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SERVICE ROBOTS AND COVID-19: EXPLORING PERCEPTIONS OF PREVENTION EFFICACY AT HOTELS IN GENERATION Z

Purpose: COVID-19 is expected to enhance hospitality robotization because frontline robots facilitate social distancing, lowering contagion risk. Investing in frontline robots emerges as a solution to recover customer trust and encourage demand. However, we ignore how customers perceive these initiatives and, therefore, their efficacy. Focusing on robot employment at hotels and on Generation Z customers, this research analyzes guests' perceptions about robots' COVID-19 prevention efficacy, and their impact on booking intentions.

Design/methodology/approach: This study tests its hypotheses combining an experimental design methodology with partial least squares. Survey data from 711 Generation Z individuals in Spain were collected in two periods of time.

Findings: Generation Z customers consider that robots reduce contagion risk at hotels. Robot anthropomorphism increases perceived COVID-19 prevention efficacy, regardless of the context where the robots are employed. Robots' COVID-19 prevention efficacy provokes better attitudes and higher booking intentions.

Originality/value: This study combines preventive health, robotics, and hospitality literature to study robot implementation during the COVID-19 pandemic, focusing on Generation Z guests —potential facilitators of robot diffusion.

Research limitations/implications: The sampling method employed in this research impedes our results generalization. Further research could replicate our study employing random sampling methods to ensure representativeness, even for other generational cohorts.

Practical implications: Employing robots as a COVID-19 prevention measure can enhance demand, especially if robots are human-like. Hoteliers need to communicate that robots can reduce contagion risk, particularly in markets more affected by COVID-19. Robots must be employed in low social presence contexts. Governments could encourage robotization by financially supporting hotels and publicly acknowledging its benefits regarding COVID-19 prevention.

Keywords: Robots, COVID-19, prevention efficacy, anthropomorphism, social presence, Generation Z

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1. INTRODUCTION

Service robot employment in hospitality firms occurs within a more general trend of replacing interpersonal encounters with technological interfaces (e.g., Kim and Qu, 2014; Lee *et al.*, 2018). These robots are system-based machines furnished with artificial intelligence, that interact, communicate, and deliver a wide variety of customer services (Wirtz *et al.*, 2018). They are expected to become a relevant competitive asset for the hospitality industry in the near future (Murphy *et al.*, 2019). Service robot adoption by hospitality firms will take place in a context dominated by COVID-19, at least during its early phases—as suggested by the evolution of the disease (World Health Organization, 2021). COVID-19 is likely to accelerate robotization processes in the hospitality and tourism industries (e.g., Cha, 2020; Seyitoğlu and Ivanov, 2020; Zeng *et al.*, 2020), in spite of the unfavorable context of demand contraction provoked by the virus, because robots, as other automation technologies, are advantageous tools to implement a necessary social distancing during the pandemic (Ivanov *et al.*, 2020). Thus, for example, some hotels from the Hilton and Marriott chains have already incorporated robots for this purpose (Hospitality Technology, 2020). Social distancing concerns will persist in the post-pandemic world (Goretti *et al.*, 2021), thus making investments in this technology also profitable in the long term.

Embracing a customer point of view is critical to advance in our comprehension of robotics in hospitality (e.g., Belanche, Casaló and Flavián, 2020a, 2020b; Tussyadiah and Park, 2018; Xu *et al.*, 2020). Therefore, managers' decisions to implement service robots as a means of achieving social distancing have to be evaluated from the customer's perspective. Restoring customer confidence is essential for business recovery in this pandemic (Jiang and Wen, 2020), but we do not know whether customers really consider that robots can lower the contagion risk or, even more, the impact of these initiatives of customer preferences. In other words, we lack a proper evaluation of such initiatives, beyond their health benefits, which impedes a confident implementation of them in hospitality firms. Thus, the purpose of this study is exploring how customers evaluate robot employment in frontline tasks at hospitality firms, particularly at hotels, in terms of COVID-19 prevention, and the impact of such assessment on booking intentions.

We conduct our empirical analysis on Generation Z customers—individuals born between 1995 and the late 2000s (Băltescu, 2019). Generation Z constitutes an interesting group to study for several reasons. First, despite being an attractive market segment for hospitality firms as potential or actual high spenders (Dimitriou and Abouelgheit, 2019), they have seldom been researched in hospitality from a consumer perspective (e.g., Bravo *et al.*, 2020; Haddouche and Salomone, 2018) and not regarding to service robot acceptance. Second, Generation Z members are technology savvy and use social media extensively (Turner, 2015), which makes them potential facilitators of robot diffusion. Finally, the younger generation's perceptions of robots will guide robot design in the future (de Kervenoael *et al.*, 2020), making Generation Z customers an appealing group to study.

Hence, this research contributes to extant literature by analyzing how potential hospitality customers—particularly Generation Z members—perceive service robot adoption by firms in terms of COVID-19 prevention. We respond to research calls on frontline automation in the context of COVID-19 (Jiang and Wen, 2020). We study how this perception generates attitudes toward such technology and its impact on booking intentions. We find that customers from Generation Z consider that robots can reduce COVID-19 contagion risk at hotels. However, hotel managers cannot use them indiscriminately in all frontline tasks. We provide managerial recommendations involving robot adoption by hotels and communication strategies, together with cues for policy makers aiming to help hospitality firms. Throughout this paper, the term "robot" refers to "service robot," unless otherwise specified.

2. LITERATURE REVIEW

COVID-19 has provoked an unprecedented crisis in the hospitality and tourism industries (Matiza, 2020). Beyond mobility and occupation restrictions, this disease has increased health concerns among the population and reduced revenues in hospitality firms due to people's beliefs about being susceptible to COVID-19 (Jiang and Wen, 2020; Neuburger and Egger, 2020), expecting a long-lasting effect beyond the current pandemic (Matiza, 2020). Robots already performed frontline tasks in hospitality before the pandemic (concierges, waiters, bartenders, etc.). This technology allows enhancing customer experience and achieving cost reductions (e.g., Belanche, Casaló and Flavián, 2020b; Cha, 2020; de Kervenoael *et al.*, 2020; Shin and Jeong, 2020). Nowadays, COVID-19 is

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spawning another incentive for robotization: recovering customer trust due to a higher social distance (Jiang and Wen, 2020). However, we ignore whether robotization initiatives responding to this motivation are valid. Customer acceptance of robots is typically studied in the light of customer- robot- and service encounter-related factors (Belanche, Casaló, Flavián, *et al.*, 2020a), and omit customer assessment of robots as a means of preventing COVID-19. We next propose a research model that considers the impact of such assessment on booking intentions by integrating robot acceptance and preventive health care literature.

Generation Z customers—the generational cohort selected to study customer assessment of robots as a means of preventing COVID-19—are usually described as digital natives, fully connected virtually, technology open and savvy, and willing to accept innovative products and services (Băltescu, 2019; Bravo *et al.*, 2020; Dimitriou and Abouelgheit, 2019). Research focusing on robots' acceptance by Generation Z is scarce. Generation Z hospitality students –future managers in this industry– consider that robots can perform service tasks properly as hospitality workforce (Ivkov *et al.*, 2020). Thus, their general knowledge of technology could enhance their acceptance of robotics systems also as customers, due to a better understanding of their benefits (Belanche *et al.*, 2019; Belanche, Casaló and Flavián, 2020b). Nevertheless, this generational cohort does not show necessarily a positive emotional response toward robots, indeed leaning more toward fear and anxiety (Fenech *et al.*, 2020). Beyond Generation Z-focused research, extant literature that controls for age effects reports either counterintuitive results regarding younger people's motivations for hospitality robots adoption (Cha, 2020), or a non-significant influence of age (Belanche *et al.*, 2019). Thus, previous research does not provide clear clues to understand Generation Z acceptance of service robots as hospitality customers, neither in general nor for the current pandemic. Similarly, preventive health care literature about Generation Z members and COVID-19 does not consider robotization or other technologies either, focusing on what media are appropriate for conveying information about the disease to this generational cohort (Kamenidou *et al.*, 2020). Thus, we conduct our literature review without circumscribing it to any generational cohort or age group.

Model overview

Our model includes three main constructs, namely prevention efficacy, anthropomorphism, and social presence (customer-, robot-, and service encounter-related

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factors respectively). Prevention efficacy captures the extent to which a person considers that robots reduce this health threat. Anthropomorphism is a perception of human-like traits in a non-human agent (Epley, 2018). Particularly, we focus on physical human likeness. Social presence captures the "sense of being with another" (Biocca *et al.*, 2003; Heeter, 1992). These three constructs determine attitudes toward being attended by a robot, which influence booking intentions. We borrow prevention efficacy and some of its drivers that apply to our research from the Extended Health Belief Model (Burns, 1992), hereafter EHBM. This model explains the decision process through which individuals move regarding preventive health actions. The model states that, due to antecedents that include individual factors among others, people first evaluate the risk associated with an illness (stage 1). Next, individuals assess potential remedies (stage 2). Finally, individuals assess the outcome of such remedies after implementing them (stage 3). From this model we take three concepts for our research: health history, health importance, and perceived susceptibility. Health history relates to past illness experiences; health importance indicates the degree to which a person values good health; perceived susceptibility captures beliefs about being susceptible to a disease (Abraham and Sheeran, 2015; Kirscht, 1998).

Thus, grounding on the EHBM, we propose that individuals who have been more affected in some way by COVID-19 are more concerned about health importance; and that health importance leads to a higher perceived susceptibility and a better evaluation of robots as a means to reduce contagion risk. Such evaluation provokes better attitudes toward being attended by a robot, that is, better affective reactions (Ahadzadeh *et al.*, 2015; Venkatesh *et al.*, 2003). We propose that better attitudes lead to higher booking intentions at the hotels employing robots for reducing the COVID-19 risk of contagion.

We augment the EHBM by including anthropomorphism and the social presence of the context where the robot will be used, as additional determinants of prevention efficacy. Previous literature suggests that individuals evaluate service robot performance taking into account anthropomorphism (Goudey and Bonnin, 2016; Gursoy *et al.*, 2019; Kim *et al.*, 2019; Park, 2020; Yu, 2020; Zhu and Chang, 2020). Hence, we consider it plausible that anthropomorphism also might affect prevention efficacy perceptions. Given that prevention efficacy indeed occurs because robots reduce social contact, we expect that the degree of social presence associated with a context also affects prevention efficacy assessments. Hence, we argue that both anthropomorphism and social presence might influence attitudes toward being attended by a robot through their impact on prevention efficacy. Additionally, more in line with previous research, we propose that there could be also a direct influence of anthropomorphism and social presence on attitudes toward being attended by a robot (e.g., Ivanov *et al.*, 2020; Lu *et al.*, 2019; Tung and Au, 2018).

2.1. Prevention efficacy of robots for COVID-19 contagion risk.

The EHBM (Burns, 1992) deals with the adoption of preventive health behaviors by healthy subjects through three stages. Our research focuses on the first two: threat assessment and preventive health action assessment.

Threat assessment depends on several factors. We highlight three of them: health history, health importance, and perceived susceptibility. Health history refers to past health experiences. People experiencing a serious illness, either directly or in close family members, develop positive feelings toward preventive actions (LeSeure and Chongkham-ang, 2015; Reiter *et al.*, 2020). Previous research shows that people who know that a relative or a friend has been infected by COVID-19 are more concerned about their own health (Asare *et al.*, 2020; Shmueli, 2021). Given our research focus, we operationalize health history as the degree to which potential guests or their close relationships have suffered from COVID-19; and health importance as the importance attributed to health during a stay at a hotel, where contagion might occur due to sharing space with other people. Thus, consistent with previous literature, we expect that people in any way affected by COVID-19 will consider health as more important when staying at a hotel.

H1: Health history is positively associated with health importance.

Next, we posit that the higher the health importance, the more prone people are to consider themselves as more susceptible to COVID-19 exposure (that is, they have a higher perceived susceptibility for this disease). COVID-19's omnipresence in daily life makes people aware of contagion risk. Media coverage of the disease can increase perceived susceptibility (Ranjit *et al.*, 2021; Zemke *et al.*, 2015). Due to selective distortion, we consider that this effect must be more intense in the case of people worried about health issues. Consistently, previous research suggests that people who are more concerned about their health or are more health-conscious consider themselves more susceptible to COVID-19 (Shmueli, 2021; Wong *et al.*, 2021). Thus, we argue that health importance during a hotel stay increases the perception of being potentially exposed to COVID-19.

H2: Health importance is positively associated with perceived susceptibility.

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After assessing the disease threat, individuals evaluate preventive health actions. Therefore, customers can evaluate the prevention efficacy of COVID-19 prevention measures adopted by companies. People with higher levels of perceived susceptibility have a greater motivation to adopt a health-oriented behavior (e.g., Ahadzadeh *et al.*, 2015; Cahyanto *et al.*, 2016; Scarinci *et al.*, 2021) and hence positively assess prevention measures. For example, individuals who consider themselves susceptible to being infected by COVID-19 tend to perceive more benefits from vaccination (Shmueli, 2021). Similarly, given that robots decrease human-to-human contact, we expect that customers with higher perceived susceptibility will consider robots more positively as a prevention measure than customers with lower levels of perceived susceptibility.

H3: Perceived susceptibility is positively associated with prevention efficacy.

Subsequently, the EHBM proposes that after evaluating the value of a preventive action, subjects develop a predisposition to action. Thus, people who positively evaluate the benefits of COVID-19 vaccines are more willing to receive them (Reiter *et al.*, 2020; Shmueli, 2021; Wong *et al.*, 2021; Zampetakis and Melas, 2021). Similarly, if people consider that COVID-19 safety measures are beneficial (for example, using face masks and sanitizers, keeping social distance), they will be more likely to adopt such measures (Asare *et al.*, 2020; Tong *et al.*, 2020). We expect a similar effect for prevention efficacy of robots. We consider that if customers perceive robots can reduce the COVID-19 contagion risk, they will develop positive attitudes toward being attended by a robot. Additionally, consistent with technology acceptance models (e.g., Davis *et al.*, 1992; Kim & Qu, 2014; Kim *et al.*, 2010; Lee *et al.*, 2018), we expect that positive attitudes toward being attended by a robot will elicit higher booking intentions at the hotel employing robots to prevent COVID-19 contagion.

H4: Prevention efficacy is positively associated with attitudes toward being attended by a service robot.

H5: Attitudes toward being attended by a service robot are positively associated with booking intentions.

2.2. Anthropomorphism

Robot anthropomorphism influences potential users' perceptions, attitudes, and behaviors regarding robots (Goudey and Bonnin, 2016; Park, 2020; Zhu and Chang, 2020). This feature can originate from both psychological and physical features (e.g., Gray and

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Wegner, 2012). The uncanny valley theory states that human likeness positively influences individual evaluations of robots, up to a point at which it provokes adverse reactions. This theory has received contradicting empirical support (Belanche, Casaló and Flavián, 2020a; Goudey and Bonnin, 2016) and has seldom been studied in hospitality (Shin and Jeong, 2020). Hospitality literature concludes that human likeness predominantly provokes positive perceptions about robots (Tussyadiah and Park, 2018). Consequently, anthropomorphism increases robot adoption intentions in hospitality and tourism settings (Tussyadiah, 2020; Tussyadiah and Park, 2018). Nevertheless, several studies find also a negative impact of human likeness (Kim *et al.*, 2019; Lu *et al.*, 2019; Yu, 2020)¸ and even report that human-like robots are not necessarily preferred by hospitality customers (de Kervenoael *et al.*, 2020; Shin and Jeong, 2020). Thus, the effects of anthropomorphism on attitudes are still controversial (Zhu and Chang, 2020), making this robot feature worthy of investigation (Tussyadiah *et al.*, 2020).

Anthropomorphism influences how people perceive a robot in terms of two aspects: warmth and competence (van Doorn *et al.*, 2017). Regarding warmth, anthropomorphism is positively associated to it (Kim *et al.*, 2019; Zhu and Chang, 2020). Robots sharing human features are perceived as more helpful or caring, because human characteristics make robots more trustworthy (Tussyadiah, 2020; Tussyadiah and Park, 2018) and sociable (Broadbent *et al.*, 2013; Li *et al.*, 2010). Given these effects of human likeness, we argue that anthropomorphism can increase expectations about COVID-19 prevention efficacy.

H6: Robot anthropomorphism is positively associated with prevention efficacy.

Regarding competence, robot anthropomorphism is associated with robot skills and efficacy. Customers indeed appreciate companies investing in human-like robots, since this technology is then not perceived just as a means of reducing costs at the expense of customer satisfaction (Belanche, Casaló and Flavián, 2020b). Anthropomorphism makes users perceive robots as being alive, which is positively associated with inferred intelligence (Bartneck *et al.*, 2009; Li *et al.*, 2010) and, therefore, with appropriate performance in a service context. Individuals attribute higher capabilities to robots when they resemble humans (Gray and Wegner, 2012; Wirtz *et al.*, 2018), such as being more able to interact with humans (van Doorn *et al.*, 2017; Shin and Jeong, 2020) and a higher effectiveness (Tussyadiah and Park, 2018). These expectations about performance can elicit more positive attitudes toward being attended by a robot.

H7: Robot anthropomorphism is positively associated with attitudes toward being attended by a robot.

2.3. Social presence

Service encounter factors involve contextual elements, important when evaluating a technology (Oyedele *et al.*, 2007) or, in general, any product or service (Fennell, 1978; Yang *et al.*, 2002). Service robots are not an exception (Tussyadiah *et al.*, 2020). Robot acceptance depends on the context where the human–robot interaction will occur (de Kervenoael *et al.*, 2020; Tung and Au, 2018). This technology can be considered more trustworthy in some situations than in others, being inadequate for some activities (Seyitoğlu and Ivanov, 2020).

A context's social presence involves the sense of being with other people. We propose that this variable will have a twofold effect. First, we argue that the perceived COVID-19 prevention efficacy of robots will be higher when employed in contexts associated with a higher social presence (H8). Second, we also expect social presence to be negatively related to attitudes toward being attended by a robot (H9). Given that we also expect a positive impact of prevention efficacy on attitudes (H4), this might imply an indirect positive impact on attitudes (H4 and H8) together with a direct negative effect (H9).

Regarding prevention efficacy, we consider that the higher social presence of a context, the riskier the situation will be perceived as it involves more human-to-human contact. Human-to-human contact is responsible for COVID-19 contagion, hence a higher social presence implies a higher likelihood of exposure to this coronavirus. Individuals who perceive a disease as more threatening are more motivated to perform preventive actions (Burns, 1992), to which they attribute a higher prevention efficacy than if they do not perceive such threat (Liu *et al.*, 2021). The more customers perceive a service context as threatening due to high social presence, the more beneficial they must perceive the substitution of humans by robots, as robots reduce human-to-human interactions. In other words, the higher the social presence in the context where a robot is employed, the higher prevention efficacy must be.

H8: Social presence is positively associated with prevention efficacy.

However, employing robots to substitute for humans in service contexts with a high social presence might generate worse attitudes toward being attended by such robots. Technological elements reducing interpersonal contact can be harmful for the relationship

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between customers and service firms (Selnes and Hansen, 2001; Valdez Cervantes and Franco, 2020). Social presence is a subjective measure of being with others (Shih *et al.*, 2019). Hence, contexts with a high social presence are associated with human-to-human interactions. Individuals usually desire to connect with other individuals and experience their social support (Shin and Jeong, 2020). Particularly, hospitality customers expect to interact with employees who personalize the customer-firm relationship (de Kervenoael *et al.*, 2020). Hospitality employees provide affective experiences to customers, whereas robots do not (Chan and Tung, 2019). Despite living in the automation age (Ratchford, 2020), machines do not fully substitute for humans yet (Ghazizadeh *et al.*, 2012) and provoke a loss of human contact during the service delivery, a key element in tourism and hospitality industries (Leung, 2019; Tussyadiah, 2020). Therefore, the higher the social presence, and hence the more human contact that the customer expects to lose due to automation, the lower the attitude toward the robot must be. Indeed, replacing humans with service robots in contexts where humans are considered necessary or at least prominent, for instance where emphatic interactions are required, is not appropriate (Reis *et al.*, 2020). Therefore, we expect that the higher the social presence in a context, the lower the attitudes toward robots.

H9: Social presence is negatively associated with attitudes toward being attended by a robot.

Thus, we posit that employing robots in contexts associated with a high social presence deters attitudes toward being attended by a robot (H9); however, this negative impact might be attenuated if individuals consider that avoiding social presence when being attended by a robot could reduce contagion risk (H4 and H8).

3. METHODOLOGY

3.1. Design and procedure

We tested our hypotheses about customer response to robot employment in hospitality contexts for COVID-19 prevention through a 3×2 experimental design, focused on hotels. First, we manipulated robot anthropomorphism by incorporating three levels of human likeness (low, medium, and high), in particular, showing respondents robot images corresponding to each level. Second, we manipulated the social presence of the context where the hotel robot was going to be employed by situating the robot in two different

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contexts: checking in at the hotel reception vs. serving a drink at the hotel bar. Robot anthropomorphism and social presence are two predictors of prevention efficacy and attitude toward robots in our model.

We assigned our respondents to one of our six scenarios. We first told respondents that the purpose of the study was evaluating robots' employment in the hospitality industry, without mentioning COVID-19. Employing a survey, respondents in each scenario were asked to evaluate the social presence of the service context presented to them. Next, we showed a picture of the service robot under evaluation. We requested respondents to evaluate anthropomorphism. Subsequently, we asked them to evaluate the remaining variables of our study.

To prevent common method bias problems, we implemented several procedural recommendations (Podsakoff *et al.*, 2003). We guaranteed responses' confidentiality to participants and their usage only for the purpose of the study. We ensured respondent anonymity to avoid misleading answers. We induced a psychological separation between our variables by using a cover story not focused on COVID-19. Finally, we included questions not related to our research objective to prevent respondents connecting our dependent and independent variables (e.g., about robot beauty).

We conducted our study among undergraduate Business students at University Carlos III in Spain, employing a non-probability convenience sampling method. Current undergraduate students mainly include Generation Z individuals, making them suitable for this research. Focusing on university students allows increasing the sample's homogeneity and minimizing the random error caused by selecting a more general public (Calder *et al.*, 1981). We collected data in two different periods: May 2020 and January 2021. During the first one, Spain was in a hard confinement phase in the country's first wave of COVID-19; during the second one, some curfews and occupancy limits were active, and cases were rising in a third wave of COVID-19. Collecting data in two different periods of time allows controlling for biases due to specific conditions during a single period of time. Thus, we gathered 372 and 339 usable questionnaires from Generation Z individuals in the first and second periods respectively. Regarding demographics, our respondents were between 18 and 25 years old and homogenous in terms of gender and nationality across periods (Table 1). Such homogeneity allows confidently pooling the data (n=711)—we include time period in our model to control for differences arising from the date of data collection (for example, in terms of health history

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due to a higher spread of COVID-19). The number of questionnaires across scenarios oscillated between 108 and 123, far beyond the minimum number of cases in each scenario required in experimental designs (Cohen, 1988).

3.2. Measurement

Except for health history of the respondent or surrounding people, we employed scales taken from previous research. We directly asked the extent of COVID-19 impact in a seven-point scale ranging from not at all to extremely, and from indirectly to directly. We measure anthropomorphism using a one-item scale taken from Kim *et al.* (2019), consistent with our focus on the robot's human likeness (Lu *et al.*, 2019; Zhu and Chang, 2020). We adapted the scales for social presence, perceived susceptibility, health importance, and prevention efficacy from Gefen and Straub (2003); Cahyanto *et al.* (2016); Zemke *et al.* (2015); and Moon *et al.* (2017) respectively. We did not circumscribe the measurements of health history and health importance just to the respondent. This facilitates achieving enough variability in these two constructs, even if the respondent does not stay at hotels regularly or has not been affected directly by the disease. We took the attitude toward being attended by the service robot in a specific context from Davis *et al.* (1992); Kim and Qu (2014); Kim *et al.* (2010); and Lu *et al.* (2019). Finally, we employed Amaro and Duarte (2015) and Reimer and Benkenstein (2016) scales for booking intention. We operationalized the control variable capturing the period of data collection as a dummy variable with zero value for the first period of data collection, and one for the second period.

3.3. Data analysis

We tested our hypotheses using partial least squares structural equation modeling (PLS-SEM). Regarding ANOVA, this technique allows examining the multiple causal relationships of our model (Lei *et al.*, 2008), controlling for measurement error, and assessing reliability, and validity (Bleijerveld *et al.*, 2015). Regarding covariance-based structural equation models, PLS-SEM is more adequate for theory development, in the earlier stages of studying a phenomenon, and for research testing manifold relationships between exogenous and endogenous constructs; PLS-SEM also allows working with fewer items per construct. Additionally, this technique can assess whether the causes of a phenomenon in a model generate adequate predictions, i.e., the model's practical relevance (e.g., Hair, Risher, *et al.*, 2019; Hair, Sarstedt, *et al.*, 2019; Shmueli *et al.*, 2019).

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4. RESULTS

4.1. Manipulation checks

The manipulations of our experiment were successful. Our measurement of anthropomorphism ranges from 1- not at all human-like, to 7- very human-like. The anthropomorphism for each level is consistent with our intended manipulation ($Mean_{low}$=2.32, $Mean_{medium}$=3.01, $Mean_{high}$=5.57), with significant differences across levels ($p\text{-}value_{low\text{-}medium}<.01$, $p\text{-}value_{medium\text{-}high}<.01$, $p\text{-}value_{low\text{-}high}<.01$). Similarly, the social presence when being attended at a hotel bar is significantly lower than when checking in at the hotel reception ($Mean_{bar}$=4.51, $Mean_{reception}$=4.80, $p<.01$).

4.2. Measurement model

We first evaluated constructs' reliability. We detected that one loading from perceived susceptibility was lower than .7, which we depurated from our scale. After this, all the items of our constructs are above .7, showing indicator reliability. The Cronbach's α values of our variables (Table 2) are higher than .7 (Nunnally, 1978). Composite reliability and ρ_A are also higher than .7. This supports the reliability of our variables. Regarding convergent validity, the average variance extracted (AVE) of our variables is higher than the common threshold value of .5 (Fornell and Larcker, 1981).

Subsequently, we successfully assessed the discriminant validity of our constructs through three criteria: the loadings of the indicators of each variable are higher for their construct than for other variables; the AVE of all variables are greater than their absolute correlations with other variables (Fornell and Larcker, 1981; table 2); the heterotrait-monotrait ratio of the correlations between variables are all lower than .85 (Clark and Watson, 2003; Kline, 2011; table 2).

Finally, we discarded common method bias problems in our sample by inspecting whether the correlations among constructs are all below .9 (Pavlou *et al.*, 2007); and by applying the full collinearity assessment approach (Kock, 2015). These checks did not reveal any problem. Additionally, we followed Liang *et al.* (2007) procedure as an extra assessment: we converted each indicator to a single-indicator construct; we incorporated a common method factor in the model; and we computed the percentage of each indicator variance explained by the common method factor and by its substantive factor. On average, the common method factor explains less than 4% of the variance of indicators for our sample, hence confirming that common method bias is not present.

4.3. Hypotheses testing

We evaluated the standardized root mean residual (SRMR) of our model as an indicator of its global fit. This is .07, which is considered adequate (Hu and Bentler, 1998). Next, we evaluated the adjusted-R^2 of our endogenous variables. These are 1.08% for health importance, 10.13% for perceived susceptibility, 5.82% for prevention efficacy, 26.14% for attitude, and 34.81% for booking intention. We also assess the predictive power of our model, through the cross-validated redundancy measures and the PLSpredict procedure. The former jointly capture both the in-sample and out-of-sample predictive power of a model. The latter focuses on out-of-sample predictive power (Shmueli *et al.*, 2019), thus offering a clearer picture of the practical relevance of the model. The cross-validated redundancy measures of health importance, perceived susceptibility, efficacy, attitude, and booking intention are .01, .08, .05, .19, and .26. All are above 0, hence providing first evidence of our model predictive relevance (Hair, Risher, *et al.*, 2019). Similarly, the PLSpredict procedure also supported the predictive power of our model. PLSpredict splits the sample into k groups, estimating the model using data from all groups except one, making predictions for the data that has not been used in the estimation. As the assignation in the k groups is random, the procedure must be repeated multiple times to ensure the stability of results. Particularly, we applied PLSpredict with 10 repetitions and k=10 (Shmueli *et al.*, 2019). We focused on prevention efficacy as the main construct of our model. This procedure first evaluates the $Q^2_{predict}$ statistics of the variable indicators. Positive values indicate that the model outperforms the predictions produced by the means of the indicators of the training sample. We obtained positive $Q^2_{predict}$ statistics, between .01 and .02. Next, PLSpredict compares the model predictions with the forecasts from a linear model through root mean squared error. Our model outperformed the linear model in two out of three indicators, thus showing a medium out-of-sample predictive power.

Regarding our hypotheses, we used a non-parametric bootstrapping procedure (10,000 samples, no sign change) to assess path coefficients significance in our model. We find support for all hypotheses except H8 in our Generation Z sample (Figure 1). Therefore, health history is positively related to health importance in our sample (H1:.11; p-value<.05); health importance positively influences perceived susceptibility (H2: .31; p-

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value<.01); perceived susceptibility is positively associated with robot efficacy to prevent COVID-19 for Generation Z individuals (H3:.17; p-value<.01); robot efficacy to prevent COVID-19 positively influences attitudes toward being attended by a robot in hospitality contexts (H4: .44; p-value<.01); and attitudes toward being attended by a robot in hospitality contexts positively affects booking intention in our Generation Z sample (H5:.59; p-value<.01). Regarding anthropomorphism, we find a positive influence on robot efficacy to prevent COVID-19 (H6: .11; p-value<.01) and on attitudes toward being attended by a robot (H7: .22; p-value<.01) for our sample. Regarding social presence, our results do not support a positive association between this variable and robot efficacy to prevent COVID-19 (H8: .03; p-value>.05). In contrast, social presence is negatively associated with attitudes toward being attended by the robot at the hotel (H9: -.08; p-value<.05).

Post-hoc analysis of indirect and total effects of prevention efficacy, anthropomorphism and social presence

According to our results, prevention efficacy might have an indirect effect on booking intentions, mediated by attitudes toward being attended by a robot. Similarly, both anthropomorphism and social presence might have an indirect effect on attitudes toward being attended by a robot, mediated by prevention efficacy. This indirect effect could also reach booking intentions. We next analyze these potential indirect effects.

Our bootstrapping procedure computes indirect effects by multiplying the effect of the independent variable on the mediating variable (IV→MV) by the effect of the mediating variable on the dependent variable (MV→DV). For example, the indirect effect of prevention efficacy on booking intentions is calculated in our research as prevention efficacy → attitudes × attitudes → booking intentions. These computations can be extended in a straightforward way in case of having more than one mediating variable. If a direct effect also exists, the total effect of a variable over another one is computed as the sum of its direct and its indirect effects (in case of not having direct effects, total effects are equal to indirect effects).

Regarding prevention efficacy, our results indicate that it has an indirect effect on booking intentions, mediated by attitudes (.26; p-value<.01). Thus, the effect of prevention efficacy on booking intentions is positive and significant for our sample.

Our results also reveal that anthropomorphism has an indirect effect on attitudes, mediated by prevention efficacy (.05; p-value<.01). Thus, anthropomorphism positively influences attitudes, both directly and indirectly. The total effect of anthropomorphism on attitudes is positive and significant for our sample (.26; p-value<.01). Moreover, the total effect of anthropomorphism on booking intentions is positive and significant for our sample (.16; p-value<.01).

Social presence has direct and indirect effects on attitudes. These effects have an opposite sign. The direct effect is negative, whereas the indirect effect is positive although non-significant (.01; p-value>0.10). Together, both effects lead to a total negative effect on attitudes that is significant at a 90% level (-.07; p-value<.10). Likewise, the total effect of social presence on booking intentions is negative and significant at a 90% level (-.04; p-value<.10).

5. DISCUSSION

COVID-19 is likely to accelerate service robot adoption by hospitality firms, aiming to recover customer confidence and hence service demand (e.g., Cha, 2020; Zeng *et al.*, 2020). This study assesses whether this motivation is valid. Particularly, we explore whether the Generation Z cohort of potential hotel guests perceives robots as an effective means to reduce contagion risks, and how this perception influences guest attitudes toward being attended by a robot and their booking intentions. Additionally, we study whether robot anthropomorphism and the social presence of the context where the robot will be employed influence prevention efficacy perceptions, as well as attitudes and booking intentions directly.

Regarding prevention efficacy, our study indicates that robots are considered by Generation Z an appropriate means to reduce COVID-19 contagion risk. Our results show that individuals' exposure to the virus makes them consider health more important when traveling, which provokes a higher level of perceived susceptibility toward the disease and, consequently, a higher perceived prevention efficacy of technological solutions that reduce social contact: robots, in our research. Therefore, our findings are consistent with the chain of effects proposed by the EHBM (Burns, 1992). Extant literature has applied these variables for studying COVID-19 prevention measures (e.g., Asare *et al.*, 2020; Shmueli, 2021). Our novel application of service robots at hotels suggests that Generation

Z individuals understand that technological solutions that ensure social distancing are effective at reducing COVID-19 contagion risk, therefore constituting their implementation by hotels a preventive action. This could be due to their familiarity with other technological solutions that aim at avoiding human-to-human contact (for example, digital menus at restaurants, or videoconferences instead of face-to-face meetings). Thus, our results confirm the view of studies that suggest that robotization is an appropriate means to recover customer trust in hospitality services (Jiang and Wen, 2020), against some practitioners' opinions (Villacé-Molinero *et al.*, 2021).

The more human-like a robot, the higher the prevention efficacy attributed to the robot by our Generation Z sample. This relationship, not yet studied by extant literature, might be due to warmth attribution arising from human characteristics (Kim *et al.*, 2019; Zhu and Chang, 2020)—making the robot more trustworthy (Tussyadiah, 2020; Tussyadiah and Park, 2018) and, probably, more caregiving and protective. Additionally, our results reveal that anthropomorphism generates positive attitudes toward being attended by a hotel robot. Some studies have detected a negative influence (Kim *et al.*, 2019; Lu *et al.*, 2019; Yu, 2020), arising from feelings of discomfort; whereas other studies indicate that human likeness has a positive impact on hospitality customers (Tussyadiah, 2020; Tussyadiah and Park, 2018), due to associations with higher intelligence, capabilities, interactivity, and effectiveness (e.g., van Doorn *et al.*, 2017; Tussyadiah and Park, 2018; Wirtz *et al.*, 2018). Our research is consistent with the latter ones. Apart from customers' associations to anthropomorphism, our sample's preferences for technological advances might partially explain our findings, as more anthropomorphic robots might be considered less rudimentary by our Generation Z respondents. Finally, our results regarding the impact of anthropomorphism on attitudes do not allow us to conclude that being attended by robots with anthropomorphic forms is preferred over other options. Other robot forms or humans might indeed be preferred by hospitality customers (de Kervenoael *et al.*, 2020; Shin and Jeong, 2020). Beyond of the scope of our research, we do not provide any explicit comparison in this regard.

Contrary to our expectations, we find that social presence associated to the context where the customer will be attended by the robot does not influence prevention efficacy perceptions. Our sample might consider that checking in and ordering a drink at the hotel bar are tasks that can be completed quickly enough to be safe, hence not constituting health threats. This would suggest the existence of a threshold from which social presence

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could affect prevention efficacy perceptions. Social presence below such a threshold would not influence prevention efficacy. However, the more social presence is expected in a context where the robot will be implemented, the lower the attitudes toward being attended by a robot. Our sample does not consider appropriate substitution of humans by robots in contexts where more intense human-to-human interactions are expected. This result is in line with previous research that highlights the importance of human contact in services (Chan and Tung, 2019; Gómez-Suárez and Veloso, 2020; Leung, 2019; Tussyadiah, 2020), where automation cannot fully substitute for humans (Ghazizadeh *et al.*, 2012)–especially in situations where empathy and information-sharing expectations are high (de Kervenoael *et al.*, 2020; Reis *et al.*, 2020). Additionally, this finding is aligned with previous studies that indicate that robot acceptance is context-dependent (de Kervenoael *et al.*, 2020; Tung and Au, 2018). We advance such studies by identifying a specific context feature that determines attitudes toward being attended by a robot. This effect might be stronger for individuals with more intense social needs (Belanche, Casaló, Flavián, *et al.*, 2020b).

6. CONCLUSION, IMPLICATIONS AND LIMITATIONS

6.1. Conclusion

Generation Z individuals previously affected in some way by COVID-19 are more conscious of health risks when traveling. This increases their perceptions of COVID-19 susceptibility. As a result, they consider being attended by robots in hospitality contexts as an appropriate means to reducing the COVID-19 contagion risk. This perception leads to a positive attitude toward being attended by a robot and, consequently, to higher booking intentions. Robot anthropomorphism increases prevention efficacy perceptions and generates more positive attitudes toward being attended by the robot. Positive attitudes toward robots are lower in contexts with a high social presence. These results are circumscribed to our sample of Generation Z customers. However, given the inconclusive results of previous research regarding younger people’s response to robots (Belanche *et al.*, 2019; Cha, 2020; Fenech *et al.*, 2020; Ivkov *et al.*, 2020), we consider that our exploratory study constitutes a valid first approximation to our phenomenon and can set a solid base for further research about the topic. We next explain the theoretical and managerial implications derived from our study.

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6.2. Theoretical implications

This study advances extant literature in several ways. First, we contribute to hospitality research by extending its boundaries through the incorporation of theories from other disciplines, namely the EHBM. Our results confirm the appropriateness of this model for studying health concerns for hospitality sectors. Further research in this regard needs to consider perceived susceptibility as a key construct that determines perceived efficacy of health prevention measures in hospitality establishments and, therefore, attitudes toward such measures.

Second, we test the effects of anthropomorphism on customer perceptions, confirming previous research that identifies a positive influence of robot human likeness on robot acceptance (e.g., Belanche, Casaló and Flavián, 2020b; Tussyadiah and Park, 2018) and extending it by incorporating anthropomorphism' impact on customer assessment of robots for COVID-19 prevention. Anthropomorphism positively influences attitudes, directly and mediated by prevention efficacy, thus generating higher booking intentions. Robotics studies conducted under health threats must take into account such twofold influence.

Third, we find that robot acceptance in hospitality depends also on the context where the robot is employed, particularly on its social presence. Further studies about service automation must control for the robot usage context, and could incorporate findings from usage context literature (e.g., Fennell, 1978; Yang *et al.*, 2002) to better understand robots' acceptance.

Fourth, our also study contributes to preventive health care literature by adding artificial intelligence tools for service automation implemented by companies as a prevention measure, and by evaluating individuals' reactions to such a measure.

6.3. Managerial implications

This study offers interesting novel insights for managers considering employing robots to enhance COVID-19 safety perceptions. Given our focus on Generation Z, these managers need to evaluate the applicability of our insights in their companies before implementing them. Service automation through anthropomorphic robots can be an effective way to recover guest confidence in hotels, despite practitioners' concerns regarding robots' impact on customers' emotions (Villacé-Molinero *et al.*, 2021).

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Additionally, hotel managers should consider that more human-like robots produce better results in terms of recovering guest confidence. Our results also recommend employing robots in contexts where social presence is lower. Hotels should not incorporate robots to attend customers in contexts where they expect a high social presence (for example, in case of a service failure); in these contexts, hotels must take extra precautions, as it is more difficult to avoid human-to-human contact successfully.

Our results offer clues in terms of hotel communication strategies about robot implementation. Companies implementing robots (or, in general, service automation) as a tool to reduce contagion risk must clearly convey this beneficial effect of technology, as prevention efficacy improves attitudes toward the safety measure and increase booking intentions. These messages are especially relevant for markets where COVID-19 has spread more intensively and therefore customers are more concerned about their health, as our results indicate. Generation Z might facilitate the spread of these messages if properly targeted through digital media. Additionally, managers must carefully select the context where the robot is shown to enhance a positive communication impact.

Despite robots' prices decreasing trend (Belanche, Casaló and Flavián, 2020a, 2020b), investing in this technology might be still difficult for many hospitality firms in a situation of demand contraction. A call for action from the World Tourism Organization (2020) encourages governments to invest on hospitality firms for mitigating the socioeconomic impact of COVID-19 and accelerate recovery. These investments could be fruitful if devoted to increasing hotel robotization, given its effectiveness in enhancing guest perceptions of prevention efficacy (and more important, guest and staff safety if accompanied by strict protocols and hygienic measures ensuring that human-to-human contact and exposure to the virus are indeed minimized). Additionally, governments could consider robot implementation as an important feature if developing COVID-19 safety seals. Investments in robots will provide hotels with resilience and competitive advantage beyond this pandemic. Robot implementation can provoke employment losses (Tussyadiah, 2020; Villacé-Molinero *et al.*, 2021), particularly in 'low-tech' jobs. However, policy makers can smooth this potential negative consequence of automation through programs aiming at retraining hospitality professionals (Xu *et al.*, 2020).

6.4. Limitations and further research

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This exploratory research has several limitations. First, our results must be taken cautiously in terms of generalizability due to our convenience sampling procedure. Further research could replicate our study, employing random sampling methods that guarantee sample representativeness, even regardless of generational cohorts. Second, our model omits variables related to technology acceptance, such as ease of use, trust, etc., that could influence robot acceptance (Wirtz *et al.*, 2018). Further research on the topic might incorporate these variables, to provide a better picture of attitudes toward being attended by robots. Third, our sample comprises individuals of several nationalities. Despite nationality not determining Generation Z belongingness, controlling for cultural differences might have been desirable. Further research could evaluate whether cultural differences moderate our results, especially for uncertainty avoidance. Fourth, our research does not consider the hotel type (e.g., budget, mid-market, or luxury) where the robot is implemented, which might influence attitude toward robots (Chan and Tung, 2019; Shin and Jeong, 2020). Further research could investigate whether hotel type moderates our results to provide more accurate recommendations to managers.

Furthermore, our study could be enriched through the inclusion of factors that might contribute to explaining prevention efficacy and customer attitudes. Robot employment could be evaluated in a wider range of contexts, classified in terms of other variables beyond social presence. Robot features such as gender, tone of voice, dressing etc., could be relevant to explain safety perceptions and attitudes toward robots. This fascinating topic is already capturing the attention of hospitality researchers, as reflected in this special issue. Beyond COVID-19 prevention efficacy, hospitality managers need to understand how their customers accept interacting with service robots. We expect our study to be helpful in this promising research stream.

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Table 1. Sample demographics

		First period	Second period	Total sample	χ^2 test
Age	18-25	100%	100%	100%	-
Gender	Male	44.62%	41.00%	42.90%	χ^2=1.89 (p-value=.39)
	Female	53.76%	58.11%	55.84%	
	Not reported	1.62%	0.89%	1.26%	
Nationality	Spanish	72.85%	77.29%	74.96%	χ^2=3.63 (p-value=.30)
	European	13.17%	10.03%	11.67%	
	Latin American	7.26%	5.01%	6.19%	
	Others	6.72%	7.67%	7.17%	

Note: p-values above .05 denote sample homogeneity across periods

Table 2. Measurement model

	α	ρ_A	CR	AVE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Health history (1)	.76	.97	.89	80	**.89**	.11	.12	.04	.06	.04	.03	.04	.13
Health importance (2)	.87	.92	.91	.71	.11	**.85**	.32	.18	.11	.17	.01	.15	.06
Perceived susceptibility (3)	.88	.88	.92	.80	.12	.31	**.90**	.19	.20	.26	.08	.04	.07
Prevention efficacy (4)	.90	.90	.93	.83	.03	.16	.17	**.91**	.50	.46	.10	.04	.15
Attitude (5)	.90	.91	.93	.72	-.04	.11	.18	.45	**.85**	.64	.29	.10	.03
Booking intention (6)	.92	.92	.94	.76	.00	.16	.24	.42	.59	**.87**	.21	.11	.05
Anthropomorphism (7)	1.00	1.00	1.00	1.00	.00	.00	.07	.10	.28	.21	**1.00**	.11	.10
Social presence (8)	.85	.87	.89	.62	.03	.11	.02	.03	-.10	-.09	-.11	**.79**	.03
Control variable: period (9)	1.00	1.00	1.00	1.00	.11	.05	-.07	.14	.01	-.04	-.10	.02	**1.00**

Notes: α = Cronbach's alpha, CR = CR, AVE = average variance extracted.. Bold Numbers on the diagonal show the square root of the AVE; numbers below the diagonal represent construct correlations; numbers above the diagonal represent the HTMT ratio

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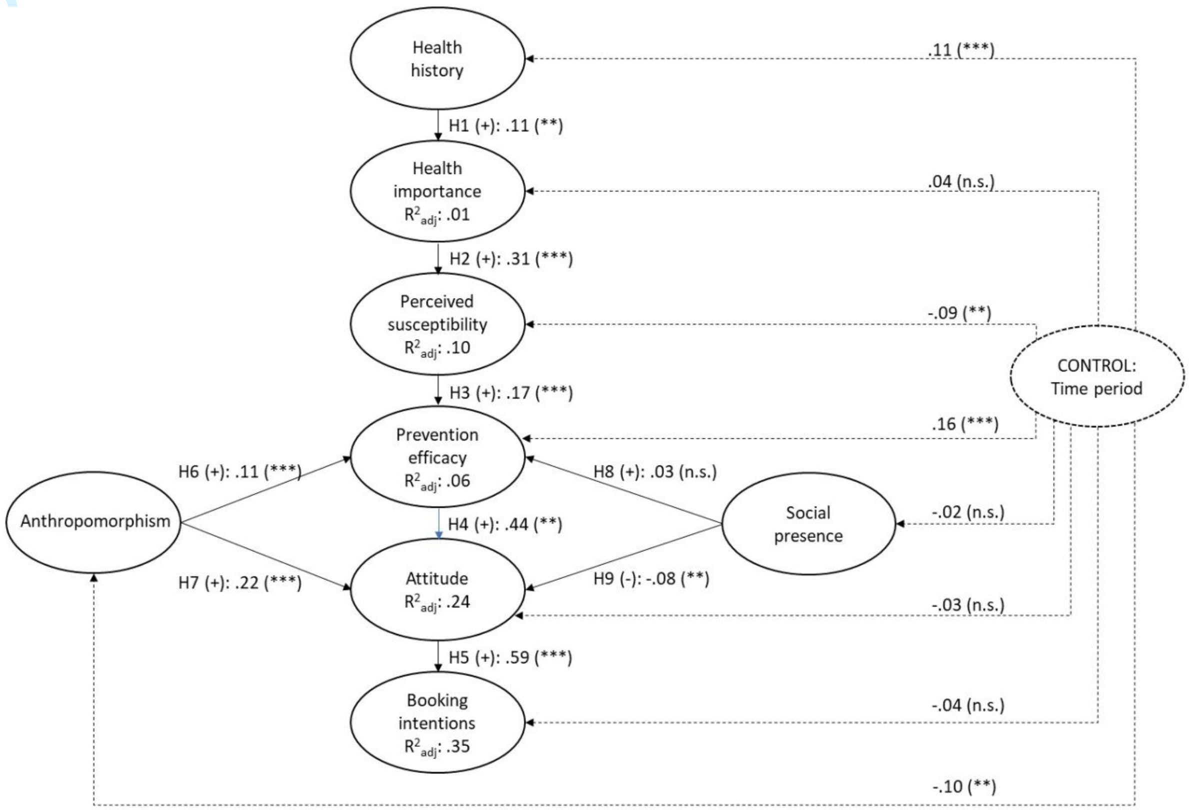
Figure 1. Model results



**: significant at a 95% level
***: significant at a 99% level
n.s.: non-significant