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The role of emotions in the consumer meaning-making of interactions with social robots

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ABSTRACT

The interaction with social robots is supposed to be a unique and emotionally charged activity. Based on the diffusion of innovations literature, subjective feelings represent a driver of the innovation diffusion process. Yet, to date, no study has comprehensively assessed consumers' emotional responses over time to interactions with social robots. Thus, the study aims to address this research gap by combining innovation diffusion and psychology literature. The emotional content of customers' self-reported communication on social robots deployed across international hotels is categorized through Plutchik's wheel of emotions by using advanced text analytics techniques to track and analyze its evolution over time. Findings show that consumers generally express positive emotions towards social robots. *Trust*, *anticipation* and *joy* are the most frequently expressed emotions. Empirical results from multivariate regression analysis indicate that *joy* has the greatest magnitude and that *anticipation* and *surprise* do not significantly influence consumers' opinions and comments. Negative emotions are less frequent but have a significantly negative impact, which might be considered by hotel managers willing to introduce social robots.

1. Introduction

In recent years, the adoption of robots has gone beyond the assembly line, gradually embracing the service industry (Campa, 2016). In service settings, robots are seen as social entities that can actively affect customer experience, and have been named “social robots” (Wirtz et al., 2018). Indeed, the innate tendency of human beings to anthropomorphize robotic entities (Waytz et al., 2010), and the growing sense of *active agency* associated with them, have made social robots a relational actor to all effects (Jörling et al., 2019). This has brought about novel and emotionally charged interaction experiences for service consumers (Young et al., 2011). These experiences are supposed to completely revolutionize the service encounter (Larivière et al., 2017). For this reason, social robots are a crucial technological component in the framework revolving around the *fourth industrial revolution* (Mariani and Borghi, 2019) and, in turn, they are considered the workforce of the future in a wide range of service settings (Choi et al., 2020b).

The uniqueness of human–robot interactions and their increasing importance in the foreseeable future have sparked scholarly interest in this new relational entity. In the first place, researchers have tried to conceptualize the role played by social robots to devise meaningful relationships for empirical testing (i.e., Larivière et al., 2017; van Doorn et al., 2017; Wirtz et al., 2018; Xiao and Kumar, 2021). Conceptual efforts have been recently followed by empirical examinations, revolving around specific traits of human–robot interactions, such as intention to use (Chuah et al., 2021), acceptance (Borau et al., 2021), trust (Chi et al., 2021), consumer attribution of responsibility (Jörling et al., 2019), service failure (Choi et al., 2020a), social vulnerability (Khaksar et al., 2016) and robot anthropomorphism (Mende et al., 2019). Nonetheless, as portrayed by recent literature reviews, a comprehensive understanding of the impact of social robots has not yet been achieved (Belanche et al., 2020; Tussyadiah, 2020), especially in the post-service consumption phase (Lu et al., 2020). In particular, despite acknowledging that human–robot interactions can be associated with a mixed set of emotions, either positive or negative (Tung and Au, 2018), and that the emotional content is among the most frequently referenced aspects in consumers' evaluations of this new form of interaction (Fuentes-Moraleda et al., 2020), to date no study has conducted a comprehensive examination of consumers' emotional responses to social robot encounters. From a diffusion of innovation perspective, this is rather surprising; subjective feelings are of paramount importance in the *innovation-decision process* and, in turn, individual opinions exert

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significant explanatory power in devising the shared *meaning* of an innovation in a social system (Rogers, 2003). Besides, in psychology literature, emotions are considered an integral part of the *meaning-making* process that guides the formation of consumers' mental representation of a specific entity (Osgood et al., 1957). Therefore, shedding light on the emotional reaction during the interaction with social robots will not only unveil users' acceptance of social robots but, above all, will provide precious insights into the diffusion process. This is even more compelling as social robots are supposed to become more widespread in a post-pandemic world (Henkel et al., 2020), potentially improving employee work conditions (Goeldner et al., 2015) and possibly significantly contributing to the growth of labour productivity, just as in the case of their industrial counterparts (Jaeger et al., 2015; Kopp et al., 2020).

To bridge the aforementioned research gaps, this paper aims to provide an answer to the following interrelated research questions: 1) What emotions are expressed by consumers after human–robot interaction? 2) What is the relationship between emotions and the meaning that consumers make of social robots?

Grounded in the bodies of literature dealing with diffusion of innovation and psychology, this paper adopts Plutchik's (1980) *wheel of emotions* as the main conceptual framework to capture the emotional content of people-to-people communication revolving around social robots. In particular, advanced text analytics techniques pertaining to the sentiment analysis and emotion recognition domains are deployed to classify online communications belonging to a group of 19 international hotels adopting social robots. We decided to focus on hotel companies since they are considered a remarkable application domain for social robots in the marketplace (Ivanov et al., 2017; Tussyadiah, 2020). On the one hand, due to the importance of the time dimension in the diffusion of innovation literature – through a one-factor repeated-measures design (Myers et al., 2010) – emotional response trends are described and tracked over time. On the other hand, multivariate regression is deployed to examine the relationship between basic emotions and customers' opinions, using emotions as antecedents of the meaning-making process. To the best of the authors' knowledge, this is the first attempt to systematically analyze consumer response to social robots over time through a theory-consistent framework. Moreover, the novelty of this manuscript stems from the fact that we are not only examining the sign of the emotional dimensions' coefficient, but also their magnitude. This allows us to comprehensively single out the individual contribution of each and every basic emotion to the consumer's meaning-making of social robots (proxied by opinion polarity). Accordingly, this work makes a distinctive contribution at the intersection of human–robot interaction and electronic word-of-mouth.

The paper unfolds as follows. Section 2 provides an overview of the literature on the diffusion of innovation theory, on social robots and on the conceptual framework used in this study, which stems from psychology literature. In Section 3, the empirical setting and the phases of data collection and preparation are described, as are the empirical strategy and operationalization of the focal variables. Results and findings are discussed in Section 4, while Section 5 explores the research contributions and practical implications of the study. Lastly, Section 6 summarises the findings and illustrates limitations and future research directions.

2. Literature review

2.1. Diffusion of innovation: setting the foundation of the study

The study of innovation diffusion has become an established research area in a wide range of scientific disciplines (Rogers, 2003). Yet, the formation of the classical diffusion paradigm can be attributed to two distinctive studies belonging to the *rural sociology* and *public health and medical sociology* research domains (Valente and Rogers, 1995). Indeed, the study of Ryan and Gross (1943) pertaining to the investigation of the adoption process of hybrid seed corn in two distinctive Iowa communities during the agricultural revolution sets the foundations of the research field. The authors' findings suggested that the adoption rate formed an S-shaped curve over time. As pointed out by Valente and Rogers (1995), several elements, such as theoretical framework, methodology and interpretation of the results deployed by Ryan and Gross (1943), have played a major influence in the investigation of subsequent scholars. Nonetheless, it was not until the research on drug diffusion conducted at Columbia University during the 1950s and 1960s (i.e., Coleman et al., 1957, 1966; Menzel and Katz, 1955) that the importance of interpersonal networks was found to play a major role in the diffusion process (Rogers, 1994). Indeed, as initially postulated by Ryan and Gross (1943), subjective evaluations exchanged by the members of the social system were found by Columbia's researchers at the heart of the diffusion of innovations process, with opinion leaders playing the most crucial role. This ultimately led to the conceptualization of innovation diffusion as a social process (Rogers, 2003).

To devise a unified research field in the diffusion of innovation, Everett Rogers published his first seminal book *Diffusion of Innovation* in 1962, which has been followed by a new edition every ten years since. Thus, as depicted in his latest book, diffusion of innovation can be considered: "The process by which an innovation is communicated through media over time among members of a social system" (Rogers, 2003, p. 5). This definition includes the four elements of the diffusion of innovation process: 1) the innovation, 2) communication channels, 3) time and 4) social system (Rogers, 2003). Following Rogers' framework, innovation is "an idea, practice, or project that is perceived as new by an individual or other unit of adoption" (Rogers, 2003, p. 12). At this stage, it is important to notice that the diffusion of innovation is linked to a certain degree of uncertainty that pushes an individual to search for information to fill their knowledge gap. Information about the innovation is spread across a series of communication channels, such as mass media and interpersonal networks, with the latter playing a crucial role through word-of-mouth (WOM) (Rogers, 2003). Yet, with the advent of the Internet, this framework can be extended by including electronic word-of-mouth (eWOM) as a specific form of WOM communication happening over the Internet (Hennig-Thurau et al., 2004). The third element of diffusion of innovation is time. This is because the innovation-decision process, which guides people in their adoption decisions, can be effectively divided into five main phases: 1) knowledge-awareness, 2) persuasion, 3) decision, 4) implementation and 5) confirmation (Rogers, 2003). In the first phase, the individual acquires information about the innovation. This is followed by an evaluation of the information gathered to form an attitude towards the innovation, which can lead the person to adopt or reject the innovation. In the former case, in the implementation phase, the individual effectively adopts and tests the innovation which would ultimately confirm or disconfirm their initial attitude. Nonetheless, not all individuals display the same level of *innovativeness,* conceived as "the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas" (Rogers, 2003, p. 22). Thus, based on the latter concept, adopters can be classified into five distinctive categories: 1) Innovators, 2) Early Adopters, 3) Early Majority, 4) Late Majority and 5) Laggards. One of the crucial phases of the innovation-decision process lies in the persuasion stage, since this is "when an individual forms a favourable or unfavourable attitude towards the innovation" (Rogers, 2003, p. 20). While in the knowledge stage, mental activity is mainly cognitive, at the persuasion level a crucial role is played by affective (or feeling) thinking. Knowing about a new idea is the first step towards the formation of an attitude. However, subjective perceptions of other users trying the innovation have been found to elicit a significant influence, especially on the Early Majority. Therefore, being that the adoption by the Early Majority is the point where the diffusion curve actually "takes off", it is clear how social mechanisms can be paramount to define the success of an innovation.

This brings us to the fourth element of the innovation process, namely the social system (Rogers, 2003). Communication about the new idea is spread in a network of entities where social ties and opinion leaders shape the diffusion process. Opinion leaders are rarely the first to adopt the innovation but since their judgement is sought as a reliable source of information by a multitude of individuals, it carries a critical weight in the speed and breadth of innovation diffusion (Cho et al., 2012; Van Eck et al., 2011). This is because they are usually more knowledgeable about the innovation and their judgement is less prone to be affected by norms (Van Eck et al., 2011). Nonetheless, despite distinct types of opinion leaders exerting different effects, the latter is substantial only if a critical mass of initial adopters has been reached in the diffusion process (Cho et al., 2012). Thus, the social system is actively involved in the definition of an innovation's consequences. This is due to the fact that change agents, in a wide range of cases, can predict and anticipate an innovation's *form* and *function*, but they are rarely able to envision an innovation's *meaning*, expressed by consumers through their subjective perceptions (Rogers, 2003). Accordingly, as suggested by Rogers (2003, p. xxi), "the meaning of an innovation is thus gradually worked out through a process of social construction". Thus, per se, the diffusion of innovation is a social process and not simply a technical matter. The sociological literature on audiences and categories (e.g., Hannan, 2010) in the field of innovation has clearly pointed out that innovations are socially construed (Borup et al., 2006).

Despite providing a solid theoretical ground for studying the diffusion of innovation, Rogers' (2003) framework seems to have been overlooked by scholars investigating the deployment of a new form of innovation, under the guises of social robots (Tussyadiah, 2020). Social robots are supposed to completely redefine the service experience (Larivière et al., 2017). Nonetheless, as suggested by extant literature reviews (i.e., Belanche et al., 2020; Blut et al., 2021; Ivanov et al., 2019; Lu et al., 2020; Sarrica et al., 2019; Tussyadiah, 2020; Wirtz et al., 2018), much more scholarly effort is needed to develop a comprehensive and unified understanding of the impact of social robots. The next section introduces social robots and provides an overview of extant studies revolving around the subject.

2.2. The rise of social robots

In the past few years, industrial robots deployed by manufacturing companies (Pillai et al., 2021) have been gradually equipped with social characteristics, which have allowed them to become an attractive source of innovation beyond industrial settings (Campa, 2016). In particular, this has happened thanks to the infusion of artificial intelligence in machines, one of the major forces of the so-called *fourth industrial revolution*, a phenomenon developed in the manufacturing sector, which is gradually embracing the service industries (Fosso Wamba et al., 2021; Mariani and Borghi, 2019).

As suggested by Young et al. (2011, p. 54), robots themselves elicit "unique, emotionally charged interaction experiences". This is because when human beings interact with robotic entities, they tend to anthropomorphize them (Hegel et al., 2009; Waytz et al., 2010). They also attribute intentionality to robots, which strengthens a sense of *active agency* of robots (Young et al., 2011). Despite people being prone to humanize a wide range of non-living "things" in their social context, extant literature confirms their predisposition towards robots over other technologies (Young et al., 2011). The arguments put forward by Young et al. (2011) have been recently used by Jörling et al. (2019) and Wirtz et al. (2018) in defining social robots. In particular, emphasizing the importance of interaction capabilities, Wirtz et al. (2018, p. 909) defined social robots as "system-based autonomous and adaptable interfaces that interact, communicate, and deliver service to an organization's customers". Hence, a social robot – leveraging on its high level of agency and its physical embodiment – can be perceived by a customer as a *social agent* (van Doorn et al., 2017). Based on this assumption, van Doorn et al. (2017, p. 44) introduced the term "automated social presence" defining it "as the extent to which machines (e.g., robots) make consumers feel that they are in the company of another social entity". Thus, a social robot is not merely seen as a cog in the assembly line but rather as a social entity that can actively affect the customer experience.

The interest in this novel type of relational actor has flourished in recent years among management (Lu et al., 2020), service marketing (Belanche et al., 2020; Mariani et al., 2022; Wirtz et al., 2018) and, especially, tourism and hospitality scholars (Ivanov et al., 2019; Tung and Law, 2017). This is because the service consumer experience and, most notably, the "tourist" experience is supposed to undergo a profound transformation due to the introduction of social robots (Larivière et al., 2017; Tung and Law, 2017). Yet, according to recent literature reviews, research on human–robot interaction (HRI) is still highly conceptual (Ivanov et al., 2019) and fragmented (Lu et al., 2020). There is a nascent field of empirical studies aiming to generate useful knowledge in the research field (Belanche et al., 2020). However, as pointed out by Tussyadiah (2020), the adoption process and impacts of intelligent automation have not been fully understood. For instance, scholars have analysed a multifaced set of aspects in HRI, such as attribution of responsibility (Jörling et al., 2019), acceptance (Borau et al., 2021), anthropomorphism (Mende et al., 2019), trust (Chi et al., 2021), intention to use (Chuah et al., 2021; de Kervenoael et al., 2020), social vulnerability (Khaksar et al., 2016) and service failure (Choi et al., 2020a). Yet the main sources of data of the aforementioned studies were represented by laboratory experiments and surveys without taking into account people-to-people communications revolving around social robots.

Through the lens of the diffusion of innovation theory this can be seen as a remarkable research gap since, as mentioned in the previous section, the subjective opinions of individuals can effectively shape the collective meaning attributed to the innovation by the social system. Hence, building on the research tradition embracing the study of the diffusion of innovation through the examination of people-to-people communications (i.e., Chevalier and Mayzlin, 2006; Liu, 2006), a new research trajectory is taking shape within the HRI domain, involving the analysis of this type of content (Borghi and Mariani, 2021; Chuah and Yu, 2021; Fuentes-Moraleda et al., 2020; Mariani and Borghi, 2021; Tung and Au, 2018; Yu, 2020). As far as social robotic service encounter experiences are concerned, Tung and Au (2018) were the first scholars relying on online reviews (ORs) to explore qualitatively customers' perceptions while using social robots across a wide range of HRI dimensions related to the user experience. Using a small and limited sample of 329 ORs from four international hotels with a different degree of robotic adoption, the authors found that robotic service encounters could lead to a new level of experience co-creation, since consumers seem to establish a sort of "relationship" with social robots. By embracing a netnographic approach to online content, including also ORs, Gretzel and Murphy (2019) assessed the ideological positions of consumers towards the use of robotics in tourism and hospitality and found evidence supporting all the four ideological fields studied: techtopian, green luddite, work machine and techspressive. (For a more comprehensive understanding of the four technology ideologies, please refer to Table 1 in Gretzel and Murphy (2019)). Taking this a step further, Fuentes-Moraleda et al. (2020) devised a social robot acceptance model from the manual and automatic coding of robot-related ORs. Interestingly, their exploratory data analysis reveals that the social-emotional dimension is among the most relevant features when discussing HRIs. Moreover, by examining comments to two robot-related YouTube videos, Yu (2020) highlights how the dimensions of perceived safety, animacy, intelligence, anthropomorphism and likeability shape the attitude to use social robots. On the same line of research, Chuah and Yu (2021) analysed the influence of robots' affective behavior on customers' feelings, assessing that the expressions of happiness and surprise by the social robot have a positive influence on consumers' opinions. Yet, in the last two cases, the authors did not leverage communications stemming from first-hand experiences, but rather from potential HRIs by analyzing comments made by online users to video stimuli. Lastly, Borghi and Mariani (2021) performed a quantitative exploration of self-reported HRI through ORs in the hotel setting, bringing time into the picture. They assessed how ORs covering social robots have increased over time, reaching a share of 19.2 % over the total number of ORs after 18 months. All in all, the abovementioned works represent the first attempts to analyze people-to-people conversations covering social robots. Yet, despite the studies' findings, there are still significant research gaps to be filled.

Indeed, critically analyzing recent investigations from a diffusion of innovation perspective, we can assess why the adoption of social robots has not truly taken off yet. If we take Borghi and Mariani's (2021) results as a potential proxy of consumers' adoption, we are between the early adopters and early majority categories in the S-shaped diffusion curve. Therefore, we might argue that we are in a crucial stage in the diffusion process where early adopters' opinions can effectively influence other innovation adopters and innovation-decision process. As suggested by Rogers (2003), in the persuasion stage, individual thinking is guided by the feelings (or affective) component. Hence, this would suggest that an in-depth investigation of subjective feelings embedded into HRI communications would aid researchers to gain valuable knowledge to forecast the outcomes of the diffusion of social robots. Interestingly, extant studies have pointed out the relevance of emotional features in shaping consumers' understandings of the meaning of social robots (Chuah and Yu, 2021; Fuentes-Moraleda et al., 2020). However, they have not delved deeper into the understanding of the emotions associated with this type of content. On the one hand, despite examining the overall sentiment polarity of online reviewers' comments, Chuah and Yu (2021) did not further explore its emotional composition in a granular manner. On the other hand, Fuentes-Moraleda et al. (2020) did not leverage any theory-consistent framework to assess the emotional content of online communications and only provided a descriptive exploratory analysis without testing any association between emotional dimensions and the polarity of consumers' opinions. Other studies leveraging surveys and laboratory experiment data have only focused on specific emotions, such as trust (i.e., Chi et al., 2021), without disentangling a more comprehensive set of emotions. Thus, this study aims to bridge the aforementioned research gap by examining the emotions reported in people-to-people communications over time and their role in shaping consumers' social robot meaning-making.

To provide a solid theoretical ground to our investigation of consumers' emotional responses to social robots, the next section provides a brief overview of the psychology literature revolving around the concepts of *meaning* and *emotions*, and portrays the conceptual framework used in the study.

2.3. Meanings, meaning-making and emotions

For human beings, *meanings* represent a crucial aspect of their life (Frankl, 1963) due to our natural inclination to use them to define our view of reality and inform our actions (Krauss, 2005). In the literature about the diffusion of innovation, *meaning* can be defined as "the subjective perception of the innovation by the clients" (Rogers, 2003, p. 33). Yet the study of meaning is rooted in the psychology, social psychology and sociology literature, where research on the topic has seen a growing interest over time (Park, 2010). Despite the proliferation of definitions (Park, 2010), meaning can be defined as a "mental representation of possible relationships among things, events, and relationships. Thus, meaning connects things" (Baumeister, 1991, p. 15). In particular, *meaning-making* is related to the processes enacted in people's minds to reduce the discrepancy between global (individuals' general orienting system) and appraised beliefs, goals and subjective feelings of an event (Park, 2010). Thereby, emotional or affective reactions play a crucial role in the meaning-making process (Osgood et al., 1957). This kind of reaction can be seen as "creative responses to external and internal stimuli that trigger biological and constructed schema to differing degrees" (Rahmani et al., 2019, p. 194).

In the psychology and cognitive science literature, there is an ongoing debate about the classification of emotions into useful taxonomies (Mohammad and Turney, 2013). Some psychological theories classify emotions through the identification of basic building blocks (i.e., Ekman, 1992), while others consider them as a more complex construct (i.e., Zajonc, 1984). Yet, this debate seems only to be a matter of definition (Plutchik, 1985) since there is a significant overlap between basic and complex emotions (Mohammad and Turney, 2013). On this note, a wide range of psychological theories has been put forward to devise basic emotions (i.e., Ekman, 1992; James, 1884; Plutchik, 1962). For instance, three emotional categories have been suggested by Francisco and Gervás (2006), namely: activation, dominance and pleasantness. Ekman (1992) proposed six emotional dimensions, such as anger, joy, sadness, fear, surprise and disgust. Yet, Plutchik (1980) suggests an emotional framework made of eight basic emotions, adding to Ekman's (1992) dimensions, the basic emotions of anticipation and trust. Plutchik's (1980) framework has been graphically represented by the author through a wheel since, in his theorizing, the eight basic emotions create opposing pairs: anger–fear, anticipation–surprise, joy–sadness, and trust–disgust. In particular, in line with the work by Plutchik (1980), joy captures expressions of happiness and pleasure, while sadness refers to moments of great unhappiness. Anger is an expression of hostility or annoyance towards an entity, whereas fear focuses on the perceptions of a potential threat or a danger. Trust relates to beliefs of good quality and reliability, while disgust depicts a strong feeling of disapproval or dislike. Lastly, anticipation and surprise occur when individuals look forward to a certain situation or they find themselves dealing with an unexpected event, respectively. Interestingly, this framework has been embraced by several research communities, such as computational linguistic (i.e., Mohammad and Turney, 2013), management (i.e., Nguyen et al., 2020) and service science (i.e., Rahmani et al., 2019), mainly to classify social media communication (Wang et al., 2019). Indeed, as suggested by Nguyen et al. (2020), Plutchik's (1980) eight basic emotions can be effectively used to categorise the emotional content of social media-based WOM. This is due to the fact that emotions are not only expressed through human behaviours, such as facial expressions, but also from words reported in written communications (Mohammad and Turney, 2013). Thus, we chose Plutchik's (1980) emotional wheel as the reference emotional framework for our study, since: 1) it is strongly rooted in the psychology literature; 2) it has been used empirically to map people-to-people social media communication; and 3) it represents a more balanced superset of other potential choices (i.e., Ekman, 1992).

As such, we are confident that the use of the eight basic emotions conceived by Plutchik (1980) can aid us in unravelling the complexity of consumers' emotional responses to social robots and, in turn, can help us examine how they are related to the meaning attributed by consumers to this new form of innovation. Fig. 1 depicts the conceptual framework of the study.

3. Methodology

3.1. Empirical setting and data collection

To address the research questions formulated in this study, we needed to select an empirical setting where companies have introduced social robots in their operations and consumers' opinions about social robots are publicly available. As such, we decided to focus on hotel companies, since they can be considered a remarkable example of the introduction of social robots in the marketplace (Tussyadiah, 2020). Indeed, as suggested by extant literature in tourism and hospitality, hotels represent one of the main application domains for social robots (Ivanov et al., 2017). Moreover, the global adoption of social robots is gradually rising in the chosen empirical setting, since robots are considered the workforce of the future (Choi et al., 2020b). Our reasoning is also supported by the increasing number of studies leveraging the same empirical setting (Borghi and Mariani, 2021;

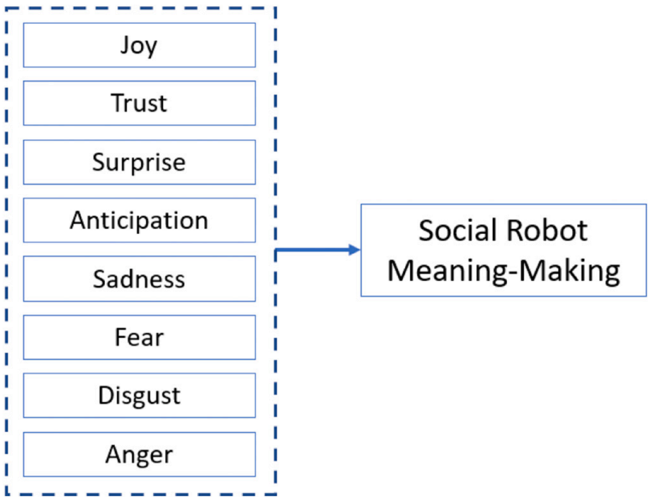

Fig. 1. Conceptual framework.

Fuentes-Moraleda et al., 2020; Tung and Au, 2018).

Thus, the first phase of the data collection entailed the determination of prominent international hotels leveraging social robots in their operation. To this aim, we followed the sampling guidelines provided by Inversini et al. (2010). Thereby, we first performed extensive online research using keywords pertaining to the role of social robots in hotel companies, as portrayed by Ivanov et al. (2017), combined with the keyword “hotel”. From the exploration of the queries' results, we were able to devise a preliminary set of hotels to include in our final sample. For each company identified at this step, we also collected a series of additional information from external sources (e.g., online and social media presence information, company reports and news materials). This was necessary to gather further information about the business and the social robot introduced in their day-to-day endeavours. Two inclusion criteria were used to select hotels for the final sample: 1) the hotel should have had a TripAdvisor account and 2) the period of deployment of the social robot could be identifiable. Therefore, the final sample of the study is composed of 19 hotels operating worldwide in three different continents, namely Asia, Europe and North America. Table 1 provides detailed information about the hotel location and the type of social robot deployed.

Having identified the set of hotels, the second phase of the data collection process was related to the gathering of ORs displaying individual opinions about the customer experience. For this task, the research team selected the OR platform TripAdvisor due to its popularity among online travellers and because it hosts the largest number of travel and hotel ORs to date (Bi et al., 2019). Indeed, existing literature has emphasized that TripAdvisor is considered an important source of information by online readers in their decision-making process (Nilashi et al., 2018). Thus, the complete set of ORs publicly available on the TripAdvisor page of the selected 19 hotels was collected. The task was performed in November 2019 and led to the harvesting of 49,209 ORs. It is important to observe that, simulating the interaction of an English online reader on the OR platform, we were able to collect the automatic English translation of the user-generated content made available by TripAdvisor. Thus, this language homogenization allowed us to leverage the entire set of ORs for the analyses and use the English ORs sample for robustness check purposes. For each OR, apart from its textual information, a series of features at the reviewer and hotel level were collected.

Due to the focus of the current project on communications revolving around the innovation brought about by social robots, solely those ORs mentioning social robots explicitly were retained in the final empirical sample. As suggested by Tung and Au (2018), the latter were identified as OR embedding either the keyword “robot” or the proper name of the social robot (if the hotel has assigned it one). Accordingly, 3627 ORs were used for the analyses.

Table 1
Social robots sample description.

Hotel ID	Hotel location	Type of social robot deployed
Hotel 1	United States of America	Butler
Hotel 2	United States of America	Butler
Hotel 3	United States of America	Butler
Hotel 4	Japan	Front desk, luggage, room assistant, concierge, butler
Hotel 5	United States of America	Concierge
Hotel 6	United States of America	Butler
Hotel 7	Republic of Singapore	Butler
Hotel 8	United States of America	Butler
Hotel 9	Republic of Singapore	Butler, chef
Hotel 10	Germany	Concierge
Hotel 11	Republic of Singapore	Butler
Hotel 12	United States of America	Security
Hotel 13	United States of America	Butler
Hotel 14	United States of America	Butler, luggage, concierge
Hotel 15	Republic of Singapore	Butler
Hotel 16	United States of America	Butler
Hotel 17	United States of America	Butler
Hotel 18	United States of America	Luggage
Hotel 19	Republic of Singapore	Butler

3.2. Data preparation for text analytics

To discern how users are making sense of social robots, we leverage a data science approach deploying text analytics (Kayser and Blind, 2017; Kim et al., 2017; Mariani et al., 2018; Mariani and Baggio, 2021). This is because the written text in an OR can be associated with the evaluation of the service experience (Sridhar and Srinivasan, 2012), and also embed the emotional response of consumers (Mohammad and Turney, 2013). More specifically, in this work, we deploy sentiment analysis (Alaei et al., 2019; Hutto and Gilbert, 2014) and emotion recognition (Mohammad and Turney, 2013; Nguyen et al., 2020) techniques to analyze the general opinion towards social robots and their emotional components.

However, before delving deeper into the discussion related to the operationalization of the focal variables of the study, an important step of data preparation was required. Indeed, to capture the most effective insights from the analysis of the OR text we needed to extract the portion of text in the OR specifically dealing with social robots. Therefore, we adopted Bi et al.'s (2019) methodology to divide each OR into its individual textual units and aggregate them based on the attribute evaluated. Thus, we first extracted ORs' sentences using punctuations and, second, we merged all the sentences mentioning the service feature object of the analysis (i.e., social robots) (Bi et al., 2019). This allowed us to obtain from each OR the piece of text related to social robots which, in turn, would have been the unit of analysis for extracting the focal text analytics of the study. The operationalization of the latter is described in the next two sections.

3.3. Sentiment analysis

With the aim of understanding consumers' meaning-making towards social robots, we perform sentiment analysis. The latter aims to uncover opinions and private states (such as feelings, speculations and beliefs) towards a specific subject of analysis (Wiebe, 1994), examining the meaning and semantic relationships contained in an extract of text through an automated procedure (Alaei et al., 2019). Indeed, sentiment analysis usually infers the polarity or semantic orientation concerning a target entity (Mohammad and Turney, 2013). We assume that the computation of the polarity of the statement referring to social robots can be an effective proxy of the outcome of consumers' meaning-making process about social robots (including feelings but also, more generally, beliefs).

Yet, a wide range of techniques and tools have been devised over time to fulfil this task (see Alaei et al., 2019). Based on the review work of Alaei et al. (2019), we took advantage of the Valence Aware Dictionary for sEntiment Reasoning (VADER) method, conceived by Hutto and Gilbert (2014), which obtained the highest performance in the tourism and hospitality domain in the multiclassification scenario. More specifically, VADER provides a polarity score ranging from −1 (extremely negative) to +1 (extremely positive), leveraging its extensive lexicon (>7500 features) and a set of ad-hoc grammatical and syntactical heuristics (Hutto and Gilbert, 2014). Besides, VADER's sentiment lexicon has been devised to analyze social media user-generated content and it has been effectively validated through the help of human coders (Hutto and Gilbert, 2014). Lastly, the method has been successfully deployed in a recent study (Chuah and Yu, 2021) within the same research domain. Thus, leveraging VADER, we computed the main dependent variable of the study, namely the *Robot Polarity Score*, which refers to the overall sentiment polarity score associated with a comment on social robots.

3.4. Emotion recognition

The polarity score calculated in the previous step allowed the research team to comprehend the meaning associated with social robots by a reviewing hotel customer. However, with the current study, we wanted to delve deeper into the analysis of the affective state emerging from a human–robot interaction. To this aim, we decided to detect Plutchik's (1980) basic emotions embedded in the evaluation of social robots. Accordingly, in line with Nguyen et al. (2020), we extracted the emotional content in ORs using the National Research Council Canada (NRC) Word–Emotion Association Lexicon (EmoLex). Devised by Mohammad and Turney (2013) through crowdfunding, it contains 14,182 words and their association with the eight basic emotions depicted in Plutchik's (1980) emotional wheel. As suggested by Nguyen et al. (2020), EmoLex is considered a robust lexicon in extant literature. Besides, it has also recently been used in management and marketing studies (i.e., Rahmani et al., 2019; Srivastava and Kalro, 2019; Wang et al., 2019).

Following the recommendations of Nguyen et al. (2020), before evaluating the emotional association of the OR text pertaining to social robots, we first removed stop words. After this data cleaning step, for each analysed OR we created a set of eight additional variables (one for each of the emotional dimensions devised by Plutchik (1980)) which contained the number of associations we found between the OR text and a specific emotion using the EmoLex dictionary. More specifically, for each OR, we first searched each word in the OR text in the EmoLex dictionary and extracted the emotional dimensions associated with it. However, in a minority of cases, some of the words in the EmoLex dictionary were associated with multiple emotional dimensions. In those cases, two researchers of the research team classified manually and independently the small number of robot-related statements that might be related to multiple emotional dimensions. After the independent classifications were developed, they were compared. Since there was agreement between the individuals involved in the classification – Cohen's kappa (Cohen, 1960) ranging from 0.95 to 0.99 – a final classification with the most suitable emotional dimension was retained. Second, we counted the number of occurrences of a specific emotional state. For instance, if an OR presented three words associated with the emotion of joy, the corresponding value of the variable “*Joy*” for the analysed OR would have been equal to three. Yet, to normalize the results, in line with the procedure adopted by leading text analytics software, such as LIWC (Pennebaker et al., 2015), we divided the absolute number of emotional associations by the number of words in the robotic statement after data cleaning. Table A.1 in the Appendix reports examples of emotional content associated with each of the analytical emotions analysed.

3.5. Data analysis techniques

As far as the data analysis techniques used in this study are concerned, we deployed two distinctive approaches. First, due to the importance of the time dimension in the diffusion of innovations process (Rogers, 2003), which has been relatively overlooked by extant HRI literature (Tussyadiah, 2020), we deployed a one-factor repeated-measures design (Myers et al., 2010). As such, we descriptively analysed the cumulative percentage of the text analytics variables discussed in the previous sections in the first 24 months after the introduction of social robots in the hotel's activities. This descriptive analysis had the objective to evaluate the temporal development of sense-making about social robots by online reviewers.

Second, to evaluate the impact of the emotional response decomposition on the overall polarity towards social robots, we deployed multivariate ordinary least squares regression. The latter is considered a suitable technique in the sentiment analysis domain, and it has achieved consistent results when compared with more sophisticated machine learning techniques (Singh et al., 2020), whose findings, in a wide range of cases, lack interpretability (Chuah and Yu, 2021). Thus, using the *Robot Polarity Score* as our dependent variable, we estimated the following econometric specification:

$$\begin{aligned} Robot\ Polarity\ Score_{rh} =& \beta_0 + \beta_1 Anger_{rh} + \beta_2 Anticipation_{rh} + \beta_3 Disgust_{rh} + \beta_4 Fear_{rh} + \beta_5 Joy_{rh} + \beta_6 Sadness_{rh} + \beta_7 Surprise_{rh} + \beta_8 Trust_{rh} \\ &+ \beta_9 Obeserved\ Average\ Rating_{rh} + \beta_{10} Reviewer\ Experience_{rh} + \theta_1^{'} Travel\ Type_{rh} + + \theta_2^{'} Year_{rh} + \theta_3^{'} Hotel\ ID_h + \epsilon_{rh} \end{aligned} \quad (1)$$

where the subscripts r and h identify the analysed reviewer and hotel respectively. As clear from Eq. (1), we included in the econometric model a series of control variables which will be highlighted in the next section.

3.6. Control variables

As suggested by extant literature revolving around social robotics, specific characteristics at the individual and company level may impact HRIs. For instance, Tung and Au's (2018) results highlight the importance of the travel type dimension, since families seem to express more favourable opinions towards social robots than other travellers'

Table 2
Variable description.

Variable name	Description
Robot Polarity Score	It refers to the sentiment polarity score of consumers' opinions about social robots calculated through the VADER method (Hutto and Gilbert, 2014). It is associated with a continuous value in the range, having as extremes −1 and +1 respectively.
Anger	It is the ratio between the number of anger-related words and the total number of words in an OR.
Anticipation	It is the ratio between the number of anticipation-related words and the total number of words in an OR.
Disgust	It is the ratio between the number of disgust-related words and the total number of words in an OR.
Fear	It is the ratio between the number of fear-related words and the total number of words in an OR.
Joy	It is the ratio between the number of joy-related words and the total number of words in an OR.
Sadness	It is the ratio between the number of sadness-related words and the total number of words in an OR.
Surprise	It is the ratio between the number of surprise-related words and the total number of words in an OR.
Trust	It is the ratio between the number of trust-related words and the total number of words in an OR.
Observed Average Rating	It denotes the rating displayed on the hotel profile page before the online reviewer posted their OR.
Reviewer Experience	It equates to the number of reviews written on TripAdvisor by the online reviewer.
Travel Type	It refers to the travel companion during the trip. In TripAdvisor, reviewers can choose among the following categories: Solo, Couple, Business, Family or Friends.
Year	It denotes the year when the review was written and it is introduced using a set of dummy variables in the econometric model (*Year Dummies*)
Hotel ID	It represents a unique identifier associated with the hotel

Table 3
Descriptive statistics.

	Mean	SD	Min	Max
Robot Polarity Score	0.381	0.384	−0.904	0.994
Anger	0.005	0.021	0	0.250
Anticipation	0.041	0.062	0	0.500
Disgust	0.003	0.015	0	0.250
Fear	0.008	0.027	0	0.250
Joy	0.037	0.056	0	0.400
Sadness	0.009	0.029	0	0.333
Surprise	0.014	0.035	0	0.333
Trust	0.039	0.058	0	0.333
Observed Average Rating	4.379	0.306	1	5
Log(Reviewer Experience)	2.762	1.907	0	10.883
Observations	3627			

categories. Moreover, Ivanov et al. (2019) suggest that the way the company devises the service experience with the robot can affect HRI. Therefore, we include the *Travel Type* and the *Hotel ID* as control indicators in our econometric estimation. Besides these, we added as further controls the platform-level variables *Reviewer Experience* and *Observed Average Rating*. Indeed, reviewers' judgements might be influenced by the overall rating they observe online (Sridhar and Srinivasan, 2012), as well as by their experience (Bendapudi and Berry, 1997). Lastly, since the overall opinion towards innovation might change over time (Leonard-Barton, 1985; Rogers, 2003), we also included, as a time-related factor, the year when the OR was written. Tables 2 and 3 report the description and descriptive statistics of the main variables embedded in the econometric model. In light of the high skewness associated with its distribution, we used the logarithmic transformation of *Reviewer Experience* in the model.

4. Results

4.1. Findings descriptive trend analysis of social robot-related ORs

In relation to the descriptive analysis of robot-related text analytics, in the first instance, we examined the trend related to the robotic sentiment score (or polarity score). As depicted in Fig. 2, this metric portrays a rather linear development with a mean of approximately 0.38, which in the VADER polarity score interval can be considered a positive value.

Secondly, we unpacked the overall polarity score into its emotional subcomponents, which are all presented in Fig. 3. The detected emotions seem to follow a quite linear development, aside from a few exceptions. In particular, the emotions of *anticipation*, *joy* and *trust* are the most frequently associated with customers' opinions about social robots, with a cumulative average of around 4 %. Inspecting the trends of these emotional dimensions more closely, *anticipation* displays a peak in the first month. Thus, reviewers, especially in the first month, were looking forward to interacting with the social robots. Moreover, an interesting pattern is associated with the emotion of *Trust*. Indeed, the latter decreases substantially after the first month and then it gradually recovers after the third month.

Other emotions, such as *surprise*, *sadness*, *fear*, *anger* and *disgust* are present but with a lower share, between 0.3 % and 1.4 %. Among these emotional dimensions, *fear* presents a gradually decreasing trend, which may be due to the initial difficulties of some reviewing customers to devise social robots' functionalities and, in turn, be afraid of HRI. All in all, despite the entire spectrum of Plutchik's (1980) emotions being recognized in customers' opinions about social robots, positive emotions are more frequent than negative ones. So far, we have only analysed in a rather descriptive manner the emotional content embedded into the portion of OR text pertaining to HRI. Thus, at this stage, we cannot make any inference regarding the contribution, either positive or negative, of a specific emotion towards the innovation meaning-making process. The results of the abovementioned analysis are depicted in the next section.

4.2. Findings of the regression analysis

The empirical results of the regression analysis examining the individual emotion's contribution to the polarity of customers' opinions about social robots are reported in Table 4, which includes the estimated coefficients of the baseline model (containing only the eight basic emotions) and the full model. We tested for multicollinearity without finding any significant problem since all the variance inflation factor values were less than the threshold of 10 (Hair et al., 1992).

The focal emotional dimensions display comparable results in both model specifications. Yet, they are related in a heterogeneous manner to the dependent variable. In particular, *Joy* ($\beta_5 = 2.383$, $p < 0.001$) and *Trust* ($\beta_8 = 0.282$, $p < 0.1$) are found to have a positive and significant association with consumers' opinions. Conversely, there is a negative relationship between the dependent variable and the emotions of *Anger* ($\beta_1 = -1.237$, $p < 0.001$), *Disgust* ($\beta_3 = -0.980$, $p < 0.1$), *Fear* ($\beta_4 = -0.404$, $p < 0.1$) and *Sadness* ($\beta_6 = -1.799$, $p < 0.001$), with the lowest coefficient portrayed by *Sadness*. Lastly, the emotions of *Anticipation* ($\beta_2 = -0.0495$, n.s.) and *Surprise* ($\beta_7 = 0.0433$, n.s.) do not significantly relate to the overall opinion towards social robots. Therefore, knowing in advance about the social robot or feeling a sense of surprise during the encounter does not translate into more favourable statements.

Inspecting the impact of the main control variables, interesting results stem from the analysis. On the one hand, referring to *Reviewer Experience*, it is found that more experienced reviewers are more cautious than their counterparts when expressing their opinion about social robots ($\beta_{10} = -0.00896$, $p < 0.01$). This result is in line with extant literature that suggests that experts are more objective than novices in their evaluations of services and service providers (Bendapudi and Berry, 1997). Thus, also in the case of HRI, this makes more

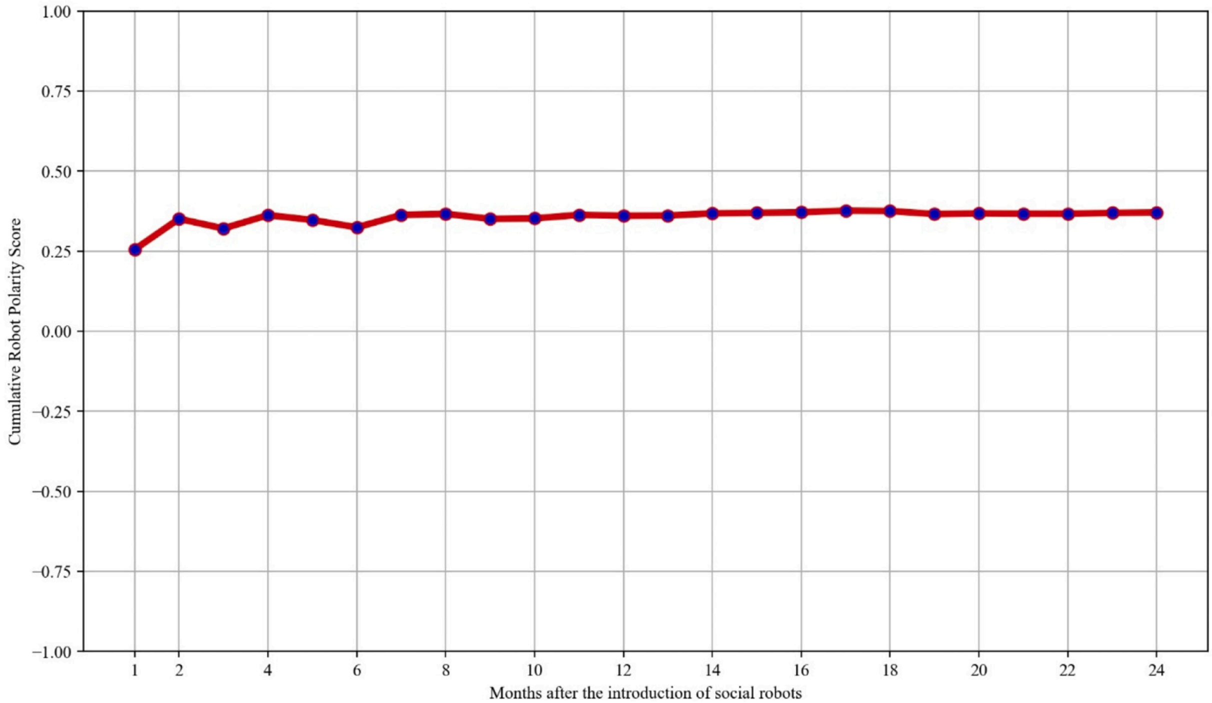

Fig. 2. Trend cumulative Robot Polarity Score in the first 24 months after the introduction of social robots.

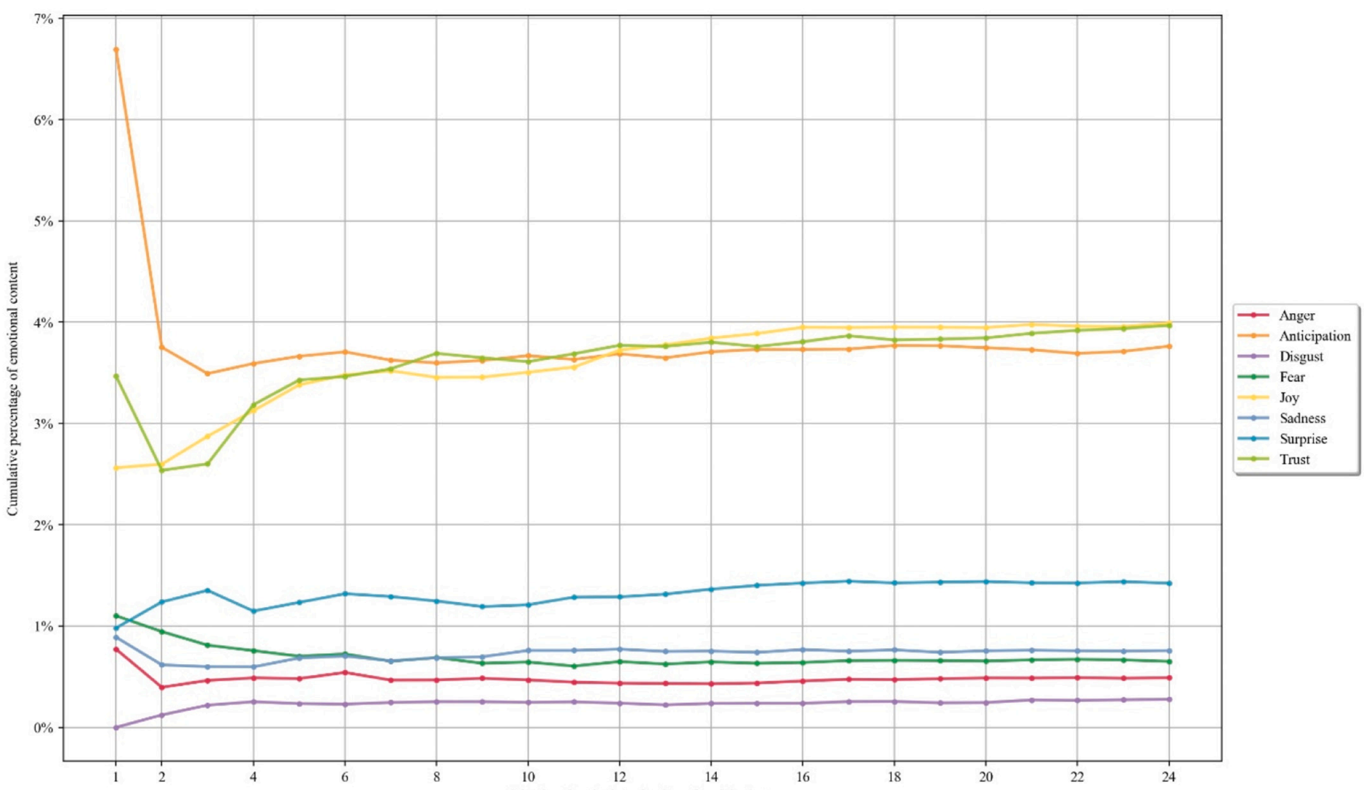

Fig. 3. Trend cumulative percentage of emotional content in the first 24 months after the introduction of social robots.

experienced reviewers less prone to share more favourable opinions. On the other hand, regarding *Observed Average Rating*, it seems that the evaluation of HRI is not affected by other customers' judgements of the overall experience at this stage ($\beta_9 = 0.0357$, n.s). This finding seems to suggest that HRI is evaluated as a distinct part of the service experience and it can be perceived as another important clue to sustaining the uniqueness of HRI (van Doorn et al., 2017; Young et al., 2011). Lastly, considering the *Travel Type*, our findings confirm and extend the exploratory qualitative results of Tung and Au (2018). In fact, it is not only families who seem to have a more favourable opinion of social

Table 4
Regression results – dependent variable: Robot Polarity Score.

	Baseline	Full
Anger	−1.296***	−1.237***
	(0.332)	(0.334)
Anticipation	−0.0701	−0.0495
	(0.0934)	(0.0987)
Disgust	−0.976*	−0.980*
	(0.529)	(0.529)
Fear	−0.598**	−0.404*
	(0.221)	(0.225)
Joy	2.518***	2.383***
	(0.121)	(0.124)
Sadness	−1.930***	−1.799***
	(0.219)	(0.235)
Surprise	0.0792	0.0433
	(0.180)	(0.188)
Trust	0.263*	0.282*
	(0.107)	(0.110)
Observed Average Rating		0.0357
		(0.0518)
Log(Reviewer Experience)		−0.00896**
		(0.00321)
Travelled on business		−0.0181
		(0.0189)
Travelled solo		−0.0244
		(0.0256)
Travelled with family		0.0214*
		(0.0113)
Travelled with friends		0.0346*
		(0.0192)
Further controls		
Year dummies		YES
Hotel ID		YES
Constant	0.312***	0.227
	(0.00780)	(0.234)
Observations	3627	3366
F-test	108.67***	154.18***
McFadden R^2	0.235	0.258
AIC	2574.6	2368.8
Log likelihood	−1278.3	−1146.4

Notes: the Full model in the second column contains less observations due to missing value in the Travel Type dimension. Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.01$.
*** $p < 0.001$.

robots, but also individuals travelling with their friends. Lastly, as a robustness check, we reran all the analyses with the sample of ORs written in English, obtaining results in line with the one presented in the study.

5. Discussion

In this section we discuss in greater depth the results of the study, comparing and contrasting them with extant literature in the field. Firstly, the mean of the results in Fig. 2 is in line with the findings of Fuentes-Moraleda et al. (2020) obtained through a manual coding procedure. Yet, interestingly, it is quite different from the one provided in the recent study of Chuah and Yu (2021), where the authors found an overall low positive polarity of 0.2 when analyzing comments of potential adopters using the same sentiment analyzer. Therefore, this could imply that there is a significant difference between consumers reacting to potential – rather than actual – HRIs, with the latter ones being considered almost twice as positive as the former ones. In addition, for explaining the descriptive results in Fig. 3, we can use the main theory underlined in Section 2.1. Indeed, based on diffusion theory, we can expect that customers belonging to the *innovators* category should have been the first ones attracted by social robots. Usually, individuals who are *innovators* gather information about the innovation in advance (Rogers, 2003). Therefore, they could have been aware of their deployment in hotels' operations and would have expected to interact with it. This would reasonably explain the peak related to the emotion of *anticipation* in the first month of social robot deployment. Besides, referring to the initial loss in *trust*, this might be due to reliability issues in HRI that were not previously anticipated by the hotel, which might have triggered organizational learning mechanisms (Levitt and March, 1988) to adjust social robots' activities and in turn, increase customers' perceived trust.

Regarding the regression analyses, comparing the magnitude of the coefficients of significative positive emotions, there is a more powerful relationship between *joy* and the dependent variable, which is in line with what has been postulated about emotional intensity by Plutchik (1980). Furthermore, and rather surprisingly, *joy* has the highest coefficient among the entire set of emotions. This might mean that, at this stage, the feeling of enjoyment can potentially overcome negative emotions about HRI. In addition, interesting implications stem from the interpretation of the results associated with the emotions of *anticipation* and *surprise* – which are not significantly related to the dependent variable. As suggested by Nguyen et al. (2020), *anticipation* and *surprise* might be associated either with negative or positive experiences, whereby their net relationship might be difficult to predict. For instance, *anticipation* can increase the positive feeling associated with a consumption experience, but it can also inflate expectations that can become difficult to meet during the HRI. The same reasoning holds for *surprise*, which is usually positively associated with HRI (Fuentes-Moraleda et al., 2020). Nonetheless, *surprise* may be also related to components of *uncertainty* and *distraction* (Plutchik, 1980) which can be reasonably associated with negative HRI experiences. Thus, combining our empirical results, we might argue that both expressions of *anticipation* and *surprise* are embedded in online communications but neither the positive nor the negative ones overshadow their counterpart, resulting in an overall neutral association.

All in all, taking into account the entire set of results, due to a more significant manifestation of positive emotions in consumer online discourse and the particularly stronger positive association between *joy* and consumers meaning-making, we would expect a positive effect of ORs pertaining to social robots on shaping future individual meaning-making. Indeed, the collective opinion of the social system analysed has been rather positive and this might result in more conservative adopters forming a favourable attitude towards the innovation. The fact that emotions and affective opinions are especially important in the persuasion stage (Rogers, 2003) makes our claim even stronger. This might well imply success for service robots' deployment in the hospitality industry and, in turn, their adoption might take off involving a wider range of firms and consumers. Nonetheless, the significant association with negative emotions (e.g., *anger*, *disgust*, *fear* and *sadness*) and the not significant results for ambivalent emotions (i.e., *anticipation* and *surprise*) might reduce the speed of the adoption process.

6. Contributions and practical implications

6.1. Research contributions

The study distinctively contributes to two streams of literature, namely HRI and eWOM. Indeed, to the best of the authors' knowledge, this can be considered the first attempt to comprehensively disentangle consumers' emotional responses to social robots by leveraging a conceptual framework informed by psychology literature. Therefore, it contributes to the recent call for empirical research on the diffusion and impact of social robots (Belanche et al., 2020; Tussyadiah, 2020), especially in the post-service encounter phase (Lu et al., 2020). First, grounded in the diffusion of innovations and psychology literature, this work reveals that opinions revolving around interactions with social robots are rather positive, confirming conceptual arguments in favour of a positive consumer reaction (Ivanov et al., 2019). Furthermore, the entire set of Plutchik's (1980) basic emotions has been recognized in the analysed sample, confirming that HRIs are emotionally charged experiences (Young et al., 2011) in which a set of mixed feelings is displayed (Tung and Au, 2018). Delving deeper into the emotional components, *anticipation*, *trust* and *joy* are the most frequently expressed emotions. Referring to *anticipation*, this result is in line with the diffusion of innovation theory (Rogers, 2003). This happens because, as adoption is gradually taking off (Borghi and Mariani, 2021), early adopters would know about social robots in advance; awareness comes first in the innovation-decision process and it is more likely to affect *innovators* and *early adopters* (Rogers, 2003). Thus, we might infer that early adopters report this emotion to better justify their judgement. Moreover, this strong sense of anticipation towards social robots might have been the reason why the service customer decided to choose that specific hotel. In terms of *trust*, our findings confirm extant conceptual and qualitative studies suggesting the creation of a "relationship" between social robots and service consumers (Tung and Au, 2018; Wirtz et al., 2018), highlighting the importance of this emotion for service consumers when assessing their HRIs. This result might relate to the uncertainty intrinsically embedded in the diffusion of innovations process (Rogers, 2003), which could lead early adopters to emphasize the reliability of social robots as relational actors. Yet, among the most frequent emotions, we found *joy*. Joy equates to pleasure during HRI and this extends extant research by suggesting that social robots can effectively enhance the level of entertainment in different service domains (Ivanov et al., 2019).

Second, this study contributes to the HRI literature, analyzing the associations between basic emotions and the overall statement polarity towards social robots. Both positive (*trust* and *joy*) and negative (*anger*, *disgust*, *fear* and *sadness*) emotions have a significant – but heterogeneous – association with robot sentiment polarity, with *joy* having the greatest magnitude overall. Hence, despite social robots being prone to service failures (Choi et al., 2020a), which might lead to negative emotions (Tung and Au, 2018), the feeling of enjoyment seems able to overcome potential service quality pitfalls. Moreover, extant literature highlights the growing importance of social media promotion of social robots (de Kervenoael et al., 2020) as well as the perception of social robots as representing a "wow factor" (Fuentes-Moraleda et al., 2020). However, neither *anticipation* nor *surprise* in our study are found to be associated with more favourable opinions, suggesting that knowing in advance or feeling a sense of surprise during HRI do not necessarily relate to consumers' opinion polarity. This finding seems therefore to suggest that robots do not necessarily represent a wow factor per se.

Third, this study contributes to the nascent field of research examining the use of eWOM communications to reveal consumers' perceptions of social robots (Borghi and Mariani, 2021; Chuah and Yu, 2021; Fuentes-Moraleda et al., 2020; Gretzel and Murphy, 2019; Tung and Au, 2018; Yu, 2020). Through the deployment of text analytics techniques, this study shows how it is possible to automatically capture not only the overall polarity of the comments related to social robots, but also consumers' emotional responses. In particular, it extends Borghi and Mariani's (2021) empirical findings tracking text analytics over time. In addition, differently from other studies (i.e., Fuentes-Moraleda et al., 2020), it leverages a theory-informed framework for discerning emotional content. As far as the overall sentiment polarity is concerned, it confirms qualitative results obtained through manual coding (i.e., Fuentes-Moraleda et al., 2020; Tung and Au, 2018), yet it displays significant differences from other studies using the same sentiment analyzer (i.e., Chuah and Yu, 2021). Comparing our results with those of Chuah and Yu (2021), it seems that real HRIs are considered twice as positive as potential HRIs. Thus, this might imply that users' perceptions systematically differ depending on the type of eWOM communications analysed.

6.2. Practical implications

This work bears a set of practical implications. As clear from the descriptive results, overall customer response to social robots is moderately positive (average Robot Sentiment Score of 0.38) and it is more frequently associated with positive emotions. Thus, as far as hotel managers are concerned, this might imply that the adoption of social robots at the company level has an overall positive association with the customer experience. Consequently, hotel companies should consider more confidently embracing this new kind of innovation in their operations. Nonetheless, as depicted by the analyses, negative emotional reactions exist and, most notably, they have a significant negative association with users' perceptions of social robots. As such, due to the critical role played by online communications in social media in shaping the consumer's acceptance of social robots (de Kervenoael et al., 2020), companies should consider putting in place an automatic procedure to not only collect but also analyze online comments. In particular, hotel managers can adopt the methodology deployed in this paper to extract the emotional response to social robots of online reviewers. This "social robot emotion-recognition system" can allow managers to track, in real-time, travellers' responses to HRI and, in turn, allow them to adjust social robot activities to better conform to customers' expectations and feelings and ultimately innovate products and services (Mariani and Wamba, 2020) related to HRIs. For instance, if a certain aspect of the HRI is expressed through negative emotions, the hotel management should consider improving that specific feature or eliminating it. Moreover, this procedure could be potentially deployed for evaluating different aspects of the service offering. Overall, this system will not only improve decision-making at the company level through data analytics (Akter et al., 2019) but will also allow the hotel to detect potential biases in the coded actions associated with social robots (Akter et al., 2021; Mariani and Nambisan, 2021).

Inspecting further the econometric results, hotel managers might ponder tailoring the social robot interaction based on guest travel type. Indeed, due to the more favourable impact associated with *families* and *group of friends*, hotels might target and promote specific HRI activities towards these customer groups. Thus, it may also be worth devising holiday packages entirely revolving around experiencing social robots. For example, the YOTEL Singapore in Orchard Road, recognized nationally for its outstanding efforts in the deployment of social robots (Singapore Business Review, 2019), has very recently introduced the novel ROBOCATION package (YOTEL Singapore, 2021). This is a special offer for guests comprising a food and beverage voucher for products delivered to your room by social robots, one pair of robot toy gifts per each booking, as well as a souvenir photo with the robots (YOTEL Singapore, 2021). However, while these initiatives might increase hotel reservations, they could also inflate customers' expectations concerning social robots. Therefore, hoteliers should effectively communicate beforehand social robots' functionalities as well as how the experience with social robots has been designed. Ensuring the responsible use of social robots might be the key to their successful adoption in companies' operations (Fosso Wamba and Queiroz, 2021).

The study's results also entail potential implications for OR platform managers. Due to the uniqueness of HRI and the fact that guests' opinions on these experiences seem not to be affected by the overall judgement of the hotel, OR platforms might consider setting up a dedicated section on the hotel profile page displaying the social robots deployed. In this section, platform developers could include ORs that mention social robots, especially highlighting the portion of the review pertaining to this new relational actor. Besides, this area might be used by online readers to ask questions about the innovation, which might be answered directly by the property management and/or by former hotel guests. This would not only spark engagement in the OR platform but also help businesses to better promote their innovation efforts while reducing consumers' uncertainty.

7. Conclusions, limitations, and future research

This work investigates the role played by emotions in consumers' communications revolving around social robots. More specifically, we discern and analyze the emotions perceived during HRIs and we evaluate how they are related to consumers' meaning-making. Leveraging extant theorization on the diffusion of innovations and psychology, emotional content is categorized through Plutchik's (1980) wheel of emotions. In particular, advanced text analytics techniques belonging to the sentiment analysis and emotion recognition domains are deployed to not only classify emotional content but also to extract the overall semantic meaning associated with it. The combination of a theory-informed framework with a data science approach to capture and examine consumers' emotional responses towards social robots makes this contribution unique. We find that consumers' opinions on social robots are moderately positive, with *anticipation*, *trust* and *joy* among the most frequently expressed emotions. Emotions are heterogeneously related to opinions' polarity, with *joy* associated with the greatest magnitude. In particular, *trust* and *joy* have a positive and significant association with our dependent variable, while *anger*, *disgust*, *fear* and *sadness* have a negative and significant association with our dependent variable. Yet, *anticipation* and *surprise* are not significantly related to consumers' opinions on social robots. Overall, HRIs elicit mixed emotions which distinctively contribute to consumers' meaning-making.

This work presents some limitations which might suggest interesting avenues for future research. First, we cannot prove and determine a causal relationship between the measured variables in the study because we are using secondary data in the form of ORs, without any experiment. Besides, OR data might be prone to response and self-selection biases as well as data reliability issues (Mariani and Baggio, 2021). Therefore, we encourage future researchers to assess the validity of our results using an experimental research design. Second, despite analyzing a wide range of people-to-people communications from the most popular OR travel platform, future scholars might consider examining other social media and OR platforms (i.e., Booking or Expedia) to further strengthen our results. Further, future researchers might control for consumers' demographic indicators such as age, gender, country of origin and cultural background/dimensions (Mariani and Matarazzo, 2021) when assessing the impact of individual emotions. As suggested by extant HRI literature (i.e., Belanche et al., 2020; Ivanov et al., 2019), these factors might contribute to shaping the consumer's attitude towards social robots. Since on TripAdvisor these indicators are disclosed by a very small number of users, a lot of demographic variables display missing values. For this reason, we decided not to use them in the current analyses. Third, since online reviews mentioning service robots might show ambivalence (e.g., embedding either positive or negative emotions), future researchers might consider working at a more granular level of analysis, measuring and assessing the impact of emotional ambivalence on consumers' meaning-making. Lastly, despite taking into account hotels that introduced social robots through hotel fixed effects, future studies might leverage a more homogeneous sample to better understand the relationship between human–social robot interaction and innovation diffusion processes.

CRediT authorship contribution statement

The authors Matteo Borghi and Marcello Mariani contributed equally to the manuscript in terms of: Conceptualization; Methodology; Data curation; Formal analysis; Writing - Original draft preparation; Writing - Reviewing and Editing.

Declaration of competing interest

The authors have no competing interests to declare.

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Appendix A

Table A.1
Examples of emotional content associated with each of the analytical emotions analysed.

Emotion	Examples
Anger	“A bit disappointed with [Robot Name] (robot in the guestroom), always keep talking.”
Anticipation (ambivalent)	Positive:
	“The robot which stores your luggage is really something special you'll never would expect.”
	Negative:
	“We were expecting to store our luggage with the [Robot Name] (which is free, by the way), but we were told to go on up to our room.”
Disgust	“The robots are a bit weird.”
Fear	“The 5-year-old was afraid of the front robot.”
Joy	“The most excited is the robot [Robot Name] and [Robot Name].”
Sadness	“Sadly not enough time to use the robots!”
Surprise (ambivalent)	Positive:
	“the visit by the robot [Robot Name] was a fun surprise for the kids”
	Negative:
	“My 6yo was super excited to see [Robot Name] the robot wondering about. He was terribly disappointed when our room service was delivered by a human being instead of [Robot Name].”
Trust	“Do watch out for the ever-reliable robot called [Robot Name] who efficiently delivers room amenities.”

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