 concern, especially for robots operating at high speeds and under heavy loads. The
135 introduction of ISO 10218-1:2011 [18] and ISO 10218-2:2011 [19] defined the main

136 hazards that can be encountered when implementing industrial robots in manufacturing
137 environments. In addition, the subsequent ISO/TS 15066:2016 [20] allowed for greater
138 robot's autonomy while working closely with humans. Zanchettin et al. [21] introduced a
139 metric to assess safety in collaborative manufacturing processes. This metric considers
140 human-robot distance, robot type and operating speed as critical variables affecting
141 safety in HRC. In addition, the sharing of space and time between humans and robots can
142 lead to stress and fatigue issues, which can affect the quality of the output produced and
143 lead to defects in products and processes. Gervasi et al. [22] have developed a conceptual
144 framework for evaluating HRC that includes variables such as mental and physical
145 ergonomics, safety, communication and interaction, team organization, and social
146 acceptance. Advanced adaptive robotic systems are also needed to improve production
147 efficiency.

148 In manufacturing, concepts such as stress, fatigue, mental workload, and
149 ergonomics have long been addressed [23–25]. Over the years, many tools and methods
150 have been proposed to assess these factors. Self-reporting instruments include the NASA-
151 TLX [26] and the Subjective Workload Assessment Technique (SWAT) [27]. However,
152 these tools have been found to be inappropriate and unreliable in manufacturing
153 environments [28]. Consequently, in recent years, attention has shifted to investigating
154 the impact of objective physiological measures, such as heart rate variability (HRV) and
155 electrodermal activity (EDA), on the operator's state during an HRC task [29–32]. Kulić and
156 Croft [33] investigated how human physiological state, measured by HRV and EDA, can be

157 affected by the movements of an industrial robot. In this study, proximity and speed were
158 shown to have a significant effect on mental stress. Similarly, Arai et al. [34] evaluated the
159 effect of robot movements, varying operating speed and distance from the operator, on
160 EDA. Kühnlenz et al. [35] studied the effects on humans through HRV and EDA of different
161 trajectory patterns of an industrial robot.

162 Physical and cognitive aspects are critical factors in the design of HRC tasks [36].
163 Colim et al. [37] provided guidelines for the design of safe and ergonomic collaborative
164 workstations. In a repetitive and hazardous assembly task, cobots can be used to reduce
165 potential risks to the operator and improve human well-being. However, few studies have
166 investigated the effect of human-robot collaboration on the mental and physical
167 workload perceived by humans. Khalid et al. [38] investigated the safety of HRC systems
168 when using high-load robots, defining potential hazards that include physical and mental
169 strain associated with a collaborative task. Galin and Meshcheryakov [39] analyzed both
170 human and robot dependent factors that may affect the efficiency of HRC. Among the
171 human factors, emotional and cognitive aspects were found to be critical for HRC
172 efficiency.

173 Overall, while much attention has been paid to safety, communication, interaction
174 and human physical and cognitive aspects in HRC, there is a lack of research exploring the
175 impact of task complexity perceived by humans on performance measures. This gap in
176 the literature provides an opportunity for further research to investigate the relationship
177 between assembly complexity and performance measures, both process- and human-

178 related measures, such as production time, defect rates and human-centred measures,
179 respectively, in HRC settings.

180

181 **3. EXPERIMENTAL SET-UP AND METHODS**

182 **3.1 Experimental system configuration**

183 An experimental campaign involving six expert operators and a single-armed
184 collaborative robot, the UR3e from Universal Robots™, equipped with an OnRobot RG6
185 gripper with two flexible fingers (see Fig. 1) was designed and carried out. The RG6
186 gripper, produced by OnRobot™, was selected for its versatility and ability to handle a
187 variety of objects, even of small dimensions. Each operator underwent preliminary
188 training sessions prior to the assembly trials in order to ensure a consistent level of
189 proficiency among the participants and to minimise the potential impact of varying skill
190 levels on the results. These training sessions were designed to familiarize the operators
191 with the assembly process and equipment.

192 During the experimental trials, each operator assembled six electronic boards (see
193 next Section 3.2) in random order with the support of the UR3e cobot.

194 Manufacturing process consisted of two phases: (i) assembly phase and (ii) quality
195 control phase. During the assembly phase of each electronic board, the cobot was used
196 to assist operators in assembly operations by passing appropriate components in a
197 predetermined sequence. The parts of the electronic boards were placed in a specific
198 position within the HRC workstation to be picked up by the cobot, since the cobot was

199 unable to recognize parts. Future research will focus on the use of visual recognition
200 systems, integrated with machine learning techniques, to enable the cobot to recognize
201 parts. The assembly sequence was determined according to circuit theory [40]. In fact, for
202 the circuit to work, a complete path must exist between the energy source (power) and
203 the lowest energy point (ground). Furthermore, the current always seeks the path of least
204 resistance to earth and between two possible paths the current goes through the path of
205 least resistance. This is because the electrical energy within the circuit is dissipated by its
206 components, converting the electrical energy into other forms of energy, such as light,
207 heat and sound. As a result, the strategy for assembling electronic boards was defined
208 based on the path of the electric current.

209 During assembly, human operators decided when activating the cobot to pick up
210 the parts and bring them to the storage area by pressing a button near the workstation.
211 The cobot used the MoveL movement for vertical actions, such as picking up and
212 depositing the parts, and the faster MoveJ movement for other actions, such as moving
213 the parts to the storage area. Table 1 shows cobot and gripper parameters used in the
214 HRC assembly.

215 After the assembly phase, in which electronic board variants were assembled
216 through HRC, a skilled quality controller checked their correct functioning and identified
217 residual defects during the quality control phase. The advantage of using electronic
218 boards is the possibility to verify their proper functioning by connecting them to the PC
219 and running the code. During the quality inspection, the operator who was in charge of

220 the assembly of the electronic board was asked to fill a questionnaire on perceived
221 complexity of the assembly, which will be presented in Section 3.4. In detail, at the end
222 of each board variant assembly, the operator evaluated perceived complexity by
223 providing evaluations on some assembly complexity criteria, while at the end of the six
224 assemblies an overall assessment of the importance of the complexity criteria was given
225 (as per Section 3.4). Furthermore, during assembly and quality control phase, data on
226 some performance measures were collected, which will be illustrated in Section 3.3.

227

228 **3.2 Product assembled**

229 For the assembly of the six electronic boards, the ARDUINO UNO Starter Kit from
230 ARDUINO® was used. This kit includes the physical components necessary for assembling
231 the electronic boards (listed in Table 2) and a software package for programming the
232 microcontrollers. In Table 2, the type and quantity of each component are indicated for
233 each product variant (Variant A – Variant F).

234 These six products have been selected to cover a wide range of product
235 complexity. According to previous studies [41–43], product variants' total complexity is
236 obtained according to the structural complexity model as a combination of complexity of
237 product components (C_1), complexity of assembly connections/liaisons (C_2) and
238 complexity of product architecture (C_3), according to Eq. (1):

$$239 \quad C = C_1 + C_2 \cdot C_3 \quad (1)$$

240 In this study, the Lucas Method [44], widely used in literature and for several
241 industrial applications, was applied to define the complexity of product components and
242 connections (C_1 and C_2). On the other hand, product architecture complexity (C_3) was
243 derived as the average of singular values of the adjacency matrix of the product [41]. In
244 Table 2, the product variants are listed according to increasing complexity C . It is
245 noteworthy that an increase in the number of parts does not necessarily imply an increase
246 in complexity C . As mentioned above, the products were assembled in random order by
247 the six operators. Randomizing the order of the six product variants during assembly
248 minimized the impact of learning effects and increased internal validity. This approach
249 controlled for potential confounding variables and prevented observed performance
250 measure differences between product variants from being attributed to increased
251 operator familiarity or experience with the assembly process or equipment. Thus,
252 although manufacturing sequence was not explicitly controlled, randomization helped
253 minimize its potential impact on the results.

254 Fig. 2 shows three examples of the six electronic boards assembled with the
255 support of cobot. The first product, Variant A, is the simplest of the six selected products,
256 Variant C is at medium-level complexity, while the last product, Variant F, is the most
257 complex.

258
259
260

261 3.3 Data acquisition

262 During the manufacturing process, some human and process performance
263 parameters were collected, including physiological data from the operators, the number
264 of total defects (both those occurring during assembly, i.e. in-process defects, and those
265 detected during offline quality control, i.e. offline defects), the assembly time, and the
266 time spent on quality control. The selected performance measures were chosen based on
267 their relevance to the objectives of the study and a thorough literature review that
268 followed the survey proposed by Coronado et al. [36]. While there are many other metrics
269 available for evaluating the performance of collaborative systems, the selected measures
270 were deemed most appropriate for this study due to their widespread use in the
271 manufacturing industry to evaluate the quality of human-robot interaction and
272 collaboration, especially in the context of Industry 5.0, and their ease of monitoring
273 throughout all stages of the production process.

274 In the first phase of the manufacturing process (assembly phase), information
275 about assembly time, in-process defects and stress were collected. On the other hand, in
276 the second phase (quality control phase), information about quality control time and
277 offline defects was collected. Those parameters, plus the total number of defects (sum of
278 in-process and offline defects), are the performance measures depicting the overall
279 manufacturing process.

280 In the HRC assembly phase, the operator clocked the minutes to complete each
281 electronic board's assembly. The stopwatch started when the cobot picked up the first

282 part and stopped when the operator considered the assembly finished. Even when errors
283 occurred, the stopwatch was never stopped. In the quality control phase, the operator
284 recorded the time in minutes spent on quality control. In this case, the time started when
285 the electronic board reached the quality control station and was stopped when the board
286 worked properly. The stopwatch was never stopped during the quality control phase.

287 Regarding in-process and offline defects, a classification was performed as follows:

288 (i) "Wrong part", i.e. a different component is used instead of the correct one; (ii) "Wrong
289 position", i.e. the component is placed in the wrong position; (iii) "Part not taken", i.e. the
290 cobot fails to pick up the part from the columns; (iv) "Slipped part", i.e. the part slips from
291 the cobot grippers during transport to the operator; (v) "Defective part", i.e. the part is
292 defective and does not allow the electronic board to function correctly; (vi) "Incorrectly
293 inserted part", i.e. the part is inserted in the correct position but not properly. Obviously,
294 for offline defects, the two categories of defects related to cobot errors ("Part not taken"
295 and "Slipped part") were not present. The assembly operators and the quality control
296 operator collected in-process and offline defects data for each electronic board, indicating
297 the number of defects found for each category.

298 During HRC assembly phase, information on the stress level of the operators was
299 collected. Physiological data were measured with the Empatica E4 wristband (Empatica
300 Srl, Milan, Italy), a non-invasive biosensor that records information on ElectroDermal
301 Activity (EDA) at a frequency of 4 Hz (see Fig. 1). EDA is commonly used as an indicator of
302 human stress response, being linked to Skin Conductance Response (SCR) [32]. In detail,

303 continuous signals of tonic and phasic activity constitute the EDA signal. Changes in Skin
304 Conductance Level (SCL) are the best indicator of tonic activity, which is defined as long-
305 term fluctuations in EDA that are not explicitly triggered by external stimuli. Instead,
306 phasic activity describes brief variations in EDA triggered by stimuli typically recognized
307 and presented externally. Skin Conductance Responses (SCRs), i.e., amplitude changes
308 from the SCL, can therefore be detected by examining the phasic activity signal. In this
309 research, the normalized peak amplitude of the SCR was employed as a metric for
310 measuring the stress levels of operators during the HRC assembly of electronic boards.
311 For each operator, the *Human stress response* can be defined as follows:

$$312 \quad \text{Human stress response} = \left[\frac{\left(\frac{\sum_{w=1}^{N_p} a_w}{N_p} \right) - a_{min}}{a_{max} - a_{min}} \right] \cdot 100 \quad (2)$$

313 where a_w is the amplitude of the w -th SCR peak, N_p is the total number of SCR peaks
314 during the assembly of a certain product variant, a_{min} and a_{max} are, respectively, the
315 minimum and maximum amplitude of SCR peaks obtained during the assembly by each
316 operator.

317 In this study, the EDA signal was analyzed using the online EDA Explorer software
318 [45]. This software cleans the raw signal of any external noise and identifies peaks in the
319 physiological signal. Fig. 3 shows an example of the software output. The trend of the
320 physiological signal (expressed in μS) is the blue line and the green vertical lines represent
321 the peaks identified by the software. In addition, the amplitude of a generic peak (a_w) is
322 shown in red as an example. Furthermore, after assembly, data on perceived complexity

323 were acquired through questionnaires submitted to operators, as described in Section
324 3.4.

325

326 **3.4 Perceived complexity assessment**

327 Complexity, a multifaceted concept that has been studied extensively and has
328 various definitions and measurements depending on context and research goals, can be
329 assessed objectively, based on inherent task characteristics, or subjectively, considering
330 both task and performer characteristics [46].

331 This study proposes a complexity assessment framework based on the 16
332 complexity criteria developed by Falck and Rosenqvist [47] and later adapted for
333 industrial manufacturing sectors [48–50]. The complexity assessments were carried out
334 in collaboration with the company's ergonomist and engineers in the manufacturing
335 engineering department. In order to ensure easy and quick assembly of the products,
336 Table 3 provides a brief description of each i -th criterion ($i = 1, \dots, 16$), expressed for an
337 easy and fast assembly [50]. For a more detailed description and guidelines for using these
338 criteria in a practical setting, refer to the papers by Falck et al. [50,51].

339 For each product j , the importance of each criterion i was determined by asking
340 each operator k to assign an importance score (I_{ijk}) using a five-level ordinal scale (see
341 Table 4), based on their perceived relevance for low product complexity. In addition, each
342 operator was asked to indicate the level of agreement (V_{ijk}) with each criterion i in relation
343 to the assembled product j , using the five-level ordinal scale shown in Table 5.

344 To obtain an estimate of perceived complexity at the individual level, the study
345 combined the operators' ratings of importance and level of agreement with the 16
346 criteria. However, as the criteria were expressed using linguistic ordinal scales, a
347 systematic method was required to process the data. To this end, the Multi-Expert Multi-
348 Criteria Decision Making (ME-MCDM) method developed by Yager [52] was adopted as
349 the synthesis approach.

350 ME-MCDM is a widely used method for aggregating individual operator
351 evaluations to obtain an overall synthetic linguistic value [52]. It combines linguistic
352 information provided for non-equally important criteria using maximum, minimum and
353 negation operators. The logic behind the ME-MCDM method is that the impact of low-
354 importance criteria on the overall aggregated value should be marginal, while high
355 important criteria should have a significant impact on the definition of the aggregated
356 evaluation. In the proposed approach, the perceived complexity of the assembly of a
357 product j expressed by the operator k (PC_{jk}) can be calculated using fuzzy logic as follows
358 [53]:

$$359 \quad PC_{jk} = \text{Min}_i [\text{Max}\{Neg(I_{ijk}), V_{ijk}\}] \quad (3)$$

360 where $Neg(L_x) = L_{t-x+1}$ is the negation of L_x , with L_x the x^{th} level of the scale and t the
361 number of scale levels, i.e. 5 in this case. For instance, $Neg(L_1) = L_5$ and $Neg(L_2) = L_4$.

362 The rating process for the perceived complexity of a product involves assigning
363 values on a five-point ordinal scale, with the highest level representing low complexity
364 and the lowest level representing high complexity. This scale is based on the criteria listed

365 in Table 3, which are considered to be low complexity criteria. Table 6 provides details on
366 the five complexity levels used for individual perceived complexity assessment.

367 To illustrate how this scoring process works, consider a hypothetical product j , and
368 an operator k , who scores all criteria as L_5 – "Indispensable" for importance and L_5 –
369 "Totally agree" for agreement. According to the proposed aggregation method, this
370 operator's individual perceived complexity PC_{jk} for product j would be L_5 - "Low",
371 meaning that the operator finds the product extremely simple and considers all criteria
372 essential for a simple assembly. Conversely, if the operator rated all criteria importance
373 as L_5 – "Indispensable" and the level of agreement as L_1 – "Totally disagree", then his
374 individual perceived complexity would be L_1 – "High". In this case, the operator considers
375 the product to be extremely complex and considers all criteria to be essential for a simple
376 assembly. In a different scenario, if the operator assigned L_1 – "Totally disagree" for
377 agreement degrees, but considers all the criteria to be negligible, resulting in L_1 –
378 "Negligible" for importance, the procedure leads to obtain L_5 – "Low" for the individual
379 perceived complexity.

380 Overall, the perceived complexity assessment process involves assigning
381 importance and agreement values to specific criteria, which are then aggregated to
382 determine the individual perceived complexity level of a product assembly.

383

384

385

386 3.5 Statistical analysis

387 The data gathered for the 6 electronic boards assembled by the 6 operators were
388 collected in a matrix, one line for each product (i.e., 36 rows) with the observed
389 parameters listed in columns. In detail, the parameters related to performance measures
390 recorded in the columns were:

- 391 • Assembly time;
- 392 • Quality control time;
- 393 • In-process defects;
- 394 • Offline defects;
- 395 • Total defects;
- 396 • Human stress response (see Eq. (2)).

397 Furthermore, additional columns were created containing values related to
398 perceived complexity assessment, as follows:

- 399 • Individual importance evaluations of each of the 16 criteria (as per Table 4);
- 400 • Individual agreement degree evaluations of each of the 16 criteria (as per Table
401 5);
- 402 • Individual perceived complexity derived according to Eq. (3).

403 The primary statistical analysis consisted of calculating the main descriptive
404 statistics for performance measures for each of the six assembled electronic boards (see
405 Table 7 in next Section 4).

406 To evaluate if the 16 criteria selected for the analysis compose a suitable set to
407 assess complexity, a pairwise correlation analysis between the evaluations on the
408 agreement degrees provided by operators for each product (V_{ijk}) was performed (see
409 Table 9). Spearman correlation coefficient was adopted being the agreement degrees

410 expressed on ordinal scale, and the significance of the correlation was assessed by
411 analyzing the p -values [54].

412 Then, a pairwise correlation analysis was performed to obtain a first indication of
413 the relationships between the agreement degrees of the 16 complexity criteria and
414 performance measures (as shown in Table 10).

415 Finally, to examine the relations between the individual perceived complexity
416 values derived according to Eq. (3) and the performance measures (see Fig. 4), an Ordinal
417 Logistic Regression (OLR) was adopted, as perceived complexity is an ordinal response
418 defined using a linguistic scale [55]. The OLR is an ordinal regression model that can only
419 be applied to data that meet the proportional odds assumption. The coefficients in the
420 model are estimated using maximum likelihood, computed by using iteratively
421 reweighted least squares [55]. To analyze and interpret the results of the OLR, two steps
422 should be followed [54,56]. First, the p -value and coefficients are examined to analyze the
423 association between the performance measures and individual perceived complexity. The
424 coefficients are useful for determining whether a change in the predictor variable makes
425 any of the events more or less likely, and the odds ratios are provided to compare the
426 odds of two events. Secondly, the p -values for the Goodness-of-Fit Tests, and the
427 measures of association are examined to determine how well the model fits the data.
428 Values of measures of association, including the Somers' D, Goodman and Kruskal indices,
429 and Kendall's index, close to 0 reveal that the model does not have predictive ability.
430 Results of OLR are reported in Table 11, Table 12 and Fig. 5 of next Section 4.

431 All calculations were performed using the software MINITAB®.

432

433 **4. RESULTS AND DISCUSSION**

434 Descriptive statistics of performance measures considered in this study are listed
435 in Table 7, separately for each electronic board assembled (Variant A – Variant F). An
436 examination of the data reveals that as the complexity of the assembly increases, there is
437 a tendency for performance measures to worsen as a negative impact on assembly time,
438 quality control time, defects rates, and human stress response is encountered.
439 Additionally, as the products move from simple to more complex (i.e., from Variant A –
440 Variant F), the variability associated with performance measures tends to increase, as
441 demonstrated by the increase in standard deviation in Table 7.

442 Table 8 presents the classification of in-process and offline defects obtained for
443 each of the six assembled product variants, according to the classification provided in
444 Section 3.3. An analysis of the data shows that in-process defects are more frequent
445 compared to offline defects. Additionally, within the typology of in-process defects,
446 "Wrong position" and "Part not taken" demonstrate the highest number of defects;
447 whereas for offline defects, "Wrong position" is the most prevalent category. These
448 findings suggest that the manufacturing process is likely facing more issues when the
449 products are in-line rather than when they are inspected offline. Furthermore, the
450 frequent occurrence of "Wrong position" both for in-process and offline defects highlights
451 the need for efficient and accurate placement of parts during the assembly process.

452 Table 9 displays the results of the pairwise correlation analysis between the
453 evaluations of the agreement degrees with the 16 criteria provided by operators for each
454 product (V_{ijk}). Only the lower triangular part of the matrix is shown in Table 9 because of
455 the symmetry of the matrix. In detail, the Spearman correlation coefficients are reported
456 and those that resulted statistically significant at 95% confidence level (thus with p -value
457 < 0.05) are asterisked. Most statistically significant correlations are positive, showing that
458 as the score on the degree of agreement of one criterion increases, the other also
459 increases. For instance, Criterion 1 is moderately correlated with Criterion 2, as operators
460 agree that few different ways of performing assembly are associated with few
461 parts/components and details and few operations. On the other hand, only a few of the
462 correlation coefficients in Table 9 are negative. For instance, there is a moderate negative
463 correlation between Criterion 12 and 15 indicating that as operators concur with the fact
464 that the structure is rigid and involves few flexible materials, they perceive a greater need
465 for adjustments. Conversely, fewer adjustments and modifications are required during
466 assembly if the structure incorporates soft and flexible materials. The results presented
467 in Table 9 indicate that the highest correlation coefficient value is 0.731, and there are no
468 correlations that approach a value of 1. Accordingly, it would not be appropriate to
469 eliminate certain criteria as redundant when assessing individual perceived complexity.

470 Table 10 presents the results of the pairwise correlation analysis conducted to
471 examine the associations between the agreement degree with the 16 complexity criteria
472 and the data pertaining to performance measures. In detail, for each complexity criterion,

473 the evaluations on the agreement degree provided by the six operators for each of the six
474 products (36 values) are correlated with the six performance measures. Spearman
475 correlation coefficients statistically significant at 95% confidence level are asterisked.
476 Almost all the values in Table 10 are negative because as the agreement with the low-
477 complexity criteria increases, operators concur that the product is simple. Therefore, the
478 simpler the product, the less assembly time, quality control time, defects and stress are.
479 The results indicate a moderate to strong correlation between several of the complexity
480 criteria and performance measures. It should be noted that some criteria do not show a
481 significant correlation with the performance measures (see for example Criteria 9-13 and
482 Criterion 15). However, many of the correlation coefficients have a p -value very close to
483 the significance level.

484 The correlation coefficients and the asterisks on significant correlation in Table 10
485 help to identify which criteria have a high degree of correlation with performance
486 measures, providing valuable information to optimize process and design. For example,
487 assembly time, in-process defects, total defects and human stress response are highly
488 correlated with Criterion 2, indicating that few parts, details, and operations lead to low
489 values of those performance measures. Thus, this information can be used to support
490 decisions towards the design of products or subassemblies with fewer parts, details, and
491 operations in order to decrease assembly time, defects and human stress.

492 In addition, Table 10 shows no significant correlations between the agreement
493 degrees with complexity criteria and both quality control time and offline defects.

494 Although these are performance measures of the production process, they appear to be
495 independent of the operators' perception of the process complexity. This suggests that
496 factors other than the complexity perception of the operators may have more impact on
497 quality control time and offline defects. Further research will be needed to understand
498 the underlying causes of these measures and how they can be improved.

499 The individual perceived complexity values derived according to Eq. (3) by the ME-
500 MCDM method were obtained by considering both importance of the 16 criteria and the
501 agreement degrees with the criteria as per Section 3.4. The obtained values range from
502 "High" to "Rather low", according to the classification provided in Table 5. Accordingly, no
503 operator considered the assembled products to be extremely simple. Fig. 4 illustrates the
504 obtained perceived complexity values and the performance measures for the six product
505 variants. It should be noted that there is a significant amount of variability in the data
506 shown in Fig. 4. This variability is typical of data obtained through self-reported measures
507 such as interviews and questionnaires and should be considered when interpreting the
508 results of this study.

509 OLR is adopted to model the relationship between quality performances and
510 obtained perceived complexity. In Table 11, the logistic regression table for assembly time
511 is provided [56].

512 In summary, the results of the analysis presented in Table 11 suggest that there is
513 a statistically significant association between perceived complexity and assembly time
514 since the p -value associated with the predictor is less than the significance level of 5%,

515 and also since the p -value for the test that all slopes are zero is less than 0.05. The odds
516 ratio of 1.19 indicates that operators are more likely to perceive products as more
517 complex as assembly time increases. The positive coefficient associated with assembly
518 time also confirms this result. In addition, the p -value of goodness-of-fit test is greater
519 than 0.05, not providing evidence that the model is inadequate. Overall, this suggests that
520 changes in assembly time are associated with changes in the probabilities of occurrence
521 of the different levels of perceived complexity, as represented in Fig. 5. The data suggests
522 that as assembly time decreases, the probability of the operator perceiving the assembly
523 as "Moderate" or "Rather low" in complexity increases, while an increase in assembly
524 time leads to an increased probability of the assembly being perceived as "High" or
525 "Rather high". However, the last data point at the maximum assembly time for "Rather
526 high" complexity deviates from this trend; further research is needed to determine the
527 specific cause of this anomaly, as it could be due to operator variability, other factors
528 affecting complexity perception, an outlier data point, or a combination of these factors.

529 Considering the measures of association reported in Table 12, high values of
530 Somers' D, Goodman-Kruskal gamma, and Kendall's tau-a indicate that the model has
531 good predictive ability [56]. These measures are obtained from the number of
532 concordant, discordant and tied pairs, which are calculated by forming all possible pairs
533 of observations (i.e. assembly time values) with the different levels of individual perceived
534 complexity. For the present case study, 459 total pairs were obtained, since 4 operators

535 perceived the assembly complexity as “High”, 13 as “Rather high”, 12 as “Moderate” and
536 7 as “Rather low”.

537 Regarding the other performance measures, the association between perceived
538 complexity and in-process defects, total defects and human stress response resulted to
539 be statistically significant. Tables and figures reporting the results of OLR for such
540 performance measures are given in the Appendix (see Tables A1-A6 and Fig. A1-A3).
541 Conversely, the association with quality control time and offline defects was found to be
542 not statistically significant, which is consistent with the results of previous correlation
543 analyses (see Table 10).

544

545 **5. CONCLUSIONS**

546 In today's market, manufacturers are required to produce high-value-added
547 products that meet customer demands and expectations at a competitive price while also
548 complying with sustainability requirements. One approach to achieving mass
549 customization is the use of flexible assembly systems that utilize collaborative robots, or
550 "cobots," which can offer increased productivity and cost savings. However, the use of
551 human-robot collaboration in assembly tasks can be impacted by the complexity of the
552 assembly.

553 This paper focused on the impact of perceived complexity on the performance
554 measures of human-robot collaboration in assembly tasks. To investigate this issue, the
555 study used a sample of skilled operators to conduct assembly of six variants of electronic

556 boards with different levels of complexity. Performance measures, including assembly
557 times, quality control times, in-process defects, offline product defects, total
558 defectiveness and human stress response during assembly, were collected and analyzed.
559 Furthermore, evaluations on the agreement degrees with 16 complexity criteria and their
560 importance provided by the operators for each product were gathered to assess
561 individual perceived complexity. Statistical analysis was conducted on the collected data
562 to quantify the effects of perceived complexity on the HRC performance measures.

563 The main findings of the present paper are that as complexity perception
564 increases, performance measures tend to worsen, with a negative impact on assembly
565 time, quality control time, in-process defects and human stress response. Furthermore,
566 for the considered electronic product variants, defects that occurred in-process were
567 more frequent compared to defects detected offline during the quality inspection. The
568 study also showed which complexity criteria are statistically significantly associated with
569 the performance measures, thus providing practical recommendations for engineers to
570 consider when designing processes that focus on reducing perceived complexity and
571 improving overall performance measures. It is important to note that, according to these
572 findings, by reducing perceived complexity, not only the human operators will feel more
573 comfortable with the task but also the process will be more efficient and less error-prone,
574 leading to an increase in productivity and a reduction in costs. Finally, the study highlights
575 that there is no significant association between perceived complexity and the quality
576 control time and the offline defects, indicating that these measures of performance of the

577 production process appear to be independent of the perception that operators have of
578 the complexity of the assembly process. This information is important for engineers to
579 consider in designing and implementing HRC systems as it suggests that a reduction in
580 perceived complexity may not necessarily result in improvements in these specific
581 performance measures. Further studies will need to be conducted to fully understand the
582 underlying reasons and identify potential strategies for improving performance measures
583 related to offline quality control in the HRC assembly process.

584 The main innovative aspect of this paper is that it considers multiple performance
585 measures linked to both the production and the quality control process, also taking into
586 account human factors such as the operator's perceived stress. By evaluating these
587 measures, this approach allows for a holistic examination of the relationship between
588 perceived complexity and performance, which can provide valuable insights and
589 recommendations for manufacturers to optimize processes and improve performance.

590 This study has some limitations that should be acknowledged. First, the cobot's
591 involvement in the study was primarily focused on performing pick-and-place operations,
592 which are relatively simple tasks. As a result, the effect of perceived complexity on the
593 cobot's performance and its potential interaction with the perceived complexity of the
594 human operator was not fully explored. Future research should aim to explore different
595 modes of human-robot collaboration, including scenarios where the cobot performs
596 more complex tasks while humans provide support and make key decisions. By
597 considering a broader range of collaboration modes, a more comprehensive

598 understanding of the effects of perceived complexity on HRC performance can be
599 achieved.

600 Secondly, the results are based on a specific set of electronic board variants and
601 the subjective concept of perceived complexity may vary among individual operators.
602 Thus, caution is needed when generalizing the findings to other HRC assembly systems.
603 Nonetheless, the study's holistic approach provides practical recommendations for
604 designers and implementers to optimize system performance by considering the
605 subjective perception of complexity by operators. Further research is needed to validate
606 the findings in different contexts and with larger sample sizes to ensure greater statistical
607 power and generalizability.

608 Additionally, although randomizing the order of the six product variants during
609 assembly helped increase internal validity by minimizing learning effects, the
610 manufacturing sequence was not explicitly controlled. Future research should address
611 this limitation by implementing more systematic control over the manufacturing
612 sequence, and by investigating learning effects and their relationship with randomization
613 in more detail.

614 Finally, based on the derived findings, future work could focus on developing
615 strategies to mitigate the negative effects of perceived complexity on performance
616 measures. One potential approach could be to implement training programs for operators
617 to improve their ability to manage complex product variants. Additionally, improving the

618 design of the assembly process, such as using ergonomic fixtures or improving layout [57],
619 could reduce the complexity of the assembly task and improve performance.

620

621 **NOMENCLATURE**

HRC	Human-Robot Collaboration
UR3e	Cobot produced by Universal Robots™
RG6	Gripper produced by OnRobot™
C_1	Complexity of product components
C_2	Complexity of assembly connections/liaisons
C_3	Complexity of product architecture
C	Product variants' total complexity
EDA	ElectroDermal Activity
SCR	Skin Conductance Response
SCL	Skin Conductance Level
a_w	Amplitude of the w -th SCR peak
N_p	Total number of SCR peaks
a_{min}	Minimum amplitude of SRC peaks
a_{max}	Maximum amplitude of SRC peaks
i	Criteria ($i = 1, \dots, 16$)

j	Products ($j = 1, \dots, 6$)
k	Operators ($k = 1, \dots, 6$)
I_{ijk}	Importance of criterion i , for product j given by operator k
V_{ijk}	Degree of agreement of operator k , for product j on the criterion i
ME-MCDM	Multi Expert-Multi Criteria Decision Making
PC_{jk}	Perceived complexity by the operator k for product j
L_x	x^{th} level of the scale ($x = 1, \dots, 5$)
Neg(L_x)	Negation of L_x
OLR	Ordinal Logistic Regression

622

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- 787
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Figure Caption List

- Fig. 1 Collaborative assembly workstation showing the single-armed cobot UR3e (Universal Robots™) with the RG6 gripper (OnRobot™), and product components assembled by an operator wearing the Empatica E4 wristband
- Fig. 2 Example of assembled electronic boards: (a) Variant A, (b) Variant C, (c) Variant F
- Fig. 3 Example of EDA signal processed with EDA Explorer
- Fig. 4 Scatterplot of individual perceived complexity versus performance measures for the six product variants
- Fig. 5 Probability of occurrence of the levels of individual perceived complexity as a function of Assembly time
- Fig. A1 Probability of occurrence of the levels of individual perceived complexity as a function of In-process defects
- Fig. A2 Probability of occurrence of the levels of individual perceived complexity as a function of Total defects
- Fig. A3 Probability of occurrence of the levels of individual perceived complexity as a function of Human stress response

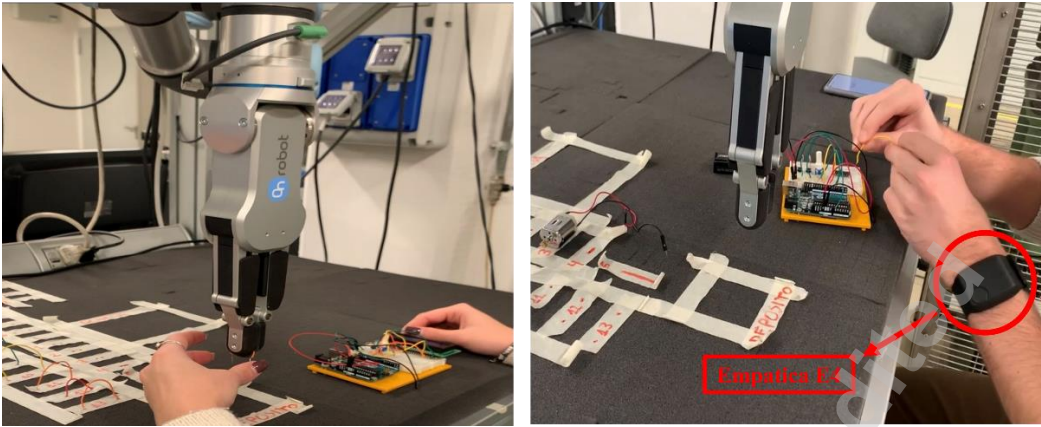
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Table Caption List

Table 1	Cobot and gripper parameters used in the HRC assembly
Table 2	Characteristics of the six assembled electronic boards
Table 3	Complexity criteria of assembly, adapted from Falck et al. [20] to suit the electronic platform assembly
Table 4	Scale levels and semantic meanings for assessing product low-complexity criteria importance (I_{ijk})
Table 5	Scale levels and semantic meanings for assessing agreement degree with low-complexity criteria (V_{ijk})
Table 6	Scale levels and semantic meanings for the assessment of perceived complexity (PC_{jk})
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Table 8	Classification of in-process (In) and offline (Off) defects for the six assembled products
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Table A2	Measures of association between In-process defects and predicted probabilities
Table A3	Logistic regression table for Total defects. Goodness-of-Fit test p -value=0.493
Table A4	Measures of association between Total defects and predicted probabilities
Table A5	Logistic regression table for Human stress response. Goodness-of-Fit test p -value=0.855
Table A6	Measures of association between Human stress response and predicted probabilities



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Fig. 1 Collaborative assembly workstation showing the single-armed cobot UR3e (Universal Robots™) with the RG6 gripper (OnRobot™), and product components assembled by an operator wearing the Empatica E4 wristband

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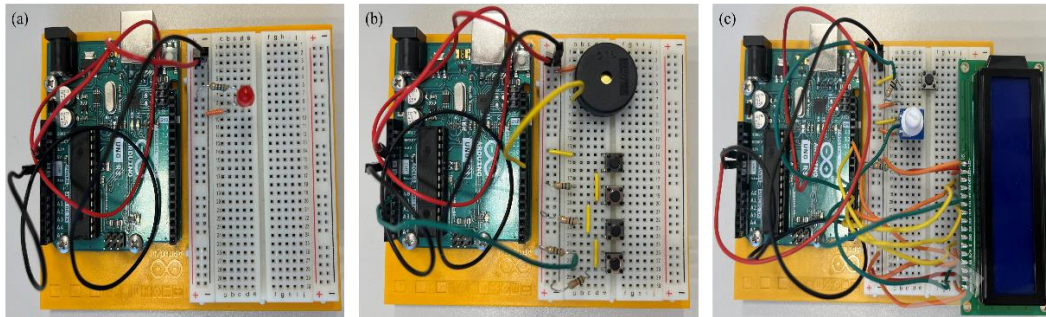
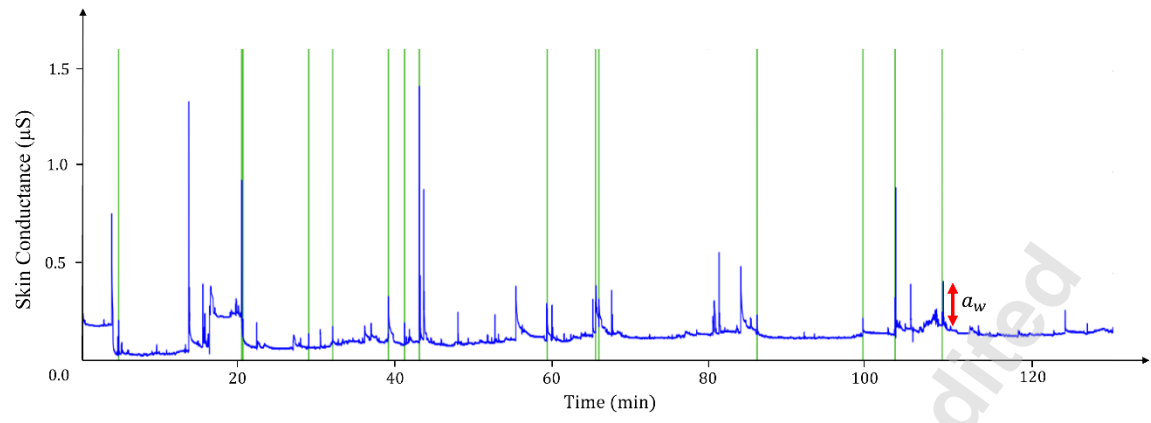


Fig. 2 Example of assembled electronic boards: (a) Variant A, (b) Variant C, (c) Variant F

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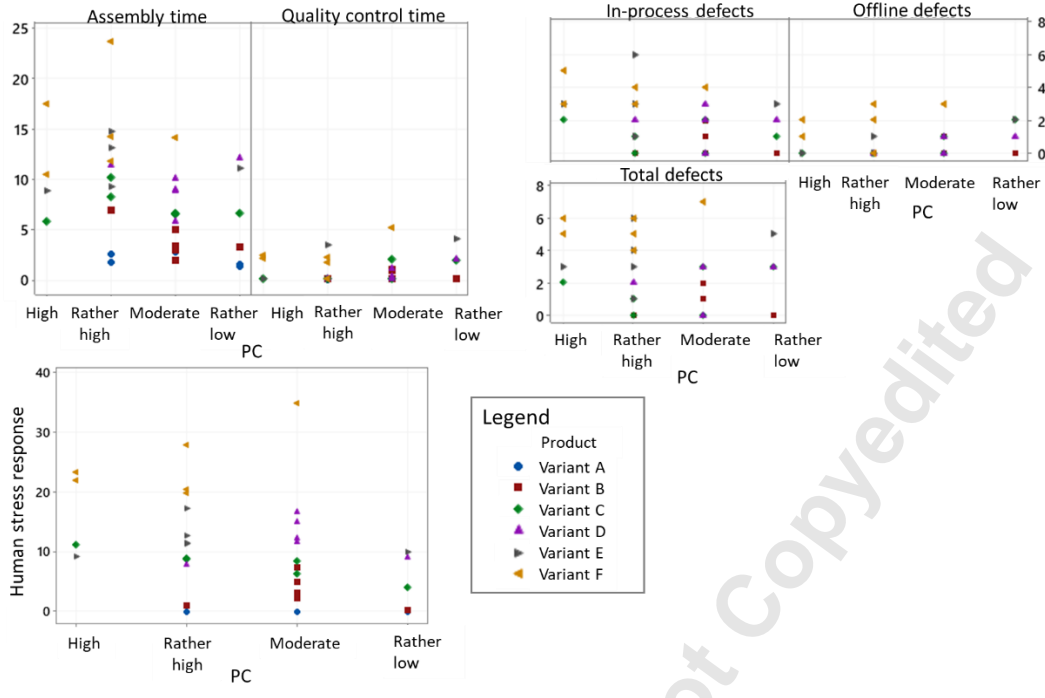
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Fig. 3 Example of EDA signal processed with EDA Explorer

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Fig. 4 Scatterplot of individual perceived complexity versus performance measures for the six product variants

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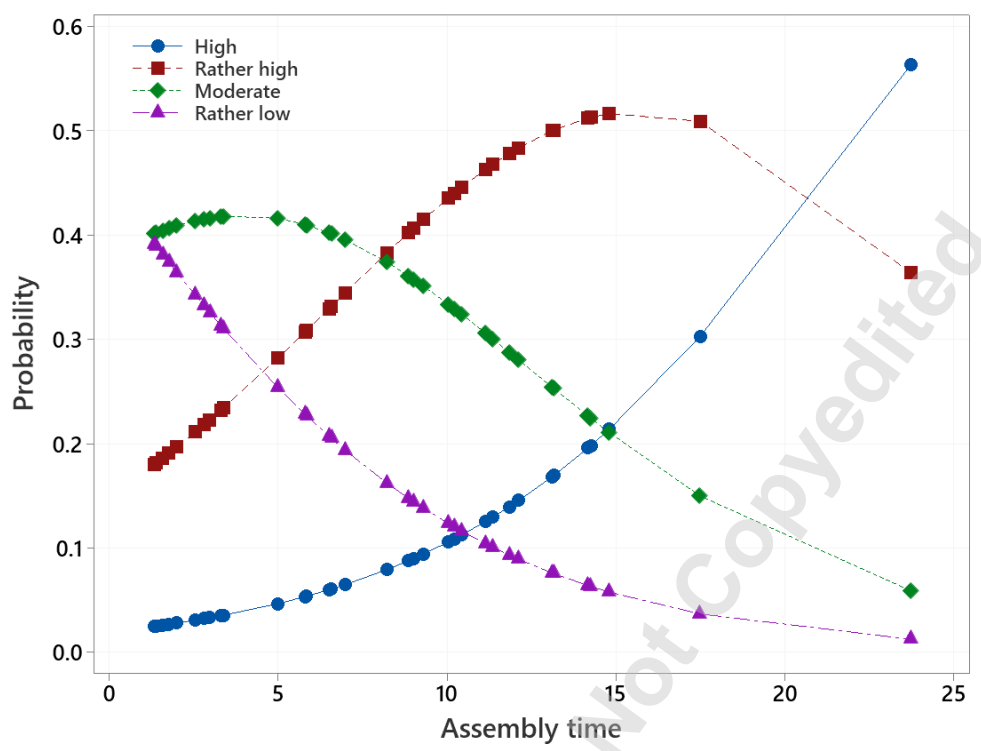
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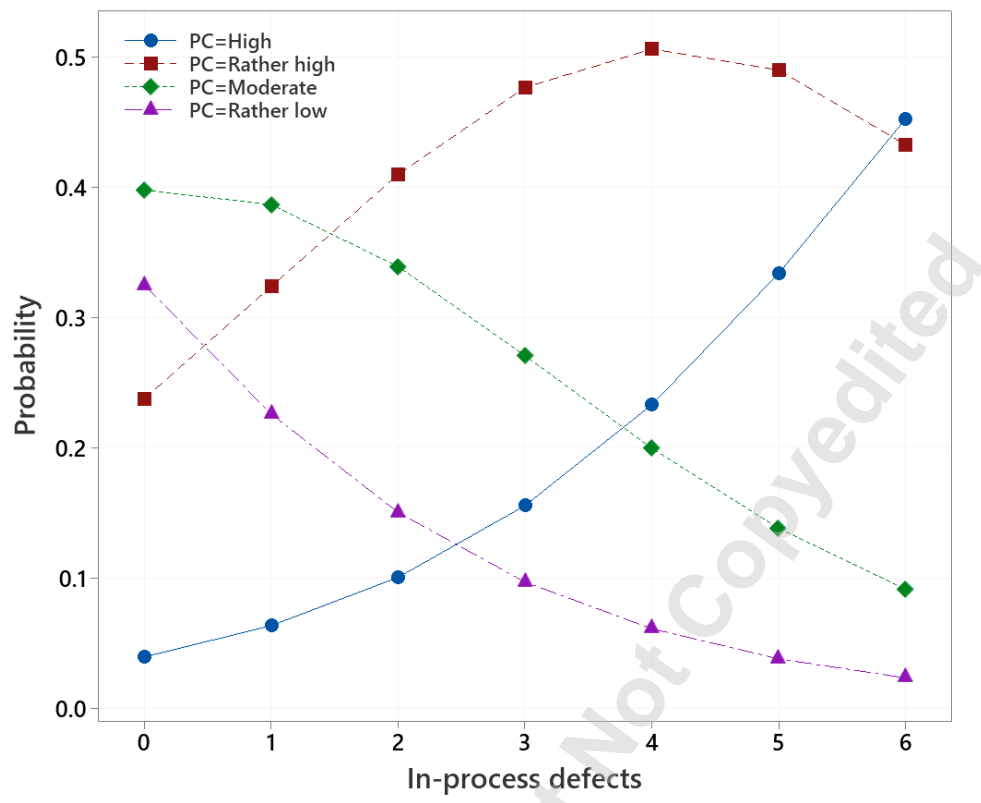
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Fig. 5 Probability of occurrence of the levels of individual perceived complexity as a function of Assembly time

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Fig. A1 Probability of occurrence of the levels of individual perceived complexity as a function of In-process defects

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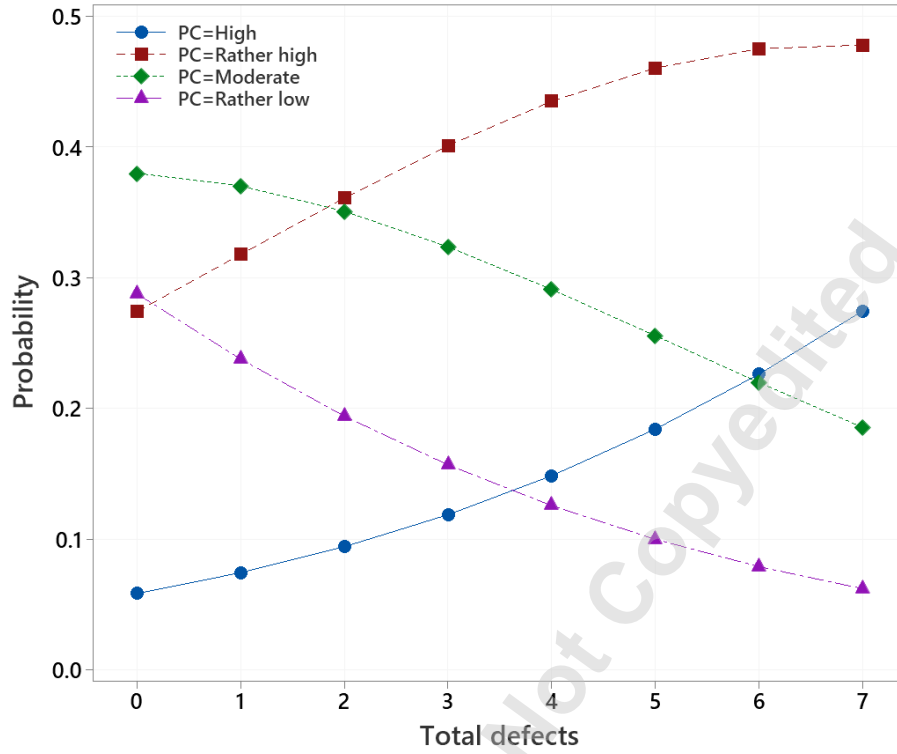
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Fig. A2 Probability of occurrence of the levels of individual perceived complexity as a function of Total defects

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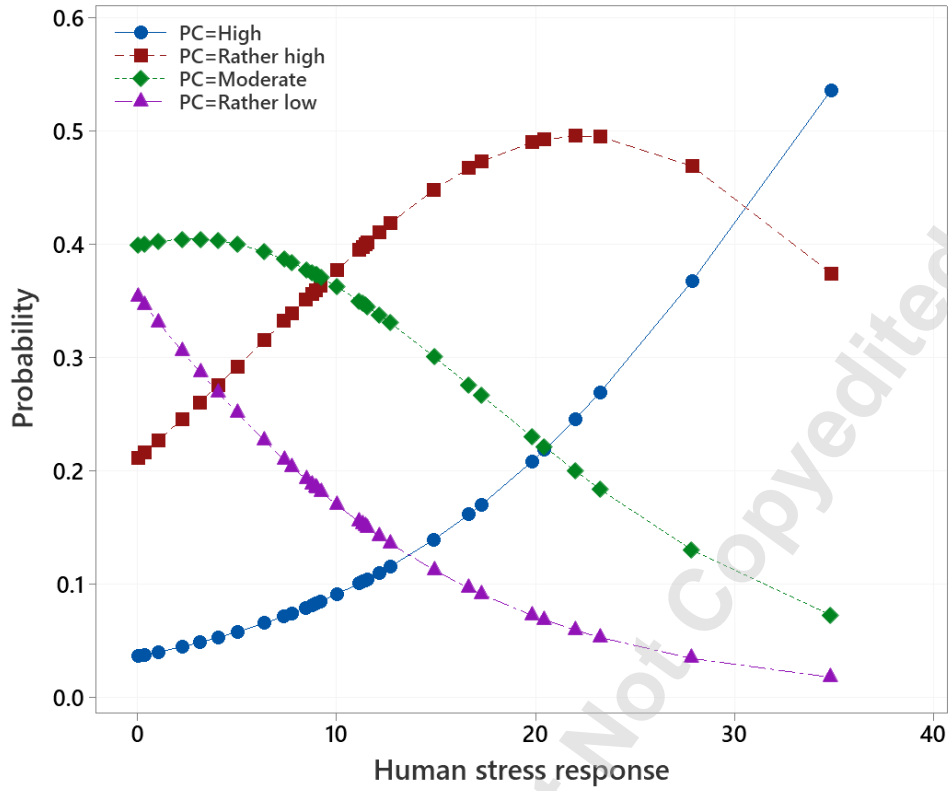
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Fig. A3 Probability of occurrence of the levels of individual perceived complexity as a function of Human stress

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Table 1 Cobot and gripper parameters used in the HRC assembly

	Cobot	Gripper
Joint speed [$^{\circ}/s$]	200	-
Joint acceleration [$^{\circ}/s^2$]	200	-
Linear speed [mm/s]	200	-
Linear acceleration [mm/s 2]	200	-
Distance [mm]	-	16
Force [N]	-	80

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Table 2 Characteristics of the six assembled electronic boards

	Variant A	Variant B	Variant C	Variant D	Variant E	Variant F
Long wires	-	1	2	8	9	13
Short wires	1	3	5	3	6	4
Resistors	1	1	4	6	2	2
Pushbuttons	-	2	4	-	2	1
LED	1	1	-	1	-	-
Phototransistor	-	-	-	3	-	-
Potentiometer	-	-	-	-	1	1
Piezo	-	-	1	-	-	-
LCD	-	-	-	-	-	1
Battery snap	-	-	-	-	1	-
DC Motor	-	-	-	-	1	-
H-bridge	-	-	-	-	1	-
N° of parts	3	8	16	21	23	22
C_1	1.39	2.87	5.10	6.35	7.25	6.72
C_2	2.98	5.44	13.84	14.58	21.79	26.02
C_3	0.94	0.90	0.90	0.93	0.83	0.84
C	4.20	7.77	17.51	19.95	25.35	28.61

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Table 3 Complexity criteria of assembly, adapted from Falck et al. [47] to suit the electronic platform assembly

Criterion i	Assembly low-complexity criterion	Description
1	Few different ways to perform assembly.	Complexity is high if the parts can be assembled/executed correctly in different ways. Otherwise, complexity is low if there is a standardized (accepted) way to perform the task.
2	Few parts/components and details and few operations.	If there are few details to assemble, a small number of operations on the parts, pre-assembly and module creation (integrated assembly), the complexity is low. Otherwise, complexity is high if there are many details and partial operations.
3	Quick and easy operations (no time demanding operations).	Complexity is low if the solutions are easy and quick to assemble (not time-consuming). Otherwise, if there are time-consuming operations, the complexity is high.
4	Clear assembly location of parts/components (immediate understanding of where to place parts within the structure).	If the assembly position of parts and components is clear, the complexity is low, otherwise it is high.
5	Good accessibility to the structure during assembly.	If the accessibility to the structure is good (i.e., sufficient for hands/tools), the complexity is low, otherwise it is high.
6	Fully visible operations (operations do not require orientation of the assembly for better visibility).	If the assembly involves visible operations (i.e., in the field of view when looking directly at the structure), the complexity is low, otherwise it is high.
7	Ergonomically easy handling of the structure.	If there are good ergonomic conditions, the complexity is low, otherwise it is high.
8	Operator-independent operations that do not require much experience to be performed correctly.	If additional training (specialized knowledge) is required beyond the common introductory sessions, then the complexity is high. If the operations do not require additional training, then the complexity is low.
9	Operations do not have to be performed in a certain order.	If the operations can be performed without following a specific order, that is, they are independent of the order of assembly, the complexity is low. Otherwise, complexity is high if the operations must be performed in a certain order/sequence to complete the assembly correctly.
10	Unnecessary intermediate visual checks during assembly to assess the quality and correctness of the structure.	If no intermediate checks are required during assembly to assess the quality and correctness of the structure, the complexity is low. Otherwise, complexity is high if visual checks, i.e., careful subjective assessment of quality, are required.
11	Operations require little precision, accuracy and attention.	If operations do not require precision and accurate assembly is not necessary, the complexity is low.
12	No need for adjustments and corrections (due to errors or inaccuracies) during assembly.	The complexity is low if no adjustments are needed due to errors or inaccuracies. Otherwise, the complexity is high.
13	Easy to assemble and self-position parts/components that can be controlled in three dimensions: X, Y, Z.	If the surrounding environment varies, where the parts and components will be assembled, or if the detail to be placed depends on the surrounding components, then the complexity is high. Examples of when the geometric environment is varied are: several holes must overlap, components not joined, and components moving relative to each other.
14	No detailed instructions are needed and the operator can proceed intuitively.	If no detailed instructions are required, i.e., the operator can proceed intuitively to make the assemblies, the complexity is low. Otherwise, the complexity is high.
15	The structure does not involve soft and flexible materials (i.e., it is form-resistant).	Complexity is low if the components are rigid and compact and do not change size or deform during assembly. If the structure involves assembling soft and flexible materials, complexity is high.
16	There is immediate feedback on correct assembly (e.g., with a clear click and/or compliance with reference points).	Complexity is low if there is immediate feedback of correct assembly, such as through a clear clicking sound and/or adherence to reference points. Otherwise, the complexity is high.

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Table 4 Scale levels and semantic meanings for assessing product low-complexity criteria importance (I_{ijk})

Scale level	Importance
L_1	Negligible
L_2	Preferable
L_3	Important
L_4	Very important
L_5	Indispensable

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Table 5 Scale levels and semantic meanings for assessing agreement degree with low-complexity criteria

(V_{ijk})

Scale level	Importance
L_1	Totally disagree
L_2	Disagree
L_3	Relatively agree
L_4	Agree
L_5	Totally agree

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Table 6 Scale levels and semantic meanings for the assessment of perceived complexity (PC_{jk})

Scale level	Perceived complexity
L_1	High
L_2	Rather high
L_3	Moderate
L_4	Rather low
L_5	Low

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Table 7 Descriptive statistics of performance measures of the six products assembled

Performance measure	Product	Mean	St. dev.	Min	Max
Assembly time [min]	Variant A	1.889	0.627	1.317	2.800
	Variant B	3.928	1.776	1.983	6.967
	Variant C	7.314	1.620	5.833	10.200
	Variant D	9.522	2.238	5.783	12.117
	Variant E	11.719	2.364	8.850	14.800
	Variant F	15.320	4.770	10.430	23.730
Quality control time [min]	Variant A	0.125	0.061	0.000	0.150
	Variant B	0.431	0.436	0.150	1.050
	Variant C	0.769	0.961	0.150	2.083
	Variant D	0.656	0.791	0.150	2.083
	Variant E	1.356	1.875	0.150	4.033
	Variant F	2.308	1.633	0.150	5.183
In-process defects [-]	Variant A	0.000	0.000	0.000	0.000
	Variant B	0.667	0.816	0.000	2.000
	Variant C	1.000	0.894	0.000	2.000
	Variant D	1.833	0.983	0.000	3.000
	Variant E	3.167	1.602	1.000	6.000
	Variant F	3.667	0.816	3.000	5.000
Offline defects [-]	Variant A	0.000	0.000	0.000	0.000
	Variant B	0.333	0.516	0.000	1.000
	Variant C	0.500	0.837	0.000	2.000
	Variant D	0.500	0.548	0.000	1.000
	Variant E	0.500	0.837	0.000	2.000
	Variant F	1.833	1.169	0.000	3.000
Total defects [-]	Variant A	0.000	0.000	0.000	0.000
	Variant B	1.000	0.894	0.000	2.000
	Variant C	1.500	1.378	0.000	3.000
	Variant D	2.333	1.211	0.000	3.000
	Variant E	3.667	1.751	1.000	6.000
	Variant F	5.500	1.049	4.000	7.000
Human stress response [%]	Variant A	0.000	0.000	0.000	0.000
	Variant B	3.180	2.620	0.330	7.350
	Variant C	7.941	2.447	4.021	11.124
	Variant D	12.00	3.390	7.750	16.650
	Variant E	11.99	2.870	9.210	17.310
	Variant F	24.72	5.740	19.840	34.870

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Table 8 Classification of in-process (In) and offline (Off) defects for the six assembled products

Product	Wrong part		Wrong position		Part not taken		Slipped part		Defective part		Incorrectly inserted part	
	In	Off	In	Off	In	Off	In	Off	In	Off	In	Off
Variant A	0	0	0	0	0	0	0	0	0	0	0	0
Variant B	0	0	1	1	3	0	0	0	0	0	0	1
Variant C	0	0	5	2	3	0	0	0	0	0	0	1
Variant D	0	0	4	3	4	0	0	0	0	0	3	0
Variant E	0	0	6	3	11	0	2	0	0	0	0	0
Variant F	0	0	11	11	10	0	0	0	0	0	1	0
Total	0	0	27	20	31	0	2	0	0	0	4	2

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996 Table 9 Correlation matrix with Spearman correlation coefficients between the agreement degree with the 16 complexity criteria for the six products assembled

Criterion	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1																
2	0.660*															
3	0.446*	0.575*														
4	0.616*	0.576*	0.467*													
5	0.600*	0.489*	0.465*	0.637*												
6	0.559*	0.526*	0.379*	0.730*	0.731*											
7	0.192	0.345*	0.594*	0.420*	0.249	0.400*										
8	0.301	0.205	0.477*	0.446*	0.231	0.295	0.718*									
9	0.240	0.074	-0.080	0.201	0.344*	0.343*	-0.154	-0.138								
10	0.501*	0.265	0.168	0.417*	0.491*	0.577*	0.068	0.173	0.673*							
11	0.085	0.286	0.025	0.259	0.318	0.442*	-0.228	-0.433*	0.500*	0.507*						
12	0.516*	0.307	0.252	0.320	0.487*	0.503*	0.093	0.313	0.614*	0.793*	0.277					
13	0.275	0.276	0.496*	0.535*	0.272	0.416*	0.646*	0.633*	0.011	0.325	-0.019	0.212				
14	-0.113	-0.017	0.187	-0.136	0.139	0.072	0.086	-0.163	-0.294	-0.191	0.225	-0.243	0.015			
15	-0.380*	-0.117	0.004	-0.081	-0.034	-0.022	0.139	-0.161	-0.563*	-0.565*	-0.106	-0.619*	-0.072	0.493*		
16	0.682*	0.486*	0.320	0.620*	0.529*	0.518*	0.437*	0.460*	0.139	0.448*	-0.010	0.441*	0.337*	-0.173	-0.211	

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998 Table 10 Spearman correlation coefficients between the agreement degree with the 16 complexity criteria for the six
 999 products assembled and the performance measures

Criterion	Assembly time	Quality control time	In-process defects	Offline defects	Total defects	Human stress response
1	-0.354*	-0.073	-0.353*	-0.107	-0.333*	-0.473*
2	-0.663*	-0.183	-0.663*	-0.129	-0.579*	-0.714*
3	-0.533*	-0.184	-0.571*	-0.150	-0.509*	-0.579*
4	-0.252	-0.108	-0.420*	-0.100	-0.366*	-0.552*
5	-0.358*	-0.067	-0.427*	-0.107	-0.389*	-0.503*
6	-0.304	-0.073	-0.302	-0.088	-0.277	-0.465*
7	-0.222	-0.209	-0.489*	-0.157	-0.451*	-0.415*
8	0.027	-0.167	-0.355*	-0.082	-0.332*	-0.225
9	-0.017	-0.019	0.142	-0.044	0.099	-0.013
10	-0.049	0.087	-0.021	0.067	0.013	-0.064
11	-0.310	0.071	0.002	0.051	0.048	-0.186
12	-0.208	-0.159	-0.160	-0.129	-0.190	-0.238
13	-0.033	-0.130	-0.258	-0.122	-0.238	-0.277
14	-0.352*	-0.045	-0.215	-0.120	-0.196	-0.212
15	-0.106	0.007	-0.252	-0.003	-0.193	-0.153
16	-0.248	-0.164	-0.446*	-0.172	-0.440*	-0.435*

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Table 11 Logistic regression table for Assembly time. Goodness-of-Fit test p -value=0.905

Predictor	Coef.	SE Coef.	p -value	Odds Ratio	95% confidence interval	
					Lower	Upper
Const(1)	-3.87808	0.924815	0.000			
Const(1)	-1.57885	0.659122	0.017			
Const(3)	0.208728	0.620473	0.737			
Assembly time	0.174226	0.0671240	0.009	1.19	1.04	1.36

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Table 12 Measures of association between assembly time and predicted probabilities

Pairs	Number	Percent	Summary Measures	
Concordant	323	70.4	Somers' D	0.42
Discordant	132	28.8	Goodman-Kruskal Gamma	0.42
Ties	4	0.9	Kendall's Tau-a	0.30
Total	459	100.0		0.42

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Table A1 Logistic regression table for In-process defects. Goodness-of-Fit test p -value=0.908

Predictor	Coef.	SE Coef.	p -value	Odds Ratio	95% confidence interval	
					Lower	Upper
Const(L_1)	-3.19119	0.756213	0.000			
Const(L_2)	-0.958176	0.501900	0.056			
Const(L_3)	0.731504	0.503596	0.146			
In-process defects	0.500009	0.210153	0.017	1.65	1.09	2.49

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Table A2 Measures of association between In-process defects and predicted probabilities

Pairs	Number	Percent	Summary Measures	
Concordant	263	57.3	Somers' D	0.35
Discordant	103	22.4	Goodman-Kruskal Gamma	0.44
Ties	93	20.3	Kendall's Tau-a	0.25
Total	459	100.0		

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Table A3 Logistic regression table for Total defects. Goodness-of-Fit test p -value=0.493

Predictor	Coef.	SE Coef.	p -value	Odds Ratio	95% confidence interval	
					Lower	Upper
Const(1)	-2.78027	0.700359	0.000			
Const(1)	-0.696589	0.490750	0.156			
Const(3)	0.907236	0.511736	0.076			
Total defects	0.258386	0.150963	0.087	1.29	0.96	1.74

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Table A4 Measures of association between Total defects and predicted probabilities

Pairs	Number	Percent	Summary Measures	
Concordant	249	54.2	Somers' D	0.25
Discordant	135	29.4	Goodman-Kruskal Gamma	0.30
Ties	75	16.3	Kendall's Tau-a	0.18
Total	459	100.0		

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Table A5 Logistic regression table for Human stress response. Goodness-of-Fit test p -value=0.855

Predictor	Coef.	SE Coef.	p -value	Odds Ratio	95% confidence interval	
					Lower	Upper
Const(1)	-3.28926	0.786844	0.000			
Const(1)	-1.11447	0.527668	0.035			
Const(3)	0.602590	0.522103	0.248			
Human stress response	0.0984811	0.0400084	0.014	1.10	1.02	1.19

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Table A6 Measures of association between Human stress response and predicted probabilities

Pairs	Number	Percent	Summary Measures	
Concordant	318	69.3	Somers' D	0.41
Discordant	129	28.1	Goodman-Kruskal Gamma	0.42
Ties	12	2.6	Kendall's Tau-a	0.30
Total	459	100.0		

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