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DOES THE IMPLEMENTATION OF ROBOTS IN HOTELS INFLUENCE THE OVERALL TRIPADVISOR RATING? A TEXT MINING ANALYSIS FROM THE INDUSTRY 5.0 APPROACH

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2 **OVERALL TRIPADVISOR RATING? A TEXT MINING ANALYSIS FROM THE**
3 **INDUSTRY 5.0 APPROACH**

4
5 **ABSTRACT**

6 This research explores the relationship between **customers'** emotions and sentiments
7 generated by the interaction with robots in hotels and the potential effect on the **hotel's**
8 rating. To this end, **text** mining techniques are applied to TripAdvisor reviews by using
9 Python 3.9.4. The results indicate a relationship between the emotions and sentiments
10 detected in the reviews, the **robots'** functional typologies and traveller categories. The
11 originality of this research is mainly found in the quantification of the relationship between
12 robot functionality, traveller type and rating given to the hotel considering the emotions and
13 sentiments that emerge from the functional dimension of robots implemented in hotels.

14 **Keywords**

15 Human-Robot Interaction, Sentiment Analysis, Robots Functionality, Traveller,
16 TripAdvisor Rating, Text mining.

17 1. Introduction

18 Industry 5.0, also called the Fifth **Industrial Revolution**, is linked to **the enhanced**
19 experience of **the** final customer by applying the different tools available considering
20 **artificial** intelligence (AI) and robotics. The introduction of a new paradigm eliminating the
21 separation between **humans** and technology is a basic principle of Industry 5.0. This
22 approach is also applicable to other areas, reaching the concept of Marketing 5.0, whose
23 strategies facilitate to develop new **experiences for** the client by combining human
24 intelligence and technology (Purcarea, 2021). The necessity of understanding **human–robot**
25 **interactions (HRI)** from a coworking perspective (Demir et al., 2019; Longo et al., 2020)
26 and the influence on the perception of the customer are crucial to implement Marketing 5.0
27 tactics (Kotler et al., 2021).

28 The use of technologies related to AI is evident in the accommodation industry, where we
29 can find an increasing number of real-world robotics applications (Tung & Law, 2017),
30 especially in Japan, following the development of service robots in South Korea, America
31 and European countries (Yu, 2020). Under this new scenario, new studies are required to
32 understand how humans interact with these technologies and the consequences of these
33 interactions for both travellers and hotels. To date, most studies that have been conducted
34 on robots in hotels follow two main topics related to their functioning. The first one refers
35 to the quality and effectiveness of robots from the engineering prism (Rodriguez-Lizundia
36 et al., 2015; Pinillos et al., 2016; Ivanov et al., 2018; Tussyadiah & Park, 2018; Ivanov et
37 al. 2019), and the other one incorporates studies about HRI from the employees', managers'
38 or **customers'** perspective (Tung & Au, 2018; Yu, 2020; Zhong & Verma, 2019; de
39 Kervenoael et al., 2020; Fusté-Forné & Jamal, 2021). HRI research in hotels has been
40 intensively dedicated to consumer experiences depending on the robot's embodiment type,
41 **referring** to its appearance and morphology (anthropomorphic, zoomorphic, functional or
42 mixed) (Tung and Au, 2018). Previous studies have also analysed different types of robot
43 functions, such as intelligent service robots (as robot concierges), intelligent mobile robots
44 **self-navigating** in indoor environments, in-room robot companions or pervasive agents on
45 headless devices and stationary industrial **robots'** mechanical **AI** (automated locker and
46 storage systems, restaurants, cafés and bars) (Tussyadiah, 2020).

47 In this study, sentiment analysis is applied. Sentiment analysis is a type of **text mining**
48 method that allows to detect and identify people's attitude about a concrete issue (Kirilenko
49 et al., 2018; Alaei et al., 2019) through analysing Big Data (Talón-Ballester, González-
50 Serrano, Soguero-Ruiz, Muñoz-Romero & Rojo-Álvarez, 2018). Sentiment analysis has
51 been previously applied to the tourism context, exploring sentiment in electronic word-of-
52 mouth (eWOM), such as positive or negative online reviews left by customers for services,
53 including hotels (Fu et al., 2015; Yan et al., 2018; Buzova et al., 2019). Through eWOM
54 analysis, it is possible to identify the value of consumer experiences (Litvin et al., 2018),
55 and in the case of tourism, online reviews are part of this type of data (Liu et al., 2018).
56 Previous research about sentiment analysis of hotel reviews that confirm correlations with
57 overall ratings on TripAdvisor concludes that sentiment analysis is well suited **for** this task

58 (Lopez-Barbosa et al., 2015). **This research** indicates the need to extend this analysis to
59 know which hotel's features are more likely to lead to positive user reviews (Lopez-
60 **Barbosa et al., 2015**). On the other hand, previous studies have shown that robot acceptance
61 is influenced by some personal characteristics (age, gender, culture, city of residence) and
62 that travellers with different travel purposes tend to rate each hotel attribute differently
63 (Rhee & Yang, 2015) and have different interactions with the robots: for example,
64 travellers with children are susceptible to interaction with robots (Pinillos et al., 2016; Tung
65 & Au, 2018; Fuentes-Moraleda et al., 2020).

66 Different techniques can be applied in sentiment analysis. **One of them is the** lexicon-based
67 approach **that is** focused on sentiment lexicon and allows **for the identification of**
68 sentiments based on precompiled sentiment terms. **This** study explores HRI in hotels to
69 understand the hotel guests' emotions and sentiments resulting from their interaction with
70 service robots considering HRI terms (robot names, robot typologies and the word 'robot'
71 linked to action verbs) presented on the reviews. Previous studies identified that customer
72 sentiments derived from robotic services have a good link with hotel service satisfaction,
73 which is a key factor in determining total customer satisfaction (Luo et al., 2021). However,
74 this influence is not measured through quantitative methods to confirm that HRI generates
75 different emotions and sentiments considering robot functionality and type of traveller. **To**
76 **fill this gap**, this study investigates the impact of robots' functionality and the typology of
77 travellers on the sentiments derived in the interaction with robots based on online reviews
78 from TripAdvisor. Considering this fact, the relationship between the overall rating of
79 hotels (TripAdvisor) **and** the emotions and sentiments expressed by the type of traveller and
80 robot is explored. Research questions that arise from this objective are **as follows**:

81 RQ1. Is there a relationship between the overall rating of hotels (TripAdvisor)
82 offering service robots?

83 RQ2. Is there a relationship between the global rating of the hotels (TripAdvisor)
84 and the emotions and sentiments derived from HRI terms according to the robot's
85 functionality?

86 RQ3. Is there a relationship between the overall rating of hotels (TripAdvisor) and
87 the emotions and sentiments derived from HRI terms expressed by traveller type?

88

89 **2. Methodology**

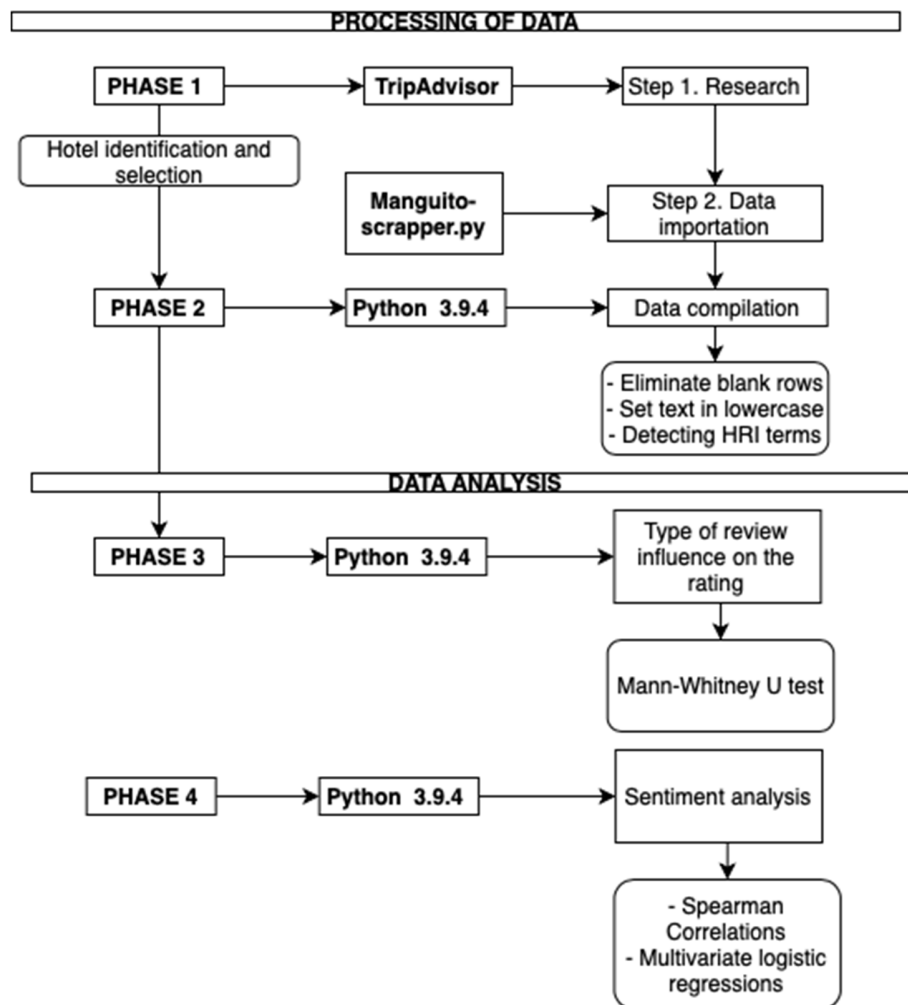
90

91 This study collected 107,663 online TripAdvisor reviews involving 80 hotels worldwide
92 using robots. After scrapping all the reviews from these hotels, we divided the reviews into
93 two groups: reviews including HRI terms (robot names, robot typologies and the word
94 'robot' linked to action verbs) and other reviews of these hotels **excluding** HRI terms. Of
95 the total reviews, 29,507 (27.40%) included terms related to HRI and 78,156 (72.60%)
96 **were** the rest.

97 First, we analysed the influence of the terms related to HRI on the **hotels' ratings** and
 98 compared the results with the influence of the rest of the reviews by conducting a Mann–
 99 Whitney U test, a nonparametric statistical test. Second, considering a positive influence on
 100 the rating when terms related to HRI appear, we applied a **text mining** method (sentiment
 101 analysis) and correlation and regression analysis (Lee et al., 2017; Li et al., 2020) using
 102 Python 3.9.4. The method followed is explained step by step in Figure 1:

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Figure 1. Study framework



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2.1. Selecting the hotels and importing the dataset

115 The first step consisted of identifying the hotels considering the use of service robots by
116 making a deep search on TripAdvisor. Online Travel Reviews (OTRs) (Marine-Roig, 2017;
117 Marine-Roig, 2019; Bagherzadeh et al., 2021) published on TripAdvisor have been widely
118 used by academic researchers in marketing, information systems, and hotel and tourism
119 literature (Xiang et al., 2015; Schuckert et al., 2015). This network is considered the
120 world's largest online travel analysis site and allows travellers to share their whole travel
121 experience (Lee et al., 2020). The site also offers various information, including ratings,
122 overviews, types of stay, length of stay, hotel styles, hotel type services or service ratings (1
123 = poor and 5 = excellent). The reviews were filtered by the words 'robot' and 'robots', and
124 we considered the reviews from the first one until August 2021. The hotels implementing
125 service robots with more than 10 reviews about HRI were selected. Once the search was
126 carried out, we identified 80 hotels with robot implementations (USA: 33 hotels; Japan: 20;
127 Singapore: 12; China: 12; Canada: 2; Australia: 1; Germany: 1; Ireland: 1).

128 The second step was focused on importing the data from the identified hotels in the
129 previous step. The data were extracted from TripAdvisor using a script created specially by
130 the authors to scrap a large amount of data from this website by using Python 3.9.4 named
131 'Manguito-scraper.py'. We considered previous studies that were focused on scraping data
132 from websites and TripAdvisor to select the data and develop our own script (Choi et al.,
133 2020; Oh & Kim, 2020; Orea-Giner & Vacas-Guerrero, 2020; Fuentes-Moraleda et al.,
134 2020). The script scraps only the reviews in English, and it creates a document with all the
135 information selected. It is essential to mention that, to check that the reviews were scrapped
136 correctly, researchers ensured that the process was carried out correctly. By downloading
137 all the reviews (107,663), 80 different files were obtained, one for each hotel, containing
138 the following information: review number, hotel name, user, URL user, date of review, user
139 location, country, rating, title, review, date of stay and traveller type.

140

141 2.2. Data compilation

142 The third step was data compilation. It was based on the data previously downloaded. The
143 dataset was adjusted to create a corpus using Python 3.9.4. This dataset was organised and
144 filtered. The data were pre-processed to eliminate blank rows and set the text in lowercase.
145 From the dataset, the next terms related to HRI were identified: robot names, robot
146 typologies and the word 'robot' linked to action verbs (e.g., 'welcoming robot').

147 The robot names identified were: 'Aura', 'yobot', 'Butler', 'Wes', 'Yolanda', 'Wally',
148 'Emc2', 'Jeno', 'Jarvis', 'Leo', 'Pepper', 'Dinosaur', 'Alina', 'Winnie', 'Cali', 'Chip',
149 'Ausca', 'Yo2d2', 'Churi-Chan', 'Suga', 'Hannah', 'Relay', 'Yoshi', 'Botlr', 'Eaton',
150 'Rose', 'Fetch', 'Robi', 'Hazel', 'Botler', 'Dash', 'Bob', 'Holli', 'Hubert', 'Jett', 'Trolley',
151 'Wang', 'Robo bar', 'Chu Lee', 'Mr Robot', 'Yuri' and 'Butlr'.

152 The identified robot names and the word 'robot' linked to action verbs helped link them to
153 their functionality (Lu et al., 2019; Tussyadiah, 2020) by making a manual search and
154 classification of the robots by their name. Regarding the robot's functionality, the

155 classification followed **was** based on Tussyadiah (2020) and Lu et al. (2019), who
156 identified the following types of robots involved in hotel services from a functional
157 perspective for this study. First, **some** robots provide room service by transporting objects
158 previously requested by guests ('room service robots'). Some are used in restaurant,
159 cafeteria and bar services for different tasks ('restaurant's robot chef and robotic
160 bartender'). Also, there are robots used for luggage storage ('cloakroom robots'). **Also**, we
161 can find robots that receive customers and welcome them to the hotel ('welcoming robots')
162 and robots that perform in-and-out functions ('front-desk robot receptionist'). Finally, **some**
163 robots use AI to answer guests' questions and provide information and suggestions about
164 activities and tourist attractions to visit ('concierge robots' or 'bellboy robots').
165 Specifically, the robots identified were mainly used for room service (96.59%), robot
166 concierges (2.24%) and cloakroom robots (0.09%). The other robots, such as welcoming
167 robots (0.25%), front-desk robot receptionists (0.01%) and restaurants and bars (0.01%)
168 were identified but not included in the final sample **because of** their low numbers. Also, the
169 type of traveller **was** considered. The **types of travellers** considering TripAdvisor's
170 classification **were** couple trip (35.18%), business trip (23.31%), family trip (22.99%), a
171 trip with friends (10.98%) and single trip (7.52%). Each review's rating is on a Likert scale
172 (1–5), where the total average is 4.188 (and 1.039 standard deviations).

173 After organising and filtering the data, 29,507 reviews were selected considering these
174 terms linked to HRI, and the rest of the reviews eliminating those containing HRI terms
175 were 78,156.

176 *2.3. Mann–Whitney U test*

177 The first test conducted was the Mann–Whitney U test, a nonparametric statistical test that
178 **allows** us to identify the influence of the two types of reviews (with HRI terms and without
179 them) on the rating. This test guarantees the relevance of analysing TripAdvisor reviews to
180 obtain conclusions about HRI and Industry 5.0 concepts. By conducting this test, we can
181 check the relationship between the overall rating of hotels given in the reviews that include
182 terms related to HRI and the rest of the reviews.

183 *2.4. Sentiment and analysis*

184 After the previous steps, sentiment analysis is developed using Python 3.9.4. This analysis
185 has experienced substantial growth over the last few years. It has been established as a new
186 **natural language processing** (NLP) research branch, which processes automatically written
187 opinions to extract insights and knowledge. The proliferation of social networks, **such** as
188 TripAdvisor, has led to a considerable amount of online-recorded text. In these platforms,
189 users are free to express their opinions about products, places and experiences, which
190 implies a high development of **sentiment analysis models** for sentiment extraction (Valdivia
191 et al., 2017). In this study, sentiment analysis is based on eight categories of emotions
192 (**anger, anticipation, disgust, fear, joy, sadness, surprise and trust**) and two categories of
193 sentiments (negative and positive) (NRC Word-Emotion Association Lexicon). The data
194 **were** classified following the models applied, as the following **examples** of narratives from
195 **Table 1** show:

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Table 1. Narratives extracted from the sentiment analysis classification

Emotions	Narrative examples
Anger	‘The luggage robot was out of order, so I had to pay a \$2 extra fee to store my luggage’.
Anticipation	‘We met the [...] robot who was a huge hit and full of very helpful advice on what to do and where to go’.
Disgust	‘We planned to use the luggage storage area, but the robot the hotel is known for was broken’.
Fear	‘The luggage robot in the lobby which they rave about was broken and looked as though it hadn’t worked for some time – this was no big deal, but a sign of things to come’.
Joy	‘Interestingly, a robot came to our room to deliver wine glasses – fun right?’
Sadness	‘I was very disappointed when I was unsuccessful in retrieving my luggage from the robot’.
Surprise	‘It is interesting to have the little robot in the lobby to answer basic info’.
Trust	‘Yobot will pick up your cases and store them in the wall of boxes in front of you. you’ll get a printed receipt with a bar code, just scan this on your return and the yobot will retrieve your luggage for you’.
Sentiments	Narrative examples
Positive	‘. . . the hotel’s droid butlers which assist with the delivery of room amenities, stand patiently in a corner ready to serve’.
Negative	‘. . . robots that supposedly bring towels and water to rooms, but didn’t know how to access them . . .’

200

201 During the analysis, examples of narratives are included linked to the results obtained.
202 These narratives include in brackets the robot’s functionality, emotion/sentiment **identified**,
203 and review rating.

204 2.5. Spearman correlations

205 Spearman correlations **were** made between the rating by **the** functional type of robot and
206 the results obtained in the sentiment analysis and the rating by **the** type of traveller and
207 emotions and sentiments. The program delivers the value of each correlation between the
208 rating given by TripAdvisor and each of the emotions and sentiments depending on the
209 functional type of robot and the type of traveller. The data **were** divided into two groups
210 from 1 to 3 and from 4 to 5 considering the average TripAdvisor rating of these hotels
211 (4.188). This division facilitates the analysis of the results.

212 2.6. Multivariate logistic regressions

213 By using the Logit class in Python, where we set the optimiser BFGS (Broyden-Fletcher-
214 Goldfarb-Shanno), a multivariate logistic regression for each robot and traveller category

215 was performed. Previous studies recommended applying multivariate logistic regressions to
 216 analyse similar data (Agresti, 2003; Thrane, 2005).

217 To apply the multivariate logistic regressions, the rating typologies were categorised into
 218 two groups as mentioned before. This measure allows us to differentiate between low and
 219 high TripAdvisor rating, grouping the information to obtain a binary dependent variable. As
 220 independent variables, previous emotions and sentiments are introduced as parameters in
 221 the model to be tested.

222 The proposed analysis consisted of a multivariate logistic regression. The odds ratio (β)
 223 indicates the greater or lesser probability that the dependent variable is of one category
 224 relative to the other as indicated by the coefficient. If it is less than 1, it causes a decrease in
 225 the rating. If it is greater than 1, it generates an increase in the rating.

226

227 3. RESULTS

228 3.1 Type of review influence on the rating

229 The results of the Mann–Whitney U test showed that there is a significant difference
 230 between the reviews including HRI terms and the rest of the reviews eliminating those
 231 terms (p-value < 0.001). This is due to a high quantity of reviews without HRI terms
 232 classified with a rating of 1, 2 and 3, while there is a higher quantity of reviews including
 233 HRI terms with a rating of 4 and 5.

234 3.2. Analysis by robot functionality

235 The results of the Spearman correlation between sentiments and rating according to robots
 236 are reflected in Table 2 for each category of robots analysed ('cloakroom robot', 'robot
 237 concierge' and 'room service robot'). The table includes eight categories of emotions
 238 (anger, anticipation, disgust, fear, joy, sadness, surprise and trust) and two categories of
 239 sentiments (negative and positive) (NRC Word-Emotion Association Lexicon).

240 **Table 2. Spearman correlations among travellers' sentiments and ratings according to**
 241 **robots' typologies**

Robots	Saif Mohammad's NRC Word-Emotion Association Lexicon									
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Positive	Negative
Cloakroom Robot	-0.237 p = 0.000***	-0.077 p = 0.210	-0.287 p = 0.000***	-0.160 p = 0.009* *	0.094 p = 0.126	-0.191 p = 0.001**	-0.093 p = 0.131	-0.001 p = 0.985	-0.014 p = 0.814	-0.260 p = 0.000***
Robot concierge	-0.274 p = 0.000***	-0.149 p = 0.000***	-0.394 p = 0.000***	-0.224 p = 0.000* **	-0.003 p = 0.933	-0.285 p = 0.000***	-0.093 p = 0.015*	-0.081 p = 0.035*	-0.090 p = 0.020*	-0.396 p = 0.000***
Room Service Robot	-0.236 p = 0.000***	-0.075 p = 0.000***	-0.304 p = 0.000***	-0.217 p = 0.000*	0.026 p = 0.000**	-0.218 p = 0.000***	-0.052 p = 0.000***	-0.028 p = 0.000***	-0.043 p = 0.000**	-0.292 p = 0.000***

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242 *** p < .001 **p < .01 * p < .05

243

244 Table 2 shows Spearman’s correlation between the main emotions and sentiments
 245 according to the NRC Word-Emotion Association Lexicon and the ratings according to the
 246 robots’ typologies and continues the path presented in our methodology above.
 247 Notwithstanding the wide range of potential sentiments that reviewers could relate to
 248 robots, a limited negative correlation seems to exist, around $r \sim -0.3$, between negative
 249 sentiments and robots, with the worst scores pointing to ‘robot concierge’, with a general
 250 negative association of $p = -0.396$, followed by ‘cloakroom robot’ ($p = -0.292$), whose most
 251 intense associated emotions were ‘anger’, ‘disgust’ and ‘sadness’. The following quotation
 252 serves as an illustration:

253 *I was looking forward to the robots – they were lame and the in room dining menu*
 254 *was so short I couldn’t find anything to order. So disappointed! (Room Service*
 255 *Robot, Disgust, Review Rating: 1/5).*

256

257 The last step of the proposed analysis consisted of performing a multivariate logistic
 258 regression to explain how ratings are assigned in reviews according to their content and the
 259 perceptions of the different categories of robots (Table 3).

260

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Table 3. Multivariate logistic regression for cloakroom, concierge and room service robots

	<i>Emotions and sentiments</i>	β	95% CI Lower Upper	p-value
Cloakroom (N = 262)	Anger	0.625	[0.411, 0.950]	0.028
	Anticipation	0.863	[0.691, 1.077]	0.192
	Disgust	0.417	[0.265, 0.657]	0.000***
	Fear	1.108	[0.711, 1.725]	0.651
	Joy	2.851	[1.927, 4.216]	0.000***
	Sadness	0.835	[0.579, 1.203]	0.333
	Surprise	0.663	[0.456, 0.963]	0.031*
	Trust	0.709	[0.541, 0.929]	0.013*
	Negative	1.164	[0.919, 1.475]	0.208
	Positive	1.250	[1.055, 1.480]	0.010*
Concierge (N = 662)	Anger	1.110	[0.887, 1.389]	0.362
	Anticipation	0.918	[0.823, 1.024]	0.124
	Disgust	0.485	[0.379, 0.620]	0.000***
	Fear	1.180	[0.963, 1.446]	0.109
	Joy	1.318	[1.151, 1.509]	0.000***
	Sadness	1.120	[0.930, 1.350]	0.233
	Surprise	0.982	[0.832, 1.160]	0.832
	Trust	1.003	[0.898, 1.119]	0.963
	Negative	0.785	[0.696, 0.885]	0.000***
	Positive	1.042	[0.971, 1.117]	0.254
Room service (N = 28501)	Anger	0.908	[0.869, 0.948]	0.000***
	Anticipation	0.942	[0.920, 0.964]	0.000***
	Disgust	0.608	[0.579, 0.639]	0.000***
	Fear	0.962	[0.921, 1.005]	0.086
	Joy	1.220	[1.185, 1.257]	0.000***
	Sadness	1.032	[0.994, 1.071]	0.101
	Surprise	0.943	[0.912, 0.975]	0.001
	Trust	0.991	[0.966, 1.016]	0.483
	Negative	0.775	[0.756, 0.794]	0.000***
	Positive	1.059	[1.044, 1.074]	0.000***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 Cloakroom robot: McFadden's pseudo R-squared: 0.190 Likelihood ratio chi-squared statistic: 40.586, p-value: 0.000*** Concierge robot: McFadden's pseudo R-squared: 0.156 Likelihood ratio chi-squared statistic: 137.403, p-value: 0.000*** Room service robot: McFadden's pseudo R-squared: 0.138 Likelihood ratio chi-squared statistic: 3065.521, p-value: 0.000***				

263

264 When talking about 'cloakroom robot', the variables 'disgust', 'joy', 'trust', 'surprise' and
 265 'positive' were significant at the .05 level. These results showed that reviews including
 266 'joy' associated with 'cloakroom robot' were 2.851 times more likely to report a better
 267 rating. Previous research has identified a relationship between the implementation of
 268 service robots and emotions like fun and excitement (Gretzel & Murphy, 2019). Reviews
 269 illustrating this issue included the following:

270
271

After that you were able to leave your bags at hotel by using the great automated bag-storage-robot, Yobot. maybe a bit slow way to do it (if lots of people doing the

272 *same thing simultaneously), but so cool! (Cloakroom Robot, Positive, Review*
273 *Rating: 5/5)*

274

275 For 'disgust', the reviews including this emotion were 0.417 times more likely to decrease
276 the rating. This emotion is linked to something unexpected such as robots' failures. Errors
277 generated by robots can generate insecurity, frustration and anger (Fuentes-Moraleda et al.,
278 2020). This is reflected in emotions such as 'disgust', 'anger' or 'fear', so anticipation of
279 service failures is considered an important aspect when adopting service robots in
280 hospitality environments. The following review serves as an illustration:

281 *The sky hotel is probably the best-known for its robot at reception. we explored*
282 *reception and found the robot, but she wasn't working. (Cloakroom Robot, Disgust,*
283 *Review Rating: 1/5)*

284 When dealing with the 'concierge robot' category, the variables 'joy', 'disgust' and
285 'negative' were significant. The reviews including 'joy' were 1.318 times more likely to
286 report a better rating.

287 *My kids love pepper (robot) in the lobby. (Concierge Robot, Joy, Review Rating:*
288 *4/5)*

289 However, the presence of 'disgust' and 'negative' emotions and sentiments are 0.485 and
290 0.785 times more likely to impact the rating negatively, respectively.

291 The results for 'room service robot' showed that 'anger', 'anticipation', 'disgust', 'joy',
292 'negative' and 'positive' were significant. For the positive relationship of 'room service
293 robot' with 'joy' ($\beta = 1.220$; $p < 0.001$) and 'positive' ($\beta = 1.059$; $p < 0.001$). The following
294 reviews reveal these ideas:

295 *They made quite an impression on me, so much so that as I was falling asleep, I was*
296 *counting Leo's and Cleo's instead of sheep. staff service was at an excellent level,*
297 *amped up to please and the robots were pretty good too. (Room Service Robot,*
298 *Positive, Joy, Review Rating: 5/5)*

299 *We had a toothbrush delivered to the room by a robot! how cool is that? thank you*
300 *for a great stay axiom. (Room Service Robot, Positive, Review Rating: 5/5)*

301

302 It is important to mention that the previous literature has analysed how room service robots
303 could be used to obtain guests' opinions in hotels (Chung & Cakmak, 2018). The robot
304 would also be able to identify dissatisfied guests while they are onsite. Also, these authors
305 argue that the robots could identify the type of customer from the beginning of the
306 interaction (Chung & Cakmak, 2018). That means they could capture their expectations and
307 emotions and sentiments of HRI from the initial interactions by asking the right questions.

308 For the emotions and sentiments that negatively impact the rating considering ‘room
 309 service robot’, the results showed that ‘disgust’ and ‘negative’ were 0.608 and 0.775 times
 310 more likely to decrease the rating. The following review serves as an example:

311 *Those robots were just creepy. (Room Service Robot, Negative, Review Rating: 2/5)*

312 **3.3. Analysis by traveller’s typology**

313

314 Table 4 presents the Spearman correlations according to traveller typologies (couple,
 315 family, solo, friends and business).

316

317 **Table 4. Spearman correlations among travellers’ sentiments and rating according to**
 318 **travellers’ typologies**

Travellers	Saif Mohammad’s NRC Word-Emotion Association Lexicon									
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Positive	Negative
Couple	-0.253 p = 0.000***	-0.052 p = 0.000***	-0.332 p = 0.000***	-0.228 p = 0.000***	0.080 p = 0.000***	-0.197 p = 0.000** *	-0.026 p = 0.000** *	-0.011 p = 0.040*	0.003 p = 0.462	-0.302 p = 0.000***
Family	-0.272 p = 0.000***	-0.037 p = 0.000***	-0.359 p = 0.000***	-0.245 p = 0.000***	0.104 p = 0.000***	-0.232 p = 0.000** *	-0.009 p = 0.138	0.034 p = 0.000** *	0.023 p = 0.000***	-0.325 p = 0.000***
Solo	-0.243 p = 0.000***	-0.046 p = 0.000***	-0.312 p = 0.000***	-0.217 p = 0.000***	0.072 p = 0.000***	-0.205 p = 0.000** *	-0.034 p = 0.003**	0.000 p = 0.939	0.002 p = 0.839	-0.286 p = 0.000***
Friends	-0.290 p = 0.000***	-0.069 p = 0.000***	-0.360 p = 0.000***	-0.268 p = 0.000***	0.055 p = 0.000***	-0.241 p = 0.000** *	-0.052 p = 0.000** *	-0.019 p = 0.039*	-0.033 p = 0.000***	-0.330 p = 0.000***
Business	-0.298 p = 0.000***	-0.032 p = 0.000***	-0.363 p = 0.000***	-0.280 p = 0.000***	0.134 p = 0.000***	-0.265 p = 0.000** *	0.010 p = 0.100	0.052 p = 0.000** *	0.043 p = 0.000***	-0.370 p = 0.000***

319 *** p < .001 **p < .01 * p < .05

320

321 Table 4 follows the same trend as Table 2, revealing a negative association among negative
 322 sentiments and words in reviews. The strongest correlations occurred in the opposite
 323 direction between negative sentiment and reviews. These results showed that the higher the
 324 presence of negative sentiment, the lower the rating given to the hotel. The words related to
 325 ‘disgust’ and ‘negative’ showed a higher intensity regarding the traveller category. The
 326 category ‘business’ presented the highest negative emotion. This means that positive related
 327 emotions and sentiments do not show any positive influence on the analysed corpus.

328 This analysis consisted of several multivariate logistic regressions to explain how ratings in
 329 the reviews are assigned according to their content and the perceptions of the different
 330 types of travellers (Tables 5 and 6), taking as a dependent variable the rating given to the
 331 hotels, by category of travellers. As independent variables, the above emotions and
 332 sentiments are introduced as parameters in the model to be tested.

333 **Table 5. Multivariate logistic regression for traveller's typologies: couple, family and**
 334 **solo**

	<i>Emotions and sentiments</i>	β	95% CI		p-value
			Lower	Upper	
<i>Couple</i> (N=34372)	Anger	0.862	[0.830, 0.895]		0.000***
	Anticipation	0.934	[0.915, 0.953]		0.000***
	Disgust	0.534	[0.512, 0.557]		0.000***
	Fear	0.838	[0.808, 0.869]		0.000***
	Joy	1.547	[1.506, 1.590]		0.000***
	Sadness	1.149	[1.114, 1.186]		0.000***
	Surprise	0.905	[0.879, 0.932]		0.000***
	Trust	0.976	[0.954, 0.998]		0.036*
	Negative	0.849	[0.831, 0.868]		0.000***
	Positive	1.161	[1.145, 1.177]		0.000***
<i>Family</i> (N=22467)	Anger	0.812	[0.776, 0.851]		0.000***
	Anticipation	0.901	[0.878, 0.923]		0.000***
	Disgust	0.571	[0.542, 0.601]		0.000***
	Fear	0.842	[0.805, 0.881]		0.000***
	Joy	1.510	[1.462, 1.560]		0.000***
	Sadness	1.119	[1.074, 1.166]		0.000***
	Surprise	0.980	[0.945, 1.016]		0.274
	Trust	1.015	[0.988, 1.043]		0.290
	Negative	0.794	[0.771, 0.816]		0.000***
	Positive	1.173	[1.153, 1.193]		0.000***
<i>Solo</i> (N=7349)	Anger	0.860	[0.796, 0.929]		0.000***
	Anticipation	0.951	[0.912, 0.992]		0.020*
	Disgust	0.590	[0.540, 0.645]		0.000***
	Fear	0.915	[0.847, 0.988]		0.023*
	Joy	1.538	[1.453, 1.628]		0.000***
	Sadness	1.063	[0.992, 1.139]		0.083
	Surprise	0.890	[0.836, 0.947]		0.000***
	Trust	0.936	[0.892, 0.981]		0.006*
	Negative	0.824	[0.786, 0.864]		0.000***
	Positive	1.201	[1.165, 1.238]		0.000***
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 Couple: <i>McFadden's pseudo R-squared: 0.042</i> <i>Likelihood ratio chi-squared statistic: 1343.495, p-value: 0.000***</i> Family: <i>McFadden's pseudo R-squared: 0.086</i> <i>Likelihood ratio chi-squared statistic: 1856.918, p-value: 0.000***</i> Solo: <i>McFadden's pseudo R-squared: 0.031</i> <i>Likelihood ratio chi-squared statistic: 210.107, p-value: 0.000***</i>					

335

336 The results analysing the relationship between the ‘couple’ category, rating and type of
337 emotions and sentiments were all significant. The emotions that related to a higher rating
338 were ‘joy’, ‘sadness’ and ‘positive’, being 1.547, 1.149 and 1.161 times more likely to give
339 a high rating, respectively. Previous work in this field has shown that couple travellers
340 value robots in hotels positively and have positive sentiments derived from the HRI
341 (Fuentes-Moraleda et al., 2020). The following quotations serve as an illustration:

342 *Cleo, the robot, is a great addition to the upgrade of service you receive (Couple,*
343 *Positive, Review Rating: 5/5)*

344 The rest of the emotions and sentiments cause a decrease in the hotel’s rating, highlighting
345 the case of ‘disgust’, which is 0.534 times more likely to be linked with a low rating. The
346 following review serves as an example of these findings:

347 *Robot’s button hard to push and it asked how your stay was, well when you say not*
348 *good, maybe someone should be contacting you, if not them don’t ask. (Couple,*
349 *Disgust, Review Rating: 2/5)*

350 The ‘family’ category presented significant results with all the emotions and sentiments
351 except for ‘surprise’ and ‘trust’. ‘Joy’ ($\beta = 1.510$; $p < 0.001$) was the most representative in
352 terms of increasing the rating, and ‘disgust’ ($\beta = 0.571$; $p < 0.001$) influenced the customers
353 in giving a low rating. This is exemplified by the following reviews:

354 *We met the delta chelsea robot who was a huge hit and full of very helpful advice on*
355 *what to do and where to go. (Family, Joy, Review Rating: 5/5)*

356 *This is not a child-friendly place – they apparently have bathrobes and slippers for*
357 *children and a stuffed animal version of their non-functioning robot Alina for*
358 *children. (Family, Disgust, Review Rating: 1/5)*

359 The positive perception of robot implementation from this category could be explained
360 considering that children show good acceptance of technology and are a particularly
361 indicated segment to embrace service robots (Belanche et al., 2019b). Moreover, in hotel
362 environments, robots attract children, so families choose accommodation with this type of
363 service (Tung & Law, 2017). In this line, Tung and Au (2018) concluded that robots
364 involve families, connecting parents and children, enabling co-creation experiences.

365 The ‘solo’ category led to significant results for all emotions except for ‘sadness’. The most
366 significant emotion with a positive influence on the ratings were ‘joy’ ($\beta = 1.538$; $p <$
367 0.001) and ‘positive’ ($\beta = 1.201$; $p < 0.001$). ‘Disgust’ is the most representative negative
368 emotion, causing a decrease in the final rating ($\beta = 0.590$; $p < 0.001$). The following review
369 reveals this:

370 *I was unsuccessful in retrieving my luggage from the robot. (Solo, Disgust, Review*
371 *Rating 3/5)*

372

373
374

Table 6. Multivariate logistic regression for traveller’s typologies: friends and business

	<i>Emotions and sentiments</i>	β	95% CI Lower Upper	p-value
<i>Friends</i> (N=10732)	Anger	0.838	[0.780, 0.900]	0.000***
	Anticipation	0.930	[0.896, 0.965]	0.000***
	Disgust	0.545	[0.503, 0.590]	0.000***
	Fear	0.836	[0.779, 0.897]	0.000***
	Joy	1.641	[1.562, 1.724]	0.000***
	Sadness	1.086	[1.022, 1.153]	0.007**
	Surprise	0.923	[0.875, 0.973]	0.003**
	Trust	0.931	[0.893, 0.971]	0.001**
	Negative	0.837	[0.803, 0.873]	0.000***
<i>Business</i> (N=22775)	Positive	1.170	[1.141, 1.200]	0.000***
	Anger	0.848	[0.810, 0.888]	0.000***
	Anticipation	0.894	[0.872, 0.917]	0.000***
	Disgust	0.588	[0.558, 0.620]	0.000***
	Fear	0.878	[0.839, 0.920]	0.000***
	Joy	1.531	[1.483, 1.580]	0.000***
	Sadness	1.067	[1.026, 1.111]	0.001**
	Surprise	1.009	[0.975, 1.045]	0.611
	Trust	0.977	[0.952, 1.003]	0.086
Negative	0.773	[0.752, 0.793]	0.000***	
Positive	1.159	[1.141, 1.178]	0.000***	
Signif. codes : *** 0.001 ** 0.01 * 0.05 Friends: <i>McFadden’s pseudo R-squared: 0.027</i> <i>Likelihood ratio chi-squared statistic: 270.062, p-value: 0.000***</i> Business: <i>McFadden’s pseudo R-squared: 0.134</i> <i>Likelihood ratio chi-squared statistic: 3410.955, p-value: 0.000***</i>				

375

376 **Regarding** ‘friends’ and ‘business’ categories, the results **were** significant except ‘surprise’
 377 and ‘trust’ for business travellers. The results revealed that there is a constant in the
 378 different categories. Considering the ‘friends’ category, the emotion that most influenced
 379 the ratings **positively was** ‘joy’ ($\beta = 1.641$; $p < 0.001$), and the emotion that **was** more likely
 380 to cause a drop in the ratings was ‘disgust’ ($\beta = 1.531$; $p < 0.001$). The following review
 381 exemplifies these:

382 *The hotel also has a robot called Alina who will cater to your every need by*
 383 *delivering requested items to your room . . . we were very impressed! (Friends,*
 384 *Positive, Joy, Review Rating: 5/5)*

385 Regarding the ‘business’ category, ‘joy’ **was** also the most influential positive emotion ($\beta =$
 386 1.641 ; $p < 0.001$), **and** ‘disgust’ **was** the most negative one ($\beta = 0.588$; $p < 0.001$). The
 387 following review provides evidence of this aspect:

388

389 *Jen is a robot that delivers room service snacks directly to your room from the lobby to*
390 *every single room in the hotel. She even talks to you :) Brilliant! (Business, Positive,*
391 *Joy, Review Rating: 5/5)*

392

393 **4. Conclusions, implications, limitations, and future research lines**

394

395 The accommodation industry is irretrievably moving towards a new paradigm defined by
396 Industry 5.0. Following the proposal of service transformation from Kandampully et al.
397 (2021), the pathway called ‘Renovation’ may be influenced by technological disruptions
398 such as the implementation of the Internet of Things (IoT) and AI, which have helped to
399 accelerate the rate at which renovation takes place within service firms. Thus, technological
400 disruptions are helping firms transform rapidly from outdated industry structures, processes
401 and practices (Buhalis et al., 2019). Wilk-Jakubowski et al. (2022) argued that it is urgent
402 to study the increasing autonomy of robots and the accompanying networks of intricate
403 interactions between them and customers. This paper offers new insights considering the
404 Industry 5.0 approach, in response to the claims of Manthiou and Klaus (2022) and Goel et
405 al. (2022) that it is urgent to analyse the different factors affecting the customer experience
406 derived from interactions with robots in tourism services.

407

408 The main theoretical implication derived from this research is that reviews including HRI
409 terms generate higher ratings than those without these terms. This means that incorporating
410 robots into the guest experience benefits the relationship with the customer by creating an
411 emotional link between customers and hotel brands. These research results are linked with
412 the effect that satisfactory experiences provoke positive reviews (reviews that give high
413 ratings) (Li et al., 2013; Nieto et al., 2014).

414

415 The results of the ordinal logistic regressions show a relationship between the categories of
416 the functionality of robots/travellers and the rating given in a review. First, ordinal logistic
417 regressions reflect that the sentiment that increases ratings the most is ‘joy’. However, the
418 occurrence of HRI terms can also provoke negative emotions and sentiments. There is a
419 link between these negative emotions and sentiments, and consumers will give lower
420 ratings to the hotel. This means that if the robots provoke negative emotions and sentiments
421 through interactions with guests, this will be reflected in a lower final rating (RQ1).

422

423 Second, in the case of the robot functionality, emotions and sentiments impact differently
424 considering robot typology. The emotion of ‘disgust’ affects ‘concierge robot’ and ‘room
425 service robot’ typologies. Even ‘joy’ provokes a higher rating than negative emotions and
426 sentiments; negative emotions and sentiments can arise when the robot is not working
427 correctly (RQ2). Conversely, reviews or comments with negative valence occur when
428 expectations are violated because of incompetence, inefficiency, irresponsible attitudes,
429 behaviours or inferior products (Barreda & Bilgihan, 2013). Expectations generated by
430 robot presence and individuals’ prior expectations could influence robot evaluation (de
431 Graaf et al., 2015). De Graaf and Allouch (2017) showed that people with high prior

432 expectations of a robot's lifelikeness would evaluate it more positively than people who
433 had low prior expectations. Emotions are aroused during an interaction with a product.
434 Users may experience satisfaction when a product fulfils their expectations, **which** may
435 further escalate to joy when their expectations are exceeded (Weiss et al., 2009; Tung &
436 Au, 2018).

437 Finally, the findings showed relevant impacts of emotions and sentiments not identified
438 previously by other studies about traveller type. These results add new insights considering
439 that previous studies only identified it in a general way without **discussing** the combination
440 of robot typology and traveller type. The findings show a relevant impact on the ratings
441 given by couple, family, solo or business travellers **as** the 'joy' emotion arises when dealing
442 with a robot, especially **for** family travellers with children (RQ3). Previous studies have
443 concluded that robots' effect is incredibly significant for children, who are strongly
444 attracted to **them** (Tung & Au, 2018).

445

446 **4.1. Practical implications**

447 Robots in hotels build a community by integrating AI tools. The application of AI tools like
448 robots must be seen as an integrated part of the service, not a merely functional aspect to do
449 easy tasks. Thus, robots are not only part of the service experience, but they also generate
450 an emotional impact on customers along with their customer journey map.

451 From the obtained results, we can synthesise three areas of focus for the hotels in the future.
452 First, hotels will need to respond to trends in demand based on traveller needs by
453 developing new offerings for all consumers. For example, families with children could see
454 service robots as an added value to their experience **because of** the emotion of 'joy' that
455 arises.

456 Second, while the robots were intended to provide a better user experience given the role
457 they play, guests communicate several negative emotions of disgust through the reviews
458 reflected in the final rating. These limitations could lead to user frustration and
459 disappointment, especially if guests experience the same challenges multiple times. This
460 negative rating is mainly linked to failures in the functionality of the robots. Thus, the
461 implementation of robots and HRI during the stay influences consumer satisfaction. This
462 means it can be positive, increasing the ratings, or negative. Therefore, it can be said that
463 HRI is a factor linked to the quality of the service and that, in this way, its proper
464 functioning is crucial, as **it** could be another characteristic of the hotel (for example, a
465 **working** elevator). Consequently, additional assistance to guests is needed to minimise
466 negative emotions and the subsequent negative ratings. Hotel managers should be aware of
467 guests' emotions and sentiments of discomfort with service robots to address possible
468 emotions of disgust or anger. They should also be aware that the deployment of service
469 robots is still relatively new in the tourism and hospitality environments, and some guests
470 may feel uneasy with the initial idea of interacting with them.

471 Finally, let us consider that those positive emotions and sentiments linked to ‘joy’ provoke
472 higher ratings on TripAdvisor for the three types of robots considered and for all traveller
473 categories except for ‘friends’. Hotels should manage the robots’ implementation in
474 hospitality environments to complement, personalise and improve HRI and customer
475 service.

476

477 **4.2. Limitations and future lines of research**

478

479 While this study contributes to both theory and practice, there are several limitations that
480 we recognise.

481 First, there is a limitation regarding the impossibility to precisely know the time of
482 interaction with robots through this type of analysis. Moreover, the travellers’ profile
483 cannot be analysed considering other variables different from the type of traveller because
484 of the characteristics of TripAdvisor information.

485 Second, there are limitations concerning Saif Mohammad’s NRC Word-Emotion
486 Association Lexicon sentiment analysis. There are difficulties in analysing the context of
487 the sentence and other elements such as irony. It is also important to mention that this
488 lexicon has more words associated with negative sentiment (7,161) than positive ones
489 (3,587) (Naldi, 2019).

490 Future research might focus on conducting a survey based on the results obtained to
491 overcome the limitations of this study and to obtain information on aspects that are not
492 present in the data. It is also possible to apply machine learning and forecasting techniques
493 to determine the effect of the emotions and sentiments identified by using the results from
494 the survey and combining them with the data used for this study.

495

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