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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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ABSTRACT

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

1. Introduction

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

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

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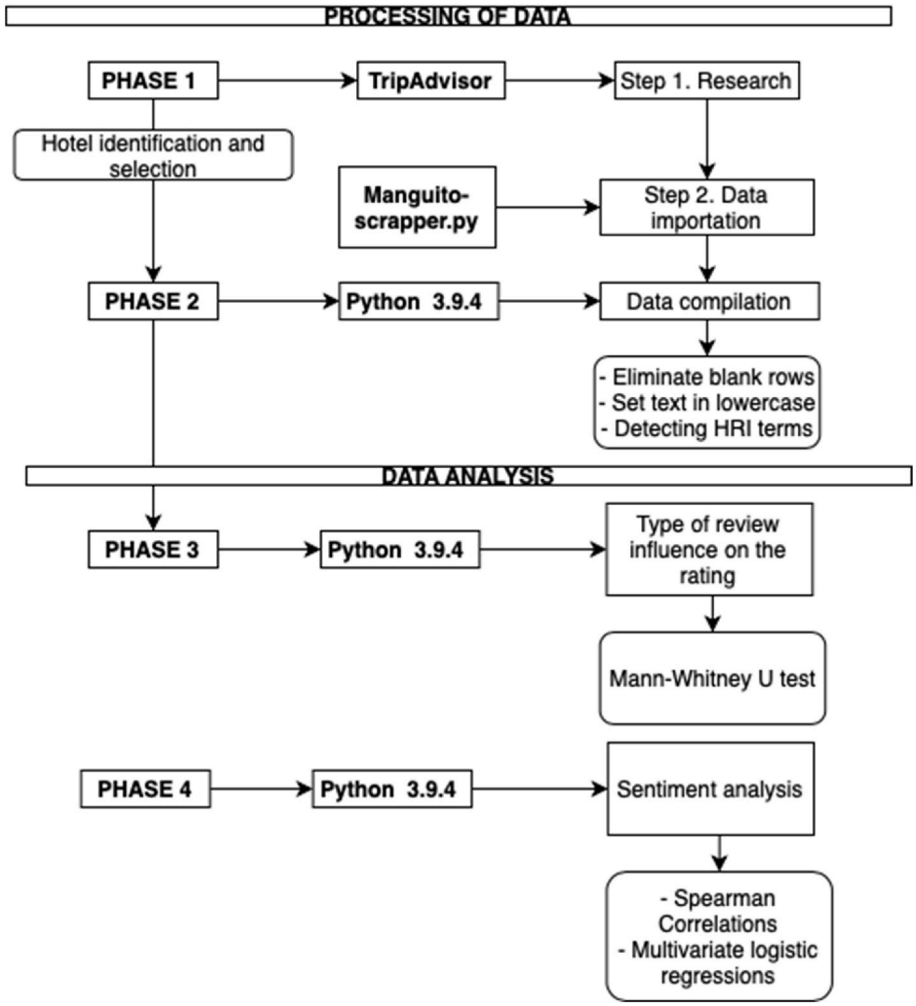

Fig. 1. Study framework.

pervasive agents on headless devices and stationary industrial robots' mechanical AI (automated locker and storage systems, restaurants, cafés and bars) (Tussyadiah, 2020).

In this study, sentiment analysis is applied. Sentiment analysis is a type of text mining method that allows to detect and identify people's attitude about a concrete issue (Alaei et al., 2019; Kirilenko et al., 2018) through analysing Big Data (Talón-Ballestero et al., 2018). Sentiment analysis has been previously applied to the tourism context, exploring sentiment in electronic word-of-mouth (eWOM), such as positive or negative online reviews left by customers for services, including hotels (Buzova et al., 2019; Fu et al., 2015; Yan et al., 2018). Through eWOM analysis, it is possible to identify the value of consumer experiences (Litvin et al., 2018), and in the case of tourism, online reviews are part of this type of data (Liu et al., 2018). Previous research about sentiment analysis of hotel reviews that confirm correlations with overall ratings on TripAdvisor concludes that sentiment analysis is well suited for this task (Lopez-Barbosa et al., 2015). This research indicates the need to extend this analysis to know which hotel's features are more likely to lead to positive user reviews (Lopez-Barbosa et al., 2015). On the other hand, previous studies have shown that robot acceptance is influenced by some personal characteristics (age, gender, culture, city of residence) and that travellers with different travel purposes tend to rate each hotel attribute differently (Rhee & Yang, 2015) and have different interactions with the robots: for example, travellers with children are susceptible to interaction with robots (Fuentes-Moraleda et al., 2020; Pinillos et al., 2016; Tung & Au, 2018).

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

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

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

RQ3. Is there a relationship between the overall rating of hotels

(TripAdvisor) and the emotions and sentiments derived from HRI terms expressed by traveller type?

2. Methodology

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

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

2.1. Selecting the hotels and importing the dataset

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

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

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… '

2.2. Data compilation

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

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

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

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

2.3. Mann–Whitney U test

The first test conducted was the Mann–Whitney *U* test, a nonparametric statistical test that allows us to identify the influence of the two types of reviews (with HRI terms and without them) on the rating. This

Table 2
Spearman correlations among travellers' sentiments and ratings according to 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***

***$p < 0.001$ **$p < 0.01$ * $p < 0.05$.

test guarantees the relevance of analysing TripAdvisor reviews to obtain conclusions about HRI and Industry 5.0 concepts. By conducting this test, we can check the relationship between the overall rating of hotels given in the reviews that include terms related to HRI and the rest of the reviews.

2.4. Sentiment and analysis

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

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

2.5. Spearman correlations

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

2.6. Multivariate logistic regressions

By using the Logit class in Python, where we set the optimiser BFGS (Broyden-Fletcher-Goldfarb-Shanno), a multivariate logistic regression for each robot and traveller category was performed. Previous studies recommended applying multivariate logistic regressions to analyse similar data (Agresti, 2003; Thrane, 2005).

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

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

3. Results

3.1. Type of review influence on the rating

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

3.2. Analysis by robot functionality

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

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

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

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

When talking about 'cloakroom robot', the variables 'disgust', 'joy', 'trust', 'surprise' and 'positive' were significant at the 0.05 level. These results showed that reviews including 'joy' associated with 'cloakroom robot' were 2.851 times more likely to report a better rating. Previous research has identified a relationship between the implementation of service robots and emotions like fun and excitement (Gretzel & Murphy, 2019). Reviews illustrating this issue included the following:

> 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

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

	Emotions and sentiments	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 = 28,501)	**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****

(if lots of people doing the same thing simultaneously), but so cool! (Cloakroom Robot, Positive, Review Rating: 5/5)

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

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

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

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

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

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

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

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

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

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

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

3.3. *Analysis by traveller's typology*

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

Table 4 follows the same trend as Table 2, revealing a negative association among negative sentiments and words in reviews. The strongest correlations occurred in the opposite direction between negative sentiment and reviews. These results showed that the higher the presence of negative sentiment, the lower the rating given to the hotel. The words related to 'disgust' and 'negative' showed a higher intensity regarding the traveller category. The category 'business' presented the highest negative emotion. This means that positive related emotions and

Table 4
Spearman correlations among travellers' sentiments and rating according to 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*****

***$p < 0.001$ **$p < 0.01$ * $p < 0.05$.

sentiments do not show any positive influence on the analysed corpus.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

The accommodation industry is irretrievably moving towards a new paradigm defined by Industry 5.0. Following the proposal of service transformation from Kandampully et al. (2021), the pathway called 'Renovation' may be influenced by technological disruptions such as the implementation of the Internet of Things (IoT) and AI, which have helped to accelerate the rate at which renovation takes place within service firms. Thus, technological disruptions are helping firms transform rapidly from outdated industry structures, processes and practices (Buhalis et al., 2019). Wilk-Jakubowski et al. (2022, p. 101935) argued that it is urgent to study the increasing autonomy of robots and the accompanying networks of intricate interactions between them and customers. This paper offers new insights considering the Industry 5.0 approach, in response to the claims of Manthiou and Klaus (2022) and Goel et al. (2022) that it is urgent to analyse the different factors affecting the customer experience derived from interactions with robots in tourism services.

The main theoretical implication derived from this research is that reviews including HRI terms generate higher ratings than those without these terms. This means that incorporating robots into the guest experience benefits the relationship with the customer by creating an

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

	Emotions and sentiments	β	95% CI Lower Upper	p-value
***Couple* (N = *34,372*)**	**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***
***Family* (*N* = *22,467*)**	**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***
***Solo* (*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:
McFadden's pseudo R-squared: 0.042
Likelihood ratio chi-squared statistic: 1343.495, p-value: 0.000***
Family:
McFadden's pseudo R-squared: 0.086
Likelihood ratio chi-squared statistic: 1856.918, p-value: 0.000***
Solo:
McFadden's pseudo R-squared: 0.031
Likelihood ratio chi-squared statistic: 210.107, p-value: 0.000***

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

	Emotions and sentiments	β	95% CI Lower Upper	p-value
***Friends* (*N* = *10,732*)**	**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***
	Positive	1.170	[1.141, 1.200]	0.000***
***Business* (*N* = *22,775*)**	**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:
McFadden's pseudo R-squared: 0.027
Likelihood ratio chi-squared statistic: 270.062, p-value: 0.000***
Business:
McFadden's pseudo R-squared: 0.134
Likelihood ratio chi-squared statistic: 3410.955, p-value: 0.000***

emotional link between customers and hotel brands. These research results are linked with the effect that satisfactory experiences provoke positive reviews (reviews that give high ratings) (Li et al., 2013; Nieto et al., 2014).

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

Second, in the case of the robot functionality, emotions and sentiments impact differently considering robot typology. The emotion of 'disgust' affects 'concierge robot' and 'room service robot' typologies. Even 'joy' provokes a higher rating than negative emotions and sentiments; negative emotions and sentiments can arise when the robot is not working correctly (RQ2). Conversely, reviews or comments with negative valence occur when expectations are violated because of incompetence, inefficiency, irresponsible attitudes, behaviours or inferior products (Barreda & Bilgihan, 2013). Expectations generated by robot presence and individuals' prior expectations could influence robot evaluation (de Graaf et al., 2015). De Graaf and Allouch (2017) showed that people with high prior expectations of a robot's lifelikeness would evaluate it more positively than people who had low prior expectations. Emotions are aroused during an interaction with a product. Users may experience satisfaction when a product fulfils their expectations, which may further escalate to joy when their expectations are exceeded (Tung & Au, 2018; Weiss et al., 2009).

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

4.1. Practical implications

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

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

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

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

4.2. Limitations and future lines of research

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

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

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

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

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Impact statement

This research presents an innovative approach considering the analysis of 107,663 online TripAdvisor reviews involving 80 hotels worldwide to analyse the influence of the terms related to Human-Robot Interaction on the hotels' rating from the Text Mining approach from the Industry 5.0 approach. The results were derived from an original methodological approach by conducting ordinal logistic regressions considering the robot typology and traveller type. Results show that reviews including HRI terms generate a higher rating than those without these terms. It means that the implementation of robots in hotels is linked with a higher value experience from the customer's point of view. The practical implications are essential for hotel managers, highlighting that they should be aware of guests' emotions and sentiments of discomfort with service robots to address possible emotions of disgust or anger because it negatively impacts the hotel rating.

Declaration of competing interest

None.

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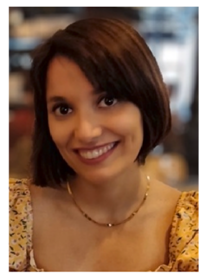

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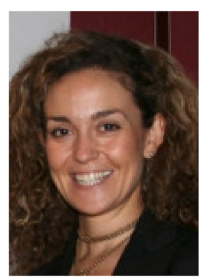

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