

1 A matter of consequences: Understanding the effects of
2 robot errors on people's trust in HRI *

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9 **Abstract**

10 On reviewing the literature regarding acceptance and trust in human-robot interaction
11 (HRI), there are a number of open questions that needed to be addressed in order to
12 establish effective collaborations between humans and robots in real-world applications.
13 In particular, we identified four principal open areas that should be investigated to create
14 guidelines for the successful deployment of robots in the wild. These areas are focused on:
15 1) the robot's abilities and limitations; in particular when it makes errors with different
16 severity of consequences, 2) individual differences, 3) the dynamics of human-robot trust,
17 and 4) the interaction between humans and robots over time. In this paper, we present
18 two very similar studies, one with a virtual robot with human-like abilities, and one with a
19 Care-O-bot 4 robot. In the first study, we create an immersive narrative using an interactive
20 storyboard to collect responses of 154 participants. In the second study, 6 participants had
21 repeated interactions over three weeks with a physical robot. We summarise and discuss
22 the findings of our investigations of the effects of robots' errors on people's trust in robots
23 for designing mechanisms that allow robots to recover from a breach of trust. In particular,
24 we observed that robots' errors had greater impact on people's trust in the robot when
25 the errors were made at the beginning of the interaction and had severe consequences.

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26 Our results also provided insights on how these errors vary according to the individuals'
27 personalities, expectations and previous experiences.

28 **Keywords**— Trust, social robotics, previous experiences, antecedents of trust, robots' er-
29 rors, faulty robots

1 Introduction

Everyday we take decisions that may potentially cause minor or severe consequences in our lives. For example, we choose what to wear, what to eat, which path to take on our journey home and so on. Our choices are the results of several factors, including individual differences, the resulting utility of the decision-task and past experiences (Kudryavtsev and Pavlodsky, 2012). In particular, the increasing presence of humanoid and human-friendly robots in daily human activities is opening two main challenges for consideration: people will need to be able to accept the presence of the robot in their living space, and they will also need to be able to trust that their robotic companion will take care of their well-being. It is important that humans trust their robot companion to not create a hazardous situation, such as starting a fire when trying to make a cup of tea, or creating an unsafe situation, such as leaving the door open unattended, or opening the door to strangers and potential thieves. Robotic companions should follow appropriate robot etiquette as proposed by Koay et al. (2013) and avoid cluttering the home environment to ensure that people can freely move without additional risk such as tripping or stumbling into the robot and get injured.

Current literature generally agrees that trust is a fundamental factor in establishing and maintaining effective relationships with assistive and service robots Ross (2008). Trust is being investigated in several disciplines, and there are different definitions of trust that link it to people’s perception of reliability in the robot’s functionalities (Mayer et al., 1995), to their willingness to take the risk of unbalanced positive outcomes and negative consequences (Deutsch, 1958), and to the attitude that the robot will help them achieve their goals in an uncertain and vulnerable situation (Lee and See, 2004). Trust can be also related to affective connection between people and robots (McAllister, 1995; Lewis and Weigert, 1985).

Nevertheless, robots placed in human-oriented dynamic environments, such as private homes, are likely to exhibit occasional behaviours perceived as unexpected or failures by people, or actual errors. For example, robots could be affected by sensor, mechanical, programming or functional malfunctions. A robot’s decision-making abilities are also limited, so while trying to “do the right thing”, it might mistakenly take the wrong decision.

In this context, we believed that a deeper exploration of the dynamics of trust between humans and robots was needed, with a particular attention to people’s perception of robot errors according to their consequences. In this paper, we discuss and summarise the research we have conducted in previous years Rossi et al. (2017b, 2018a, 2017a), and draw conclusions of the findings to help roboticists to design robots that can adapt their behaviours according

63 to the consequences that their actions have on people’s lives. Our paper allows moving a step
64 closer towards the development and deployment of companion robots that are able to engage
65 and cooperate with people in effective long-term interactions.

66 In particular, we show that the perception and the effects of robot errors on people’s trust
67 is affected by several factors such as individuals’ differences, robots’ limitations, people’s social
68 expectations and expectations related to a robot’s capabilities, and the nature of specific in-
69 teractions between people and robots (i.e. type and length). In order to identify these factors
70 and create mitigation in case of a lack of trust, this research has been carried out considering
71 the following research challenges.

72 Firstly, we investigated how people’s trust in a robot changes due to robot erroneous be-
73 haviours (see Section 4). In particular, considering that errors can have different (severity of)
74 consequences, and therefore, they might affect people’s trust in a robot in different ways.

75 Secondly, we identified which antecedents of trust affect people’s trust in robots (see Section
76 5). In particular, we investigated the effects of individuals’ differences and their trust in a robot
77 that sometimes makes errors.

78 Finally, we examined the effects of a robot’s errors on people’s trust in the robot over
79 time (see Section 6). In particular, we investigated whether people’s overall impressions and
80 judgements are principally formed at the beginning or the end of the interaction with a robot.

81 In general terms, even if there are still many open challenges for social robots when directly
82 or indirectly interacting with people Rossi et al. (2020b), the research presented in this work
83 provides an essential contribution towards the design of coping mechanisms for robots to recover
84 from a breakdown in trust. The guidelines provided in this paper contribute to the effective
85 deployment of companion and service robots in future domestic and working environments.

86 The remainder of this article is structured as follows: Section 2 discusses related background
87 that motivated our research questions, Sections 4, 5 and 6 present the results relevant to our
88 research questions. Section 7 analyses the limitations of our studies, and Section 8 summarises
89 the novel results and provides future research directions to investigate trust in human-robot
90 interaction (HRI).

91 **2 Background & Related Work**

92 Trust is a fundamental factor that plays a significant role in interpersonal and economic inter-
93 actions, and has been studied in many disciplines.

94 Among the existing definitions of trust in Human-Human Interaction (HHI), Human-Computer

95 Interaction (HCI) and Human-Robot Interaction, we were particularly interested in those that
96 could help us evaluate people’s trust when the results of a goal (e.g. a task, a person’s well-
97 being) are not clear and guaranteed, and are dependent on the robot’s capabilities involved in
98 the interaction.

99 A popular definition of trust, proposed by Deutsch (1958), is strongly connected to the risk
100 that people are willing to take when believing that a positive outcome is more likely to obtain
101 than a potential loss.

102 However, Colquitt et al. (2007) and Mayer et al. (1995) claimed that trust is based on
103 people’s perception of the agent’s ability, benevolence and integrity.

104 For the studies presented in this work, we adopted Lee’s definition of trust as “[...] the
105 attitude that an agent will help achieve an individual’s goals in a situation characterized by
106 uncertainty and vulnerability” (Lee and See, 2004, p. 51). This definition encapsulates the
107 key factors that can affect human-robot trust that are related to the person (e.g. demograph-
108 ics, personality traits, prior experiences, situations awareness, self-confidence), the robot (e.g.
109 robot’s reliability, transparency) and the context of the interaction (e.g. communication modes
110 and shared mental models between people and robots).

111 **2.1 Robots’ errors in HRI**

112 A task that requires human-robot team effort will only be achievable if people believe that the
113 robots share the same goal and will prioritise people’s safety. In this situation, the level of trust
114 people have in the robot is directly associated with their perception of the robot’s reliability
115 (Ross, 2008). However, despite people investing a substantial effort in building and nurturing
116 trust in interpersonal relationships, trust can be broken. Similarly, like many other types of
117 technologies, robots are subject to hardware and software malfunctions and failures. People’s
118 perception of a robot’s reliability depends not only on the ability of a robot to complete a task,
119 but also by its behaviours to reach a goal.

120 Studies by Short et al. (2010), Lemaignan et al. (2015) and Honig and Oron-Gilad (2018)
121 have shown that people might consider unexpected and incoherent behaviours, perceived fail-
122 ures, and actual failures as robot errors. According to Walters et al. (2011), people’s expecta-
123 tions of a robot’s functionalities and performances can affect their perception of robot erroneous
124 behaviours. For example, a robot that navigates too slowly might be considered having faulty
125 behaviours. Honig and Oron-Gilad (2018) proposed a taxonomy for classifying possible types
126 of robotic failures. They identified two principal categories of errors: technical and interaction
127 failures. Technical failures are considered errors produced by hardware or software problems,

128 which can depend on an erroneous design, communication or processing. In contrast, interac-
129 tion failures are related to social norm violations, organisational and mental-model based faults
130 in the interaction within a particular context between people and robots. However, Robinette
131 et al. (2015) has shown that the effects of robot errors on people’s trust can be mitigated if the
132 robot provides apologies, promises and additional reasons for such behaviours. In their study,
133 the robot was able to regain participants’ trust when it apologised by assuring that it would
134 not repeat the error soon after it had made the error. Aroyo et al. (2021) observed that par-
135 ticipants’ trust in an iCub robot¹ was not negatively affected by the robot’s mechanical faults.
136 In their study, the robot continued in its tasks by autonomously recovering from its errors, and
137 it used a certain level of transparency as a mitigating factor for the errors, which, contrary
138 to expectation, resulted in a decrease of participants’ perception of the quality of interaction.
139 Nonetheless, it is not clear how effective these strategies might be if it was a repeated error or
140 an error with severe consequences.

141 Reviewing the literature regarding trust in HRI it is clear that none of the studies considered
142 the magnitude of robot errors, nor the possibility for a robot to initiate a trust recovery process
143 to earn back people’s trust, similarly to that of a human-human trust recovery in romantic,
144 working, family or other type of relationships, (Desai et al., 2013; Muir and Moray, 1996;
145 Robinette et al., 2016; Salem et al., 2015). In particular, several research questions have been
146 raised that need to be investigated in order to develop robot behaviours and mechanisms aimed
147 to act in case of an error, and to regain a loss of trust. The first question to address is **RQ-1 -**
148 **How do various type of robot errors affect human’s trust in a robot?.** The aims are
149 to identify how the magnitude and the timing in which robots’ errors happen, affect people’s
150 trust in a robot.

151 In particular, we believed that people’s trust can be affected differently depending on the
152 type of errors (i.e. reoccurring vs new), frequency of errors, timing of an error and the magnitude
153 of the error consequences (severe or limited).

154 **2.2 Antecedents of Trust**

155 Individual differences have been a key subject area in psychology research for several decades
156 because they can help distinguish one person from another (Williamson, 2018), and thus can
157 be used to personalise interactions, improve relationships and improve services to people while
158 acknowledging their individuality (Rossi and Rossi, 2021).

159 People’s individual differences are also important for understanding their acceptance and

¹iCub robot <https://icub.iit.it/>

160 perception of trust in robots. Recent literature regarding the role of trust in HRI indicates
161 that people’s antecedents have a dynamic influence on their trust in robots and automated sys-
162 tems. It is important, therefore, to investigate if individual differences play any role in people’s
163 perception of trust and acceptance of robots. According to Williamson (2018, p. 1), ”Indi-
164 vidual differences are the more-or-less enduring psychological characteristics that distinguish
165 one person from another and thus help to define each person’s individuality”. Among those
166 characteristics, intelligence, personality traits, skills and aptitudes are recognised as the most
167 relevant among the differences.

168 According to Hancock et al. (2011b) people’s individual characteristics, including propensity
169 to trust and personality traits such as agreeableness and extroversion, can affect the success
170 of their teamwork with robots (Rotter, 1967; Elson et al., 2018; Barrick et al., 1998). For
171 example, people with a more extroverted personality are more comfortable having robots within
172 their personal spaces (Robert, 2018; Haring et al., 2013; Gockley and Matariundefined, 2006).
173 Similarly, people with high levels of openness to experience are more likely to accept assistive
174 robots (Daniela et al., 2017), and are open to assistive robots entering their personal space for
175 interacting with them (Gockley and Matariundefined, 2006; Takayama and Pantofaru, 2009).

176 Some studies found that people’s propensity to trust others may affect their trust in robots
177 (Adams et al., 2003; Lee and See, 2004). Costa et al. (2001) showed that the level of trust of
178 the participants towards the robot depended on their disposition for trusting others.

179 Another personality-based factor is the individual’s self-confidence and esteem which has
180 been associated with their degree of trust in a robot in HRI (Freedy et al., 2007).

181 Moreover, a person who is new to robotics technologies may be influenced by science fiction
182 narratives which often present robots that have human-like abilities and intelligence Hancock
183 et al. (2011a), and may tend to over-trust the robot and its capabilities Rossi et al. (2020b).

184 Honig and Oron-Gilad (2018) indicated that humans may adapt to robots if they are able to
185 identify and predict their behaviours during an interaction. In particular, they indicated that
186 people’s comprehension of robot errors is affected by their background (Tannenbaum et al.,
187 2006), personality (Sadeghi et al., 2012), expectations (Haberlandt, 1982), and experience (Ma-
188 cias, 2003). Another factor is people’s situational awareness of the interaction environment
189 (including robots, locations and other human agents), their awareness of the robot’s ability for
190 understanding and following human commands, their awareness of the robot’s plans and goals,
191 and their awareness of the state and stages of the cooperating task (Drury et al., 2003).

192 In Atkinson et al. (2014), we observed that people’s trust in robots was positively corre-
193 lated with increasing shared awareness of the participants involved, their activities and context

194 between people and robots. This greater awareness consequentially increases the success of
195 human-robot interaction. Tseng et al. (2013) developed a Decision Network model based on a
196 robot’s awareness of the users that enabled it to adapt and provide different responses to meet
197 the user’s expectations.

198 Our previous investigations (Rossi et al., 2018b; Rossi et al., 2019) showed that people’s
199 awareness of the robots’ functionalities, including its limitations, affects their perceptions of the
200 robot, but did not affect their trust in robots in the same. We conducted two similar studies,
201 one in a primary and the other in a secondary school, where pupils were familiarised respectively
202 with Kaspar² and Pepper³ robots. In both studies, we observed pupils interactions with the
203 robots in order to understand how a higher awareness of robots influences people’s perception
204 and trust in them. We also found that a higher awareness led the students to trust that Pepper
205 is able to handle critical situations and cognitive tasks. Contrary to our expectations, there
206 was no statistically significant evidence to corroborate the same hypothesis regarding those who
207 interacted with Kaspar. However, the differences of the two studies, in terms of participants’
208 age, sample size and exposure time, might be factors affecting the findings.

209 As can be seen from literature, antecedents of trust, including individuals’ differences in
210 terms of personality, background, age, gender, past experiences and awareness of the robots,
211 may affect people’s perception of robots. However, it is not entirely clear how they influence
212 humans’ trust in robots, in particular in a situation of uncertainty. Moreover, previous research
213 was not focused on robots’ erroneous behaviours with different levels of consequences. There-
214 fore, our research has been guided by the research question **RQ-2 - How does people’s trust**
215 **in a robot change according to their personal differences?**.

216 **2.3 Trust in long-term human-robot interactions**

217 Numerous studies investigating human-human interaction (HHI) showed that people’s mental
218 models of other humans and robots are often formed immediately after the first interaction
219 (Ambady et al., 2000; Wood, 2014). However, their mental models, and consequently their
220 attitude, might change after longer and repeated interactions (Zajonc, 1968; Lee, 2001). Several
221 studies (Reber et al., 1998; HT et al., 2011) highlighted that relationships between a robot and
222 people become stronger with increasing familiarity with the robot. However, people’s interests
223 in technologies such as robots are often linked to a novelty effect which can wear off before they
224 can become familiar or form any meaningful relationship with their robot. Paetzel et al. (2020)

²Kaspar robot <https://www.herts.ac.uk/kaspar/the-social-robot>

³Pepper robot <https://www.unitedrobotics.group/get-your-robot-ald/>

225 showed that people’s first perception of a robot was more negatively affected by a robot with
226 mechanical features than one with anthropomorphic features. They also found that participants
227 perceived the robots as a threat and unease, and this negative feeling persisted over time, even
228 if it fluctuated until the last interactive session.

229 In human-human interaction, Haselhuhn et al. (2010) showed that people in longer relation-
230 ship would recover from a breach of trust more easily than people that are in new relationships.

231 van Maris et al. (2017) investigated the effects of robots’ embodiments (a Softbank Robotics
232 NAO robot vs. a virtual representation on a NAO on a tablet) on people’s perception of trust
233 over a period of six weeks. Contrary to previous works (Rae et al., 2013; Seo et al., 2015), they
234 did not find any correlation between robot embodiment and people’s trust in the agent.

235 de Visser et al. (2020) investigated whether a relationship based on the idea of balancing
236 costs and risks, sharing the workload, and a formed perception of themselves and the robot, had
237 higher probability of success in long-term trust relationships. They proposed techniques that
238 could help to reduce the effects of people’s tendency to over-trust or mistrust of robots. Their
239 model is based on the assumption that people aim to have a successful relationship. However,
240 this may not always be true especially for people who have experienced, or are suffering, from
241 mistrust.

242 Lee et al. (2012) investigated how the personalisation of a social robot affected people’s inter-
243 actions over a four-month field experiment. The study showed that allowing the personalisation
244 of a robot positively affected the way people perceived the robot and the overall interaction.

245 In understanding the dynamics of trust between humans and robots, it is important to
246 consider how the trust could change over time, in particular, when the effects of novelty fade
247 over time, and most importantly, in the case of a breach of trust. Therefore, our research has
248 been carried out to answer the research question **RQ-3 - Does people’s trust on a robot
249 change over time if the initial conditions (positive or negative) of trust in the robot
250 change?**.

251 3 Methodology

252 Assessing people’s trust in robots requires that participants are willing to take risks that might
253 not result in a positive outcome for them Deutsch (1958). However, causing distress or endan-
254 geringing participants’ welfare raises ethical and legal issues Salem et al. (2015). Moreover, the
255 current state of the robotic technologies does not allow for fully functional robots that are able
256 to interact autonomously and naturally with the participants. For example, a robot should

257 be able to manipulate objects in real-time, navigate autonomously in cluttered environments
258 and be able to converse with users in noisy environments. To overcome these issues, we first
259 explored people’ interactions with a virtual robot to test their trust when a robot can meet
260 their expectations Rossi et al. (2020a). Then, we conducted a study with a Care-O-bot 4 robot
261 that has limited functionalities in live interactions.

262 In these studies, we aimed to investigate whether people perceive errors according to their
263 magnitude of consequences, and how these errors affect their trust in the robot. In our inves-
264 tigation, we chose to focus on the criticality and severity of consequences of the errors made
265 while performing the selected tasks. The tasks are used just to provide the context to help par-
266 ticipants to suspend their disbelief and provide appropriate responses. In this way, we hoped
267 to collect realistic responses from participants with regard to the consequences of errors the
268 robot made while performing its tasks. We believed that the task itself may not be enough to
269 capture the impact of a robot’s erroneous behaviour on the participant’s trust. For example, a
270 robot’s erroneous behaviour resulting in breaking a vase while cleaning it will impact the user’s
271 trust differently (i.e. different severity of consequences of the error) depending on the value (i.e.
272 sentimental, valuable, etc.) of the vase. For these studies, we selected four scenarios each from
273 flawless behaviour, small or trivial error, and severe or big error categories to investigate peo-
274 ple’s changes of trust in a robot that occasionally made small, or severe errors or a combination
275 of both Rossi et al. (2017b).

276 We used an interactive storyboard to study people’s choices for trusting the robot, and
277 to understand how their choices are influenced by their demographics, personalities traits,
278 disposition of trust and previous experiences with other robots.

279 Then, we wanted to integrate our studies and observations to investigate whether humans’
280 trust of a robot changes over time if the initial conditions have changed (i.e. if the robot shows
281 erroneous behaviours). The study aimed to investigate if people would trust a robot that broke
282 their trust in an initial or later stage of the interaction.

283 Both studies were approved by the University of Hertfordshire Health, Science, Engineering
284 and Technology Ethics Committee with Delegated Authority.

285 **3.1 Study 1: Interactive storyboard**

286 This study was conducted with an immersive narrative approach through a crowd sourcing
287 service. This approach allowed us overcome the difficult challenges of investigating people’s
288 trust in realistic life-threatening scenarios without endangering and distressing participants,
289 and designing a study where people interact with a robot that appears fully functional and

290 versatile to execute realistic tasks.

291 To the best of our knowledge, using interactive storyboards, as described in this article and
292 some of our previous publications Rossi et al. (2017a, 2018a) have not been used in similar large
293 scale studies to investigate HRI.

294 3.1.1 The robot

295 The robot used for this study is a 3D, fictional humanoid robot, called Jace, that was created
296 with the ability to perform human-like activities, such as performing advanced manipulation
297 tasks, moving autonomously, detecting objects and obstacles at run time, talking and per-
298 forming speech recognition. This fully-functional and versatile robot has been designed as a
299 humanoid robot with simple features to contain the participants' expectations of its functional-
300 ities. Jace has a squared head with eyes, a mouth and something that resembles ears as shown
301 in Figure 1. It can perform grasping activities using human-like arms and hands. Jace's body
302 is a "box" equipped with a screen, used to show text and images when it is required by the
303 specific scenario. The robot has wheels.

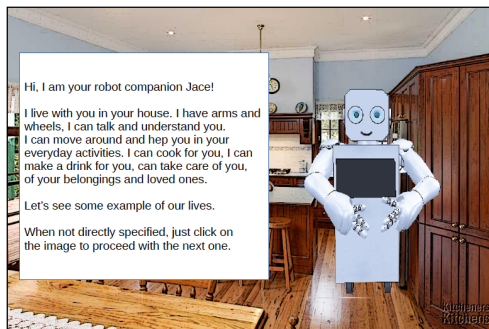


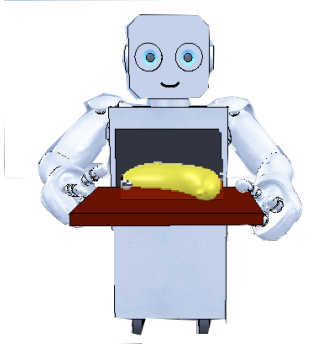
Figure 1: The robot Jace used for the interactions with the participants in the storyboard.

304 3.1.2 Motion picture generation

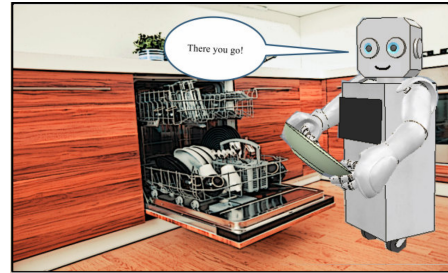
305 The robot and each scenario used for this study have been designed with a combination of 3D
306 objects and images to make it more realistic. Figure 2 shows an example of a scenario.

307 3.1.3 Experimental design

308 The study was organised as a between-participant experimental design. In the study, par-
309 ticipants interacted with a virtual robot in planned scenarios using an interactive storyboard
310 developed and deployed on an online website. The participants were asked to imagine that the



(a) *This motion picture has been composed by the robot holding a 3D tray and a 3D banana.*



(b) *This motion picture has been created with the robot on a picture of a kitchen and dishwasher as background.*

Figure 2: Two examples of motion pictures created using a combination of 3D objects and images.

311 environment in the scenario was their home, and they lived with their robot companion named
312 Jace.

313 Depending on the experimental conditions participants were assigned to, they were either
314 presented with scenarios where the robot executes its tasks flawlessly or with a mixture of
315 flawless and erroneous behaviours. Note, the errors made by the robot caused either small or
316 big consequences.

317 The participants were assigned to one of five different conditions, in each the robot performed
318 10 different tasks. Condition **C1** is the control condition where the robot performed all its tasks
319 flawlessly. For all the experimental conditions (i.e. C2, C3, C4, C5), the robot performed the
320 first 3 tasks with errors, followed by 4 error free tasks and ended with 3 tasks with errors.
321 Specifically, for condition **C2** the tasks were done by the robot with three severe errors at
322 the beginning and at the end of the interaction; in condition **C3** the scenario included tasks
323 with three severe errors at the beginning and three trivial errors at end of the interaction; in
324 condition **C4** the robot completed the tasks with three trivial errors at the beginning and three
325 severe errors at the end of the interaction; and in condition **C5** the scenario included three
326 trivial errors at the beginning and at the end of the interaction.

327 We chose the robot's errors from a previous study (Rossi et al., 2017b), in which a differ-
328 ent pool of participants rated domestic scenarios in which a robot made errors based on the
329 perceived magnitude of consequences of the errors. The selected error scenarios with flawless
330 behaviours, and small and big consequences are shown in Table 1.

331 At the end of each condition, we tested participants' trust in the robot by presenting them

Table 1: Robot errors with small and big consequences.

Big errors tasks	
Scenario	Description
Charging the phone	The user’s phone needs to be charged. The robot charged the phone in a toaster instead of the electric socket.
Leak of information	The user tells private information about themselves to the robot, and the robot reveals it to a visitor.
Hamster	the robot tells the user that it left their pet hamster outside the house in very cold weather.
Dishwashing tablet	The robot brings the user a dishwashing tablet instead of paracetamol.
Small errors tasks	
Scenario	Description
Puzzle	The robot and the user are completing a puzzle. The robot picks the wrong piece.
Trash bin	After a meal with friends, the robot puts the remaining food into the washing machine instead of the bin.
TV show	The robot asks the user which is their favourite show. The robot plays it for them but it changes channel.
Drink	The robot prepares a drink for the user. Then, it leaves the drink far away from the user’s grasp.
Flawless tasks	
Scenario	Description
Music	the robot asks the user what kind of music they would like listening, and then it plays it for them.
Feed the pet	the robot reminds the user to feed their pet dog. It asks if they want to feed it food in a can or fresh food. Then, the robot feeds the dog.
Appointment	the robot reminds the user about an appointment they have with the doctor, then it asks them if they want to call the doctor immediately or set a reminder for later.
News	The robot asks the user if they would like to watch the news on its tablet or TV. Then, it plays for them.

332 with an emergency scenario, i.e. a fire in the kitchen. Participants’ level of trust was assessed
 333 by asking them to choose one of the following options: 1) “I trust Jace to deal with it.”; 2) “I
 334 do not trust Jace. I will deal with it.”; 3) “I want to extinguish it with Jace.”; 4) “We will both
 335 leave and call the fire brigade.”.

336 We collected participants’ perceptions of the robot and the interaction through question-
 337 naires at the beginning and the end of the interaction. Objective measures were also collected
 338 to assess participants’ trust in the robot (i.e. observing participants’ choices made during the
 339 emergency scenario). Further details on the questionnaires used and the results from this study
 340 are reported in Sections 4 and 5.

341 3.1.4 Participants

342 We recruited participants using the crowd-sourcing web-service Amazon Mechanical Turk⁴. We
 343 recruited 200 participants (115 men, 85 women), with an age between 18 and 65 years old [avg.
 344 age 33.56, std. dev. 9.67]. Their country of residence was principally from 60% USA and 34%
 345 India.

⁴Amazon Mechanical Turk <https://www.mturk.com>

346 **3.2 Study 2: A repeated-interactions study**

347 The second study was conducted in “Robot House” that is a fully functional and smart house
348 belonging to the University of Hertfordshire (UK). We observed the interactions of six partici-
349 pants (5 female, 1 male), three for each of the two conditions, with an age between 24 and 47
350 years old (avg. 29.67, st. dev. 8.76). Participants were of different nationalities. Results of
351 this study are discussed in Section 6.

352 This study was organised as a between-participant experimental design. They participated
353 in repeated interactions over three weeks, twice per week, which gives a total of six interactions
354 per participant. The participants took part in one of two following conditions: 1) the robot
355 made big errors at the beginning of the interaction (i.e. on the first day of interaction); 2) the
356 robot made big errors at the end of the interaction (i.e. on the last day of interaction). The
357 days with errors were interspersed with flawless behaviours.

358 As for the first study, we asked participants to imagine living in the house with the robot
359 as their home companion.

360 Participants were welcomed by the experimenter every day, asked to keep clear the space
361 around the robot in case it was moving its arms or navigating in the room, and then they
362 were left alone with the robot in the experimental room while the experimenter monitored
363 the interaction from a side hidden room. In this study, participants interacted with a Mojin
364 Robotics Care-O-bot 4⁵.

365 Participants were engaged with the robot in different activities, which were designed to cover
366 a range of possible tasks to be used with home companion robots selected from the previous
367 study (Rossi et al., 2017b). The tasks and their order are shown in Figure 3.

368 At the end of each condition, we collected participants’ trust in the robot by presenting
369 them with an emergency fire in the garage. In this scenario, the robot told the participants
370 that a fire has started in the garage. Participants were warned of the emergency situation by a
371 red light turned on, and a fire alarm sounding in the room ⁶. The robot then asked participants
372 to choose whether they wanted to: 1) let the robot deal with the emergency, 2) deal with the
373 emergency collaboratively with the robot, 3) take a fire extinguisher and deal with the fire on
374 their own, or 4) call the fire brigade. Participants were reassured that there was no emergency
375 fire once they had made their choice, either by verbally or by making a selection on their tablet.

⁵Mojin Robotics <https://mojin-robotics.de/en/>

⁶NOTE: The emergency situation was not real, and participants were never in any danger. We played a pre-recorded audio to reproduce a fire sirens, played by the Amazon Alexa in a corner not far away from the participant’s position, and the red colour of a ceiling light in the experimental room was activated by the experimenter using a remote control. The house was situated in a residential area. In order not to upset the house’s neighbours, the alarm sound was set loud enough for the participants to hear inside the house, but not outside.

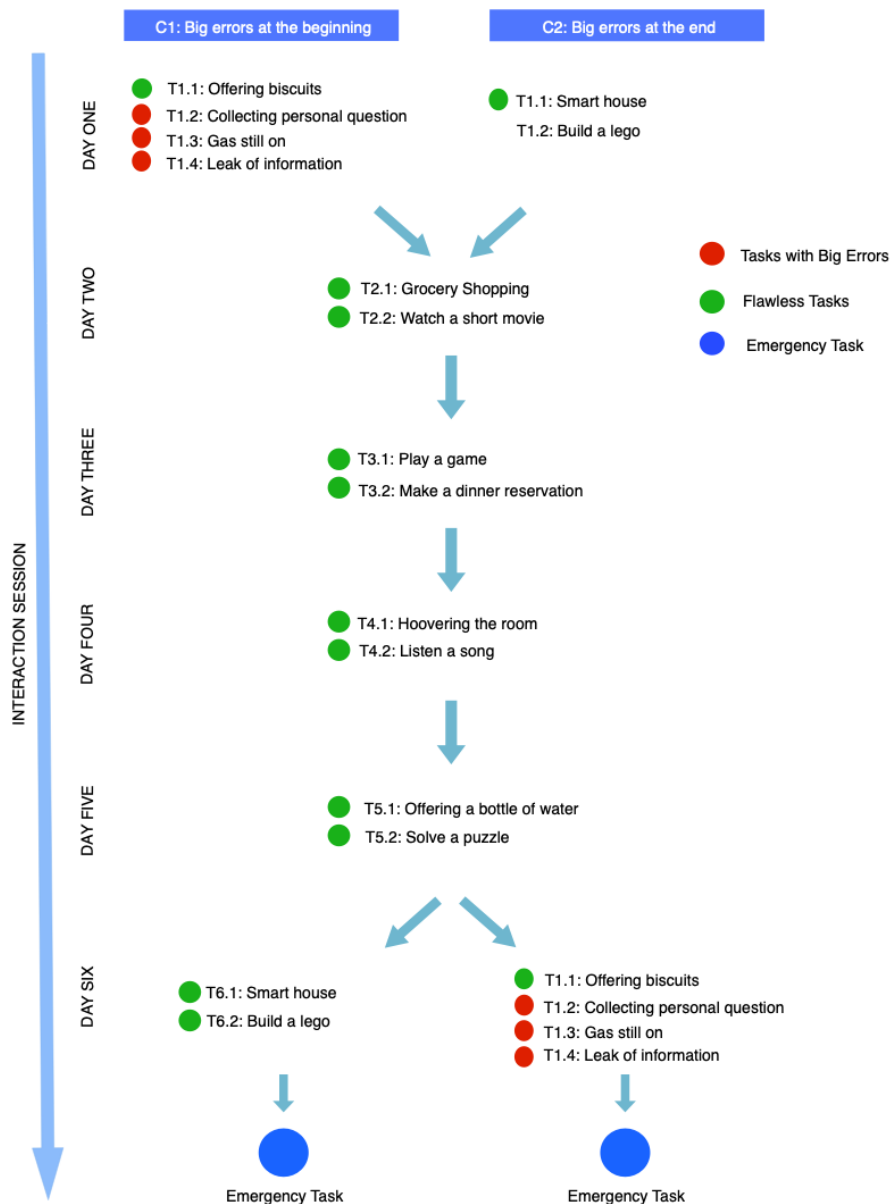


Figure 3: Experimental conditions presented to the participants.

376 On day one and six, we collected participants impressions, feelings and thoughts of the
 377 interaction, robot and scenarios through questionnaires. On the last day, we also debriefed
 378 them about the fire alarm, and any other potentially life-threatening errors made by the robot
 379 during the study.

3.3 The tasks

We selected the tasks based on our previous findings (Rossi et al., 2017b), and based on the tasks that the robot was able to complete according to its functionalities. Care-O-bot 4 engaged the participants in the tasks shown in Table 2. The robot was semi-autonomous, the majority of the robot’s behaviours were autonomous, however the experimenter controlled the robot’s speech in order to have a natural dialogue.

4 Study 1: Trust and Robot’s Errors

In this Section, we analyse and discuss the participants’ responses collected in Study 1 (see Section 3.1) through the pre- and post-interaction questionnaires, and trusting choices in the robot during the emergency scenario.

The study was conducted as an online study, so we decided to verify participants’ level of attention during the interactions by presenting them with four questions about the content of their scenario. The majority of participants (79.75%) answered correctly to the 4 attention check questions, and 13% of the participants answered to the question “Which secret did your robot Jace tell you?” with their own secret, instead of what Jace told them. We believe that those participants misunderstood the question. The final group of participants analysed consisted of 154 participants who did not fail the attention checks.

Participants rated the level of realism of the scenarios using a 7-point Likert Scale [1 = disagree strongly and 7 = agree strongly]. We considered ratings greater than 4 as “high realism” scenarios, ratings lower than 4 as “low realism scenarios”, and ratings equal to 4 as neutral. The majority of participants (69%) rated the interaction as high realistic, 20% rated it as not realistic, and the remaining did not perceive it either in one way or the other.

Participants also rated Jace’s errors, according to the magnitude of consequence of the errors and using a 7-point Semantic Differential Scale [1 = small error and 7 = big error]. We wanted to validate that the robot errors’ classification used in this study were in agreement with participants’ perception of errors’ consequences derived from a previous study (Rossi et al., 2017b). Scenarios were rated similarly as in Rossi et al. (2017b). The only exception was that participants in this study rated the scenario “After a meal, your robot Jace puts the remaining food into the washing machine instead of the bin” (mean 4.49, std. dev. 1.70, interval estimation

⁸The participants were not invited to go in the kitchen, and the experimenter only pretended that the gas was still on.

⁹The short-movie, called “The moon” in English, is a mute 2011 Pixar computer-animated short film Pixar (2011)

Table 2: Robot tasks with big consequences and flawless behaviours.

Big errors tasks	
Scenario	Description
Collect information	The robot told the participants that it cooked something for them in the oven, then it continued the interaction with the participant by asking them for personal information. It first asked if the participant ever accepted more change than they were supposed to receive. If they did not, then, the robot asked what was the participants' favourite toy when they were a child.
Leak of information	A visitor/actor visited the participant and rang the doorbell of the house. The robot asked the participant to open the door. The robot welcomed the visitor and, then, it revealed the participant's personal information to the visitor.
Gas still on	During the interaction, participants were interrupted by the experimenter who rushed into the kitchen, commenting loudly that the robot forgot to switch off the gas. The experimenter informed participants that she had switched off the gas, and let the interaction continue ⁷ .
Flawless tasks	
Scenario	Description
Offering biscuits	The robot asked the participants to sit on a couch and to eat a cookie. Cookies were already on a coffee table near the couch.
Grocery Shopping	The robot informed the participants that there was no more milk in their fridge. It asked them if they wanted it to be added to their grocery shopping list. Once the grocery list was completed, the robot read the list to the participants, and asked if they wanted to add more items to it.
Watch a movie	The robot invited the participant to watch a short-movie made by the Pixar and called "La Luna" ⁸ . The robot played the movie on its screen by tilting its body and head in the participant's direction to allow them to watch the video comfortably, they could decide to stand or sit on the couch.
Play a game	The robot engaged the participants by letting them play a game on its screen. The game consisted of moving a red cube through obstacles by using arrow keys. They could restart the game in case the cube hit an obstacle. The robot encouraged them by asking them the score, and if they were having fun. The game continued as long as participants desired.
Dinner reservation	The robot invited the participant to sit on the couch if they were not already, and turned on the TV. Then, the robot reminded them that they needed to schedule a dinner with their friend. The robot suggested a restaurant if they seemed unsure, and asked them to choose a day and a time for their dinner among a set of options. This task concluded when the plan for the dinner was confirmed by the robot and participant.
Hoover	The robot informed the participants that they needed to vacuum clean the rooms by using the cleaning robot available in the house, Roomba ⁹ . If participants agreed, the robot turned on the Roomba. If the participant preferred to postpone the cleaning, the robot told them that it was going to remind them later. While the Roomba was working, the robot engaged the participants in the next task.
Listen a song	The robot wanted to play a song for the participants. Then, it asked Amazon Alexa to play the song chosen by the participants. The task ended when participants did not want to listen to any other song.
Serve a drink	The robot invited participants to sit at the table, and it gave them a drink while engaging them in small talk, i.e. about the weather.
Solve a puzzle	The robot asked the participant to help it to solve a puzzle. We chose to use a 3D block puzzle with six different farm animals. Each puzzle was composed by nine blocks, the participant had free choice of selection between the six images. The robot showed the whole images to the participant. It also encouraged them to continue with their game, and gave them suggestions on the piece to look for to complete the puzzle.
Smart home	The robot informed the participants that it could access the sensors in the house, showing them on its screen a map of the house and the positions of the sensors. Then, the robot let the participants test its knowledge about the sensors by asking them to open and close the door of the bathroom, open and close the door of the fridge, switch on and off the power sockets in the kitchen and living room, and so on.
Lego puzzle	The robot asked the participants to assemble a Lego character in the shape of a dinosaur. Participants were sitting on the couch, and they could assemble the character on a small coffee table close to them. The robot that was standing on the other side of the coffee table, tilted its body towards the participants and showed them the instructions to build the figure. Participants enjoyed the game at their own pace, and they could navigate through the instruction by clicking on a previous or next page. The robot engaged the participants by encouraging them to continue to assemble the dinosaur, and by telling them how fun the task was.

409 4.22-4.75) as an error with ‘medium’ consequences while it was considered an error with severe
 410 consequences in the previous study Rossi et al. (2017b).

411 4.1 Participants’ trust in the robot Jace in relation to the robot errors

412 We observed that participants did not trust the robot when it made big errors, while they tended
 413 to trust to work in collaboration with the robot when the robot made small errors (see Figure 4).
 414 Indeed, we found that participants’ choices for the emergency scenario depended significantly
 415 on the experimental conditions ($\chi^2(12) = 32.91, p = 0.001$). To analyse the differences between
 416 the choices makes in the emergency scenario depending on the experimental conditions, we
 417 used the adjusted standardised residuals (called Pearson residuals (Agresti, 2002)). In Table 3,
 418 we observed that participants’ trust is affected more severely when the robot made errors with
 419 severe consequences (with adjusted standardised result = 2.7). Participants trusted the robot
 420 more when it had shown flawless behaviours (with adjusted standardised result = 3.5).

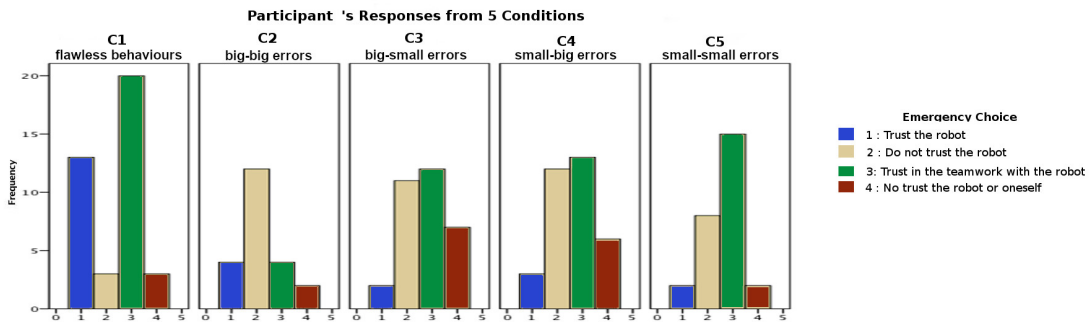


Figure 4: Participants’ choices in the Emergency Scenario according to the five experimental conditions.

421 We did not find any dependency between participants’ ages, gender or country of residency
 422 (principally from India and USA) and their choices during the emergency scenario, respectively
 423 with $p > 0.12$, $p > 0.3$, and $\chi^2(3) = 4.138, p > 0.24$.

424 4.2 Analysis of the explanations participants gave for decision-making 425 in the emergency scenario

426 Participants’ answers to the question “Why did/didn’t you trust your robot Jace?” were coded
 427 by the experimenter with different groups of categories using content analysis. Participants’
 428 responses were then classified in two hierarchical frames to support positive and negative eval-
 429 uations. Some participants’ answers fell into more than one category. The positive frame aims

Table 3: We report here the adjusted standardised residuals of the Crosstabulation between the participants’ trust choices and the experimental conditions that were statistical significant. The correlations with a * attached are values higher or lower than 1.96.

Condition	Emergency Choice			
	Do not trust the robot	Trust the robot	Teamwork with the robot	No trust the robot or oneself
<i>C1 - Flawless behaviours</i>	-3.5*	3.5*	1.4	-1.1
<i>C2 - Big-Big errors</i>	2.7*	0.4	-2.4*	-0.6

430 to identify the *motivations* that guided people to trust the robot Jace to be able to take care
 431 of the endangering situation. The negative frame includes the *reasons* behind the participants’
 432 choices to not trust the robot in the fire scenario. Participants’ motivations were grouped into
 433 the categories shown in Table 4.

434 Figure 5 shows the qualitative analysis of participants’ responses. As we can observe in
 435 the positive frame, participants principally trusted Jace because they attributed human char-
 436 acteristics to it, or they relied on Jace’s capabilities. As for the negative frame, participants’
 437 comments indicate that their choice of non-trusting the robot depends directly on the errors
 438 made by Jace prior to the emergency task. Some of their decisions were also connected to
 439 a negative perception of the robot’s anthropomorphism, and high criticality of the emergency
 440 task. While the gender identification or perceived level of anthropomorphism of the robot is out
 441 of scope, we believe that overall participants’ attribution of human traits to the robot affected
 442 their decisions. Indeed, we also observed by the qualitative analysis that 57% of participants
 443 referred to the robot with the pronouns “he/him”, the 33% of participants mentioned the robot
 444 with the name by the experimenters “Jace”, 6% and 5% of participants identified the robot
 445 Jace respectively as a “she/her” and “they/them”, and the remaining as an object using the
 446 pronoun “it”.

447 5 Study 1: Antecedents of Trust and Robot Errors

448 As part of study 1 described in 3.1, we were interested in participants’ self-reported ratings of
 449 their personality traits (extroversion, agreeableness, conscientiousness, emotional stability, and
 450 openness to experiences) (Gosling et al., 2003), and disposition of trust towards other people
 451 (benevolence, integrity, competence, and trusting stance) (McKnight et al., 2001). Ratings

¹⁰The uncanny valley refers to the hypothesis that the more human-like robots become in appearance and behaviour, the more they are accepted/familiar, up to a certain point when they appear “zombie-like” and generate repulsion MacDorman and Ishiguro (2006)

Table 4: Categories according to which participants’ motivations were grouped.

Positive Sentiment	
Category	Description
Anthropomorphism	This category includes motivations related to the attribution of human traits to the robot. For example, “Jace seemed honest, to have my best intentions in mind”, “he was very friendly”, and “Jace is a good friend of mine”.
Confidence in robot’s reliability	This codes people’s perception of Jace’s reliability. Some comments collected include: “It seemed as though he was built very well, and would be able to deal with the fire just fine”, “I trust jace because it helped me a lot”, and “It accomplished all tasks”.
Recovered trust by the robot	Some participants forgave the robot its errors made due to its ability to recover afterwards. Indeed, some commented “he made allowances for errors”.
General reliability in AI/robots	In this category, we coded participants’ extent to rely on the robots and AI. For example, they commented with “I trust technology”, and “I trusted it because they are machines built by humans to work in situations”.
Negative Sentiment	
Scenario	Description
Errors made by the robot	Participants justified that they did not trust the robot due to the amount of errors. Some comments used were: “Jace messed up several times”, “it made a few errors, like giving me dish-washing cleaner for water to take paracetamol”.
Self-confidence	Some participants were more confident in themselves than in the robot. In this category, we coded sentences such as “He always messed up everything”, and “I could have done everything better myself”.
Self-authority	In this category, we included people’s responses that highlighted their sense of control over Jace’s action. For example, some comments were “I trusted Jace to an extent. We would still want to supervise Jace”, and “It’s accepting my orders”.
Lack of robot’s reliability	As for the corresponding positive sentiment, we coded participants’ reliability in the robot. Some participant did not trust Jace because, for example, “Not smart enough” and “Jace ever do things right.”.
Criticality of the task	Participants’ decision of trusting the robot also depended on the perceived criticality of the task. Indeed, some of them commented that “he could not do the important things correctly, he made several errors which were or could have been costly to me”.
General no reliability in AI/robots	This category codes people’s reluctance in trusting Artificial Intelligence in general, or robots. For example, here we included comments such as “I don’t trust any artificial intelligence”, and “it’s a robot, not a person”.
Negative effects of anthropomorphism	In this category, we coded people’s feelings and perceptions that could be categorised as typical of the Uncanny Valley (Mori et al., 2012) ¹⁰ . For example, some participants wrote: “Too human, he had opinions which is something a robot should not have”, “Jace was creepy”, and “He is intrusive”.
Blaming the robot for the fire	We decided to code participants’ belief that the robot was responsible for the fire separately from the “lack of reliability” category. Some studies (Furlough et al., 2019) showed that people tend to attribute greater blame for a failure to robot with greater autonomy. Examples of comments are “he set the kitchen on fire” and “she started a fire”.

452 were collected using 7-point Likert Scales [1 = disagree strongly and 7 = agree strongly] where
 453 higher scores for personality traits indicate stronger propensity of being extroverted, agreeable,
 454 conscientious, emotional stable and open to experience. Similarly, higher scores were mapped as
 455 higher disposition of trusting people’s benevolence, integrity, competence, and trusting stance.

456 As part of the pre-experiment questionnaire, we collected participants’ responses about their
 457 previous experiences with robots, their perception of robots and robots’ purpose. Participants
 458 were asked about the degree to which they agree or disagree using the 7-point Likert Scales
 459 [from 1 = “disagree strongly” or “not at all”, to 7 = “agree strongly” or “very much”].

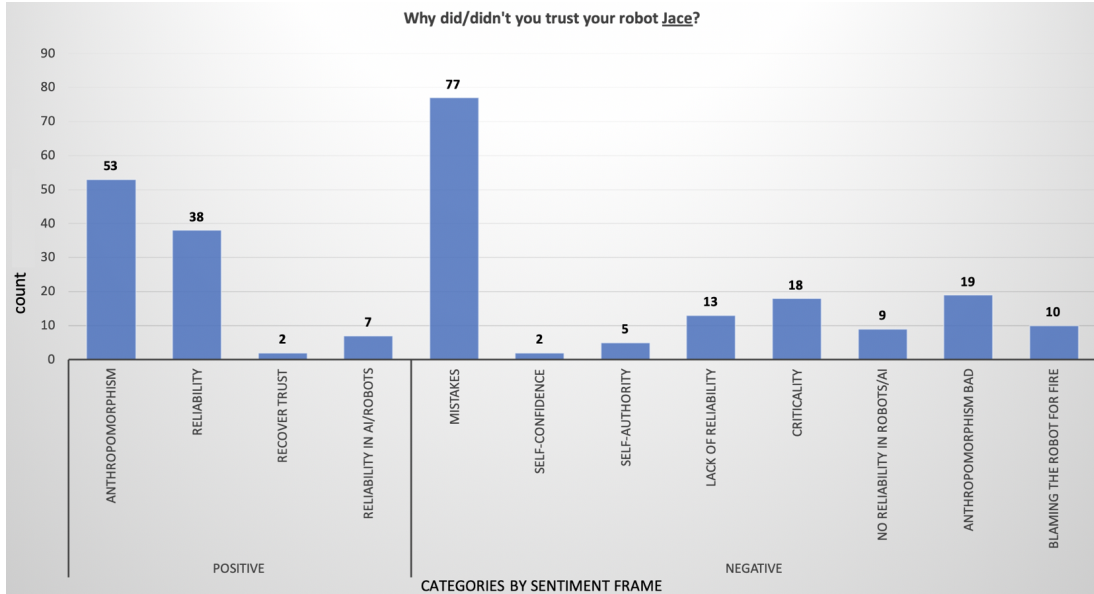


Figure 5: Qualitative analysis of participants’ responses for the reasons why they did or did not trust the robot Jace. Categories are divided by differences in trusting response, positive and negative.

460 5.1 Effects of people’s personality on trust

461 The participants’ personal characteristics (i.e. personality traits and disposition of trust) for
 462 each experimental condition are shown in Figure 6. We can observe that the participants
 463 in our study, across the different experimental conditions, have similar personality traits and
 464 dispositions of trust. We did not find any statistical correlation between the experimental
 465 conditions and people’s personality traits and disposition of trust. This means that any observed
 466 effects on participants’ trust in different experimental conditions were not influenced by the
 467 distribution of participants.

468 A Cross-tabulation between the participants’ disposition of trust and participants’ person-
 469 ality traits shows that people’s personality traits of agreeableness, conscientiousness and emo-
 470 tional stability are strongly connected to their disposition to trust other people ($p < 0.0001$).

471 Results of one-way ANOVA tests on participants’ personality traits and their propensity
 472 of trusting the robot shown that participants’ propensity for trusting the robot was correlated
 473 with conscientiousness trait ($p(3) = 0.042$, $F = 2.803$) and agreeableness trait ($p(3) = 0.022$,
 474 $F = 3.320$). We also observed that participants’ benevolence trait was positively correlated
 475 with a higher trust in Jace ($p = 0.014$, $F = 6.078$).

476 This is in line with what is known in the literature for people with high agreeableness,
 477 conscientiousness and benevolence. According to Roccas et al. (2002), agreeableness exhibits

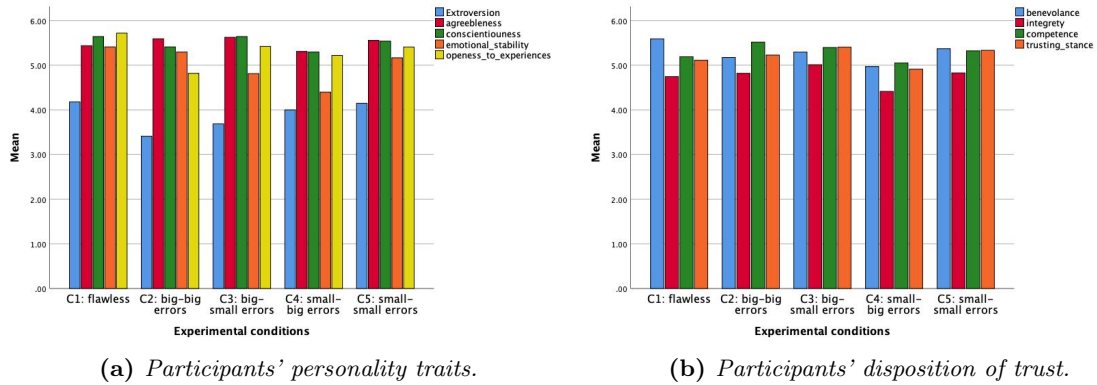


Figure 6: Plots of participants' personal characteristics with respect to each experimental condition. a) Participants' personality traits, b) Participants' disposition of trust.

478 higher correlations with conformity, tradition and benevolence, and benevolence values corre-
 479 lated with trust, straight-forwardness, altruism and tender-mindedness facets. At the same
 480 time, agreeableness and conscientiousness correlate with life, work satisfaction and happiness,
 481 and people who tend to believe others are honest and trustworthy are more likely to trust others
 482 DeNeve and Cooper (1998).

483 5.2 Effects of people's past experiences on trust

484 We used a 7-point Likert Scales from 1 = "not at all" to 7 = "very much" to measure par-
 485 ticipants' experience with robots. The majority of the participants (75.97%) did not have
 486 any experience with robots when they joined the study (min = 1, max = 6, mean 1.64, std.
 487 dev. 1.27). Participants' past experiences with robots can be classified into the following four
 488 categories: 1) taking part in other user studies = 14.93%, 2) being a developer = 5.19%, 3)
 489 observing a robot = 11.68% and 4) being a researcher = 3.89%. They had experience with
 490 the following robots (multiple choice): industrial robots (e.g. robotic arms), virtual assistants,
 491 online/virtual interaction with robot, cleaning robots (e.g. Roomba), and watching robots in
 492 the media.

493 Analysing participants' past experiences with robots and their choices for trusting/not trust-
 494 ing Jace in the endangering scenario did not show any statistically significant correlation.

495 5.3 Effects of perception of robots

496 We categorised participants' responses to the Likert questions as negative when their ratings
 497 were less than 4, as moderate when the values were equal to 4, and as positive responses when

498 their rating were greater than 4. Regarding the question “Would you feel comfortable having
499 a robot as a companion in your home?”, the majority of participants (69.48%) stated to be
500 comfortable in having a robot as a robotic companion, 14.93% indicated that they neither agree
501 nor disagree with the statement, while 15.58% did not want a robot in their homes.

502 The majority of participants (80.52%) expected to receive help from robots. Only 10.38%
503 neither agreed nor disagreed with the statement, and 9.09% disagreed that they would expect
504 help from a robot. We also noticed that participants who were more comfortable having a robot
505 companion also expected to receive help from it (61.68%).

506 Participants also chose suitable roles for robots. Results indicate that 1) friend = 10.8%, 2)
507 butler = 7.0%, 3) assistant = 24.6%, 4) tool = 18.6%, 5) companion = 11%, 6) pet = 6%, 7)
508 machine = 13%. A few participants also wrote in the “other” option (0.2%) that robots should
509 have a security role. We can observe that the majority of participants assigned the role of an
510 assistant to a robot which is coherent with their expectations of receiving help from it. This is
511 also in line with previous studies investigating the perceived role of a robot K. et al. (2005)

512 **5.3.1 Perception of a robot as a companion**

513 A Pearson correlation was run to determine the relationship between the participants’ percep-
514 tion of a generic robot as a companion with both their experience with robots and participants’
515 personality traits. We did not find any positive correlation, respectively with $p > 0.3$, $r = 0.082$,
516 and $p > 0.04$, $r = 0.161$. On the contrary, participants with higher disposition of trust in peo-
517 ples’ benevolence were more comfortable with a robotic companion ($p = 0.039$, $r = 0.166$).

518 **5.3.2 Expectation of a robot’s capabilities**

519 Participants’ perception of usefulness of a generic robot was not correlated with their experience
520 with robots ($p > 0.7$, $r = 0.026$). However, participants with a higher trusting stance ($p = 0.005$,
521 $r = 0.227$) and belief of trusting people’s competencies ($p = 0.011$, $r = 0.204$) expected robots
522 to be helpful.

523 **5.3.3 Perception of a robot’s role**

524 Mann-Whitney U-tests were performed to test the impact of the participants’ prior experience
525 and perceived role for robots. In particular, they were run to determine whether there were
526 differences in participants’ prior experiences score between those who selected or did not select
527 a specific role. Results suggest that participants with a lower level of experience with robots
528 tend to perceive them more as a machine ($p = 0.02$, $U = 1911$). Extroverted participants

529 also perceived robots as machines ($p = 0.007$). In contrast, participants with a higher level of
530 conscientiousness ($p = 0.040$) and agreeableness ($p = 0.007$) associated robots with a pet and
531 an assistant. There was no statistically significant correlation between people’s disposition of
532 trust and the attributed robot’s role.

533 **5.4 Effects of perception of the robot Jace in relation to the magni-** 534 **tude of consequences of the errors**

535 At the end of the interaction session, participants answered the same questions reported in the
536 previous Section 5.3 related to the robot Jace that was used in this study.

537 **5.4.1 Perceived companionship**

538 In particular, we asked participants whether they wanted Jace or another robot as their home
539 companion.

540 Spearman’s rank-order analysis showed a positive correlation between participants desire of
541 having Jace as home companion and both their the level of extroversion ($p = 0.001$, $r = 0.269$),
542 and the level of trust in peoples’ competencies ($p = 0.030$, $r = -0.175$). We also found a weak
543 positive correlation that was statistically significant ($p = 0.05$, $F(154) = 0.156$) between the
544 participants’ level of experience with robots and their willingness of wanting the robot as home
545 companion.

546 Further analysis found a statistically significant interaction between the effects of the level of
547 participants’ past experience with robots and their willingness of having the robot as compan-
548 ion across the five experimental conditions ($p(24) = 0.01$, $F = 1.952$). Observing the analysis,
549 we identified a statistically significant difference in means between participants’ previous ex-
550 perience with robots and their desire of having Jace as companion ($p < 0.0005$). However,
551 simple main effects of participants’ experience with robots on their acceptance of the robot
552 as a companion showed a statistically significant difference when participants were tested in
553 the flawless condition ($p(6, 32) = 0.005$, $F = 3.874$) and in the conditions with big errors
554 ($p(6, 15) = 0.027$, $F = 3.326$). Analysing the participants’ personalities and their desire of hav-
555 ing Jace as home companion across the five experimental conditions, we observed a statistically
556 significant correlation for participants who had higher level of agreeableness ($p(24) = 0.017$,
557 $F = 1.839$), and emotional stability ($p(24) = 0.029$, $F = 1.727$).

558 A Spearman’s rank-order analysis found also that participants’ experience of robots affected
559 their wish of having a robot different from Jace as a companion across the five experimental

560 conditions ($p(22, 121) = 0.006, F = 2.084$).

561 **5.4.2 Perceived reliability and faith in the ability of the robot**

562 We found a correlation ($p(154) = 0.021, F = 0.186$) between the robot's perceived reliability
563 and participants' experience of robots. Similarly, we find a statistically significant correlation
564 ($p(154) = 0.004, F = 0.229$) between the participants' propensity to rely on the robot in
565 uncertain and unusual situations and their previous experience with robots.

566 We also found a statistically significant interaction effect between people's familiarity with
567 robots and their perceived reliability of the robot ($p = 0.04, F(50, 81) = 1.546$), and their
568 propensity to rely on the robot in uncertain and unusual situations ($p = 0.001, F(51, 75) =$
569 2.147) according to the experimental conditions. In particular, we observed statistically signifi-
570 cant differences between participants' experience with robots and their perceived reliability and
571 participants' propensity of relying on the robot when participants were tested in the big-small
572 error condition (respectively $p(32) = 0.018, F = 0.415$ and $p(32) = 0.046, F = 0.355$). These
573 results are supported by de Graaf et al. (de Graaf and Ben Allouch, 2014) showing that a
574 positive interaction with a robot can positively affect people's attitude towards robots. On the
575 contrary, a negative experience with a robot can damage future interactions with other robots,
576 as it appears to have happened in this study.

577 We observed a statistically significant correlation between the perceived reliability of the
578 robot and people's level of extroversion trait ($p = 0.002, F = 2.729$), and between extroversion
579 ($p(12) = 0.014, F = 2.214$) and emotion stability ($p(12) = 0.026, F = 2.025$) and people's
580 reliability in the robot in uncertain and unusual situations.

581 **5.4.3 Perception of the robot's role**

582 A multiple linear regression analysis was run to predict participants' previous experience from
583 their perceptions of the robot and the different experimental conditions. The condition where
584 the robot showed flawless behaviours (condition **C1**) was used as the reference group for the
585 multiple linear regression analysis.

586 We observed that participants with lower experience with robots perceived the robot as a
587 friend ($p = 0.008$) and friendly ($p = 0.026$), but also as a toy ($p = 0.032$), when tested with the
588 experimental condition with only small-errors.

589 We observed that participants perceived the robot as a friend ($p = 0.019$), and warm and
590 attentive ($p = 0.025$) if they had a high level of extroversion, while those with lower extroversion
591 perceived it as a machine ($p = 0.002$), when tested with the condition having severe errors at

592 the beginning and small errors at end of the interaction (condition C3). Participants with high
593 level of conscientiousness perceived Jace less as a friend in the condition in which the robot
594 did big errors at the beginning and small errors at the end of the interaction (condition C3,
595 $p = 0.0483$), but more as a butler in the other conditions ($p = 0.030$, $p = 0.001$, $p = 0.007$).

596 **6 Study 2: Evolution of Trust and Erroneous Robot Be-** 597 **haviours**

598 In this study, we were interested in investigating if the trust of humans in a robot can be
599 recovered more easily if an error with severe repercussions happened at the beginning or end
600 of repeated interactions. Here, we discuss the human-robot interactions observed in the study
601 introduced in Section 3.2.

602 Results from the previous study (described in Section 3.1) showed that participants' trust
603 was affected more severely by the robot's errors with severe consequences, suggesting that
604 participants tended to form their mental models of the robot at the beginning of interaction.
605 However, study 2 is based on the assumption that people's trust can be recovered more easily
606 when they already have an established bond with the robot, i.e. when the trust is broken at a
607 later stage of the interaction (Schilke et al., 2013; Bottom et al., 2002).

608 Participants unanimously judged the level of realism of the scenarios with ratings higher
609 than five on a 7-point Likert Scale, ranged from 1 to 7 (disagree to agree).

610 **6.1 Trust in Care-O-bot 4 in relation to the robot's errors**

611 Participants trusted the robot more when they were experiencing robot's behaviours with big
612 errors at the end of the interaction (condition **CP1**), compared to when the errors were made
613 at the beginning of the interaction. Two out of three participants trusted the robot to be able
614 to handle the emergency situation, and one preferred to deal with the emergency situation in
615 collaboration with the robot when tested in condition **CP1**. When tested in condition **CP2**,
616 participants often did not trust the robot (1 out of 3 participants), and did not trust either
617 themselves or the robot (2 out of 3 participants).

618 A participant tested with condition **CP2** rushed towards the house's entrance (i.e. to exit
619 the house) being scared of the emergency situation, while a participant in condition **CP1**
620 blamed the robot for the fire. Another participant asked the robot for a fire extinguisher, and
621 invited the robot to call the fire brigade.

622 We also asked participants to justify their choices of trusting or not trusting the robot using
 623 an open-ended question. Their answers highlighted that their trust for the robot was based
 624 on the idea that the robot earned it during the interaction, or according to their propensity of
 625 trusting others. For example, participants stated that “I easily trust everyone” and “I believe
 626 that people know what they are doing”. A participant also commented that “he (*the robot*)
 627 was correct all the time”. In contrast, participants did not trust the robot due to its limited
 628 capabilities, i.e. in movements, dialogues, etc. Some commented that “I would trust him (*the*
 629 *robot*) with most things” and “I personally trust in robot with regular tasks such as reminding,
 630 cleaning”, and “he (*the robot*) would understand my commands correctly”, or “the responding
 631 of the Care-O-bot still slow and not precise”. Moreover, one participant was particularly
 632 concerned by the robot revealing their secret, and commented “it (the robot) promised not to
 633 tell my secret”. Figure 7 summarises the qualitative analysis ran on participants’ answers to
 634 the open-ended question.

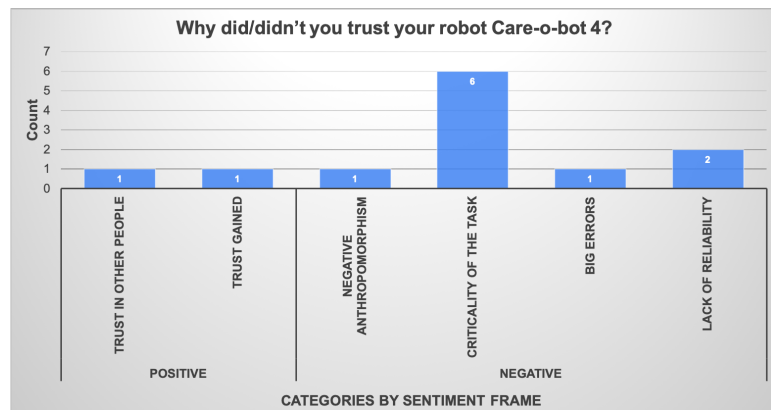


Figure 7: The participants’ motivations for trusting or not trusting the robot are here summarised according to positive and negative categories.

635 6.2 Antecedents of trust

636 We studied the effects of participants’ antecedents of trust (past experiences, personality traits
 637 and disposition of trust) on their choices of trust in the robot.

638 Participants did not have any, or very limited (i.e. participants in other studies), previous
 639 experience with robots.

640 As shown in Figure 8, there was no difference between participant’s choice of trust (in
 641 the emergency scenario) and the distribution of their personalities, and the distribution of their
 642 disposition to trust others. However, we can observe that the participants with higher conscien-

643 tiousness (Figure 8a), openness to experience, competence and trusting stance (Figure 8b) also
 644 trusted the robot. The participant with lower extroversion, conscientiousness, benevolence, and
 645 higher trusting stance trusted to work with the robot. Participants with high conscientiousness,
 646 emotional stability, benevolence and competence did not trust the robot.

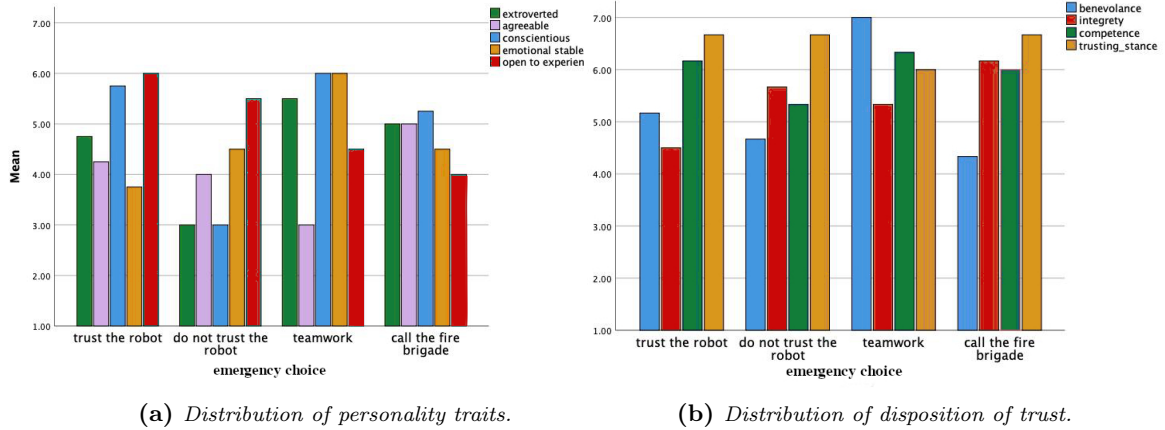


Figure 8: Distribution of participants' (a) personality traits and (b) disposition of trust by trust choice for each of their emergency choice.

647 We acknowledge that the very small number of participants cannot give us a high degree
 648 of confidence, and we will need to consider to further investigate these effects with a larger
 649 and more diverse group. However, one-way ANOVA tests showed that there was no statistical
 650 significant difference between participants' choice to trust the robot and their personal traits
 651 and disposition: extroversion ($p > 0.05$), agreeableness ($p > 0.05$), conscientiousness ($p = 0.05$),
 652 emotional stability ($p = 0.05$) and open to experience ($p > 0.05$), benevolence ($p > 0.05$),
 653 integrity ($p > 0.05$), competence ($p = 0.5$) and trusting stance ($p > 0.05$).

654 6.3 Perception of Care-O-bot 4

655 As we did in Study 1, we asked participants whether they would have wanted the robot as their
 656 home companion, and which were the roles considered suitable for the robot.

657 The majority of participants (4 out of 6 participants) stated to want Care-O-bot 4 as their
 658 robotic companion, while the remaining two participants were not positive or unsure to have
 659 the robot in their homes.

660 Participants had varied opinions on the suitable role for the robot. Two of the 6 participants
 661 perceived the robot as an assistant, the remaining four participants perceived the robot either
 662 as a tool, a companion, a friend, or a butler.

663 Measuring people’s perception of reliability and faith to perform correctly in unexpected
664 situations, we observed that participants trusted Care-O-bot 4 ($n = 4.17 \pm 0.24$) less in condition
665 **CP2** than condition **CP1**, while participants in condition **CP1** decided to call the fire brigade
666 ($n = 6.17 \pm 0.24$).

667 **6.4 Evaluation of robot errors**

668 At the end of the conditions, the robot verbally asked the participants to state whether it
669 made any errors, and to select the scenarios that contain robot’s errors. Participants provided
670 responses to both questions by selecting them on the robot’s tablet.

671 In their responses, participants stated that the robot did not make any mistakes. However,
672 when we asked them to rate the errors (including the ones made by the robot during the inter-
673 action), according to their level of consequences (i.e. with severe consequences), the resulting
674 rankings confirmed our expectations. We believe that they stated that the robot did not make
675 any errors due to a possible bystander effect, which might have inhibited participants to express
676 an open negative consideration in the presence of the culprit Voelpel et al. (2008) (i.e. the robot
677 in our study).

678 Finally, we asked participants to identify the scenarios they would entrust the robot to deal
679 with, in scenarios different from the fire emergency. They stated to not trust the robot to be
680 able to take care of life-threatening scenarios, such as “If your beloved ones were in life-danger,
681 would you trust me to deal with it?”, but they trusted the robot to be able to handle cognitive
682 and lower risks situations, such as “If you needed to take medicines regularly, would you trust
683 me to remind you of taking them?”, or to remind them of important meetings, and to manage
684 a smart house such as Robot House.

685 **7 Limitations**

686 The results of the two studies presented in this article highlight the various factors that can
687 affect people’s trust in robots. However, there are several limitations.

688 Over the last decade, online surveys, questionnaires and experiments have become standard
689 tools to conduct research both in Academia Sheehan and Pittman (2016) and Industry thanks
690 to the use of web services, as SurveyMonkey and Amazon Mechanical Turk that increase the
691 efficiency and effectiveness of the data gathering process Buhrmester et al. (2011).

692 Studies conducted through crowdsourcing services can collect participants’ responses very
693 fast. This might imply that the percentage of diversity of participants might change depending

694 on the time zone of the users of the crowdsourcing services. Future research should consider
695 investigating whether collecting responses of smaller groups of participants, by publishing the
696 recruitment according to different time zones would yield a wider diversity of the sample.

697 While the interactive scenarios were perceived by participants as very realistic and immer-
698 sive, participants might well have a different mindset in a real situation when meeting a robot
699 ‘face to face’, and where a prompt reaction may be needed or expected. Moreover, investigating
700 people’s trust in robots in real life-threatening scenario can be a challenging task due to ethical
701 and legal concerns (Salem and Dautenhahn, 2015).

702 Finding participants for in-person studies is extremely difficult. In particular, when inves-
703 tigating long-term effects and changes over time in HRIs whn participants are asked to attend
704 many sessions over several weeks. We were able to consistently establish that robot behaviours
705 affected participants’ trust in them. However, larger scale trials need to consolidate these find-
706 ings, and also provide further insights to unravel the complexity of trust dynamics between
707 humans and robots.

708 8 Conclusion & Future Work

709 The following research questions emerged from our review of related work when investigating
710 the trust dynamics between humans and robots:

711 RQ-1 How do various types of robot errors affect human’s trust in a robot?

712 RQ-2 How does people’s trust in a robot change according to their personal differences?

713 RQ-3 Does people’s trust in a robot change over time if the initial conditions (positive or
714 negative) of trust in the robot changes?

715 In this work, we presented two studies used to answer these questions.

716 **RQ-1 How do various types of robot errors affect human’s trust in a robot?** We
717 used an interactive storyboard presenting ten different scenarios in which a robot completed
718 tasks under five different conditions to explore the first two research questions. Results showed
719 that participants’ trust was affected more severely when the robot made errors with severe
720 consequences.

721 **RQ-2 How does people’s trust in a robot change according to their personal differ-**
722 **ences?** While analysing people’s individual differences, we found that participants’ individual

723 traits are correlated with their perception and trust of the robot. A strong relationship was
724 found between participants' personalities (agreeableness, conscientiousness and emotional sta-
725 bility) and their disposition to trust other people. The robot was perceived as a friend, warm
726 and attentive by extroverted participants, while it was considered a tool by more participants.
727 We also found that the extroversion trait affected participants' desire of having the robot as
728 home companion, and their beliefs in its reliability and trustworthiness in uncertain and unusual
729 situations. We found that conscientiousness and agreeableness traits correlate with participants'
730 propensity for trusting the robot. Participants' belief in benevolence of people also correlate
731 with higher trust in the robot.

732 The majority of the participants did not have experience with robots. We observed that
733 people who had negative previous experience with a robot were less inclined to trust the robot
734 that made big errors in our studies, while a positive experience with a robot consequently
735 affected people's positive predisposition towards a robot that behaved flawlessly.

736 **RQ-3 Does people's trust in a robot change over time if the initial conditions**
737 **(positive or negative) of trust in the robot changes?** Study 2 investigated if people
738 would trust a robot that broke their trust in an initial or later stage of the interaction. The
739 findings showed that people's trust was affected the most when the robot made errors at the
740 beginning of the interaction. Moreover, people's lack of trust in the robot was also connected
741 to the criticality of the task undertaken by the robot. These results corroborate the known
742 belief that people's reliability in a robot is also affected by the possibility of a negative outcome
743 (Mayer et al., 1995; Lee and Moray, 1992).

744 **8.1 Original contributions to knowledge**

745 Robot errors have been shown to reduce the perceived reliability and trustworthiness of robots
746 in several studies Desai et al. (2013); Hancock et al. (2011b); Salem et al. (2015). These works
747 highlighted that users complied with the robots' directions and suggestions discarding previous
748 robotic failures Robinette et al. (2016); Salem et al. (2015); Bainbridge et al. (2011). These
749 studies also were characterised by the fact that the robots' errors were not distinguished by
750 a different magnitude of consequences. In this paper, we have shown that errors with severe
751 consequences affected people's trust in robots more than errors with minor consequences.

752 Corritore et al. (2003) have shown that a sequence of small errors can affect people's trust
753 in robots more severely and for a longer period than one single big error. In section 3.2, we
754 have shown that the timing in which the errors occurs may impact people's trust in robots

755 differently, particularly in the case of the robot making errors that have major consequences.
756 Our findings also suggest that participants' judgements on whether to trust or not to trust the
757 robot are principally formed after a few initial interaction sessions with the robot, which is
758 inline with the finding from Yu et al. (2017).

759 Moreover, we have shown that people's perception of the robot and its errors consequently
760 also affect their trust. Indeed, the findings showed that individuals' personality traits and
761 personal dispositions, and previous experiences with robots influenced their trust in the robot,
762 particularly, when the robot was making big errors.

763 **8.2 Future works**

764 The insights gained by this research have shown that it is possible to build a successful col-
765 laboration between people and robots based on trust. However, they have also opened up
766 new directions for investigating trust in HRI, and identified a number of future challenges to
767 overcome.

768 In our investigations, we outlined several similarities and differences between the virtual and
769 real (in-person) studies. However, the unbalanced sample sizes do not allow us to make a more
770 extensive comparison between the two sets of results. In future, it would be useful to address
771 the samples sizes, to further investigate the possibility of using virtual setup to help to assess
772 in-person HRI, and to identify commonalities, as well as phenomena that would only emerge
773 uniquely in virtual or in person HRI.

774 The research presented in this article highlighted the necessity of further understanding how
775 human-robot relationships are formed, and which robot factors, including familiarity, appear-
776 ance and perception as social entity, will influence most people's trust in robots. Indeed, in
777 study 2 (see Section 6) we observed that participants were reluctant to communicate their disap-
778 proval of the robot for its errors. This most probably happened due to the effect well-known in
779 psychology and human-computer interaction (i.e., bystander effect or social inhibition of help-
780 ing). It seems to have milder effects in online interactions Chekroun and Brauer (2002). Future
781 research should investigate to what extent people's mental models, including the perceived im-
782 plications of task outcomes and consequences on their persona, inhibits their behaviours in the
783 presence of robots.

784 The results of this research have found that people's previous experiences of robots, per-
785 sonality traits, and dispositions to trust humans affects their trust in robots. However, people
786 are now becoming surrounded by digital technologies, and it is difficult to match people's ex-
787 pectations of robots with their experience with more robust and advanced AIs, such as Alexa

788 or Google Assistant. Further studies should aim to integrate modern learning techniques (i.e.
789 convolutional neural networks, deep learning etc.) that allow more fluid and rich interactions
790 in HRI studies in order to further investigate how people’s perceptions of robots affects their
791 trust in it. This will contribute to develop robots that adapt to interact naturally with people.

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