Can the humanisation of smart home speakers improve users' attitude towards covert information collection?

Abstract

Purpose – This paper analyses whether the humanisation of smart home speakers can improve users' attitudes towards covert information collection. Additionally, it examines the direct and indirect impact of trust, social presence and user's perceived surveillance on attitude toward covert information collection.

Design/methodology – A total of 679 American users of smart home speakers are surveyed, and their responses are analysed using structural equation modelling. Mediating effects are also examined.

Findings – Humanisation increases social presence, improves users' attitude towards covert information collection and has a U-shaped effect on trust. A negative effect of humanisation on perceived surveillance is demonstrated. Social presence reduces perceived surveillance levels and improves users' attitude towards covert information collection.

Originality – We examine attitude towards covert information collection as a new outcome variable. This study contributes to the growing body of research on humanisation by providing new evidence of how humanisation helps improve users' attitude towards covert information collection and generates trust in the service provider. This research indicates the important role of social presence.

Keywords: Smart home speakers; humanisation; social presence; surveillance; information collection.

1. Introduction

Smart home speakers are trying to offer value to users by addressing their requests and desires in a more interactive and personalised way (Peltier *et al.,* 2023). To achieve this personalisation, companies must first collect information from users that allow firms to learn about users' behaviour, consumption patterns, tastes or preferences (Candao *et al.,* 2023; Gao and Liu, 2022).

To collect this private information, companies may employ overt or covert collection strategies. Overt information collection involves requesting permission from the user when this collection takes place, whereas covert information collection omits this step (Aguirre *et al.,* 2015). In the latter case, users are not aware that information is being collected and do not know what personal information the firm is collecting and storing (Aguirre *et al.,* 2015; Libaque-Sáenz *et al.,* 2021). This covert collection of information represents not only a risk to the privacy of users but also a danger to the image of companies, whose reputation and trust may be compromised. According to a study conducted by Morey *et al*. (2015), only 27% of the people surveyed were aware that they were sharing their friends list and only 18% were aware that their communications history was being shared. Likewise, in research by Turow *et al.* (2015) 58% of respondents said they have little control over what companies can learn about them from the information they collect.

Frick *et al.* (2021) defined surveillance effect as "people worry that their smart devices listen in on them and relevant ads are displayed in social media feeds or websites based on recent conversation topics" Information collection by smart home speakers includes any oral information the user provides, and is collected by companies through microphones. They have a physical button to switch off the microphones. These devices should only record and listen after the wake-up word to provide the user with the information he/she has requested. This is how the devices should work. However, consumers often feel they are being continuously spied on (Frick *et al.,* 2021; Lau *et al.,* 2018; Siddike *et al.,* 2018), experience privacy concerns and stress, and show discomfort with this covert information strategy (Benlian *et al.,* 2019; Song *et al.,* 2022). Consumers are afraid about the data collected and some of them turn off the device before having private conversations to avoid unwanted surveillance (Siddike *et al*., 2018).

Similarly, as consumers perceived that are being surveyed, they may also think that companies use covert information collection, not having a positive attitude toward this type of strategy. This outcome variable is very important because a better attitude towards covert information collection means that companies can provide personalised messages without asking for permission at each interaction. It is also important for customer experience, since interruptions during the interaction may reduce customer flow. Recent research has examined perceived surveillance, its antecedents (Frick *et al.,* 2021) and consequences (Plangger and Montecchi, 2020), suggesting that trust in the device is the main factor to reduce perceived surveillance (Frick *et al.,* 2021). However, extant studies have not considered what characteristics of smart home speakers can reduce perceived surveillance, nor how to improve consumer attitudes towards covert information collection.

Based on parasocial relationship theory (PSR), research has concluded that humanisation enhances the credibility of messages (Foehr and Germelmann, 2020; Poushneh, 2021) and increases social presence during the interaction process (Kang and Kim, 2022; Toader *et al.,* 2019), generating trustworthy and close relationships akin to those that arise between friends (Han and Yang, 2018; Pitardi and Marriott, 2021). On the other hand, under the framework of uncanny valley theory and contrary to the above findings, Lavado-Nalvaiz *et al.* (2022) recently found that humanisation can diminish perceived privacy risks for low levels of humanisation, while high levels increase perceived risks of information disclosure. Nevertheless, we still do not know whether humanising smart home speakers helps to reduce the effects of perceived surveillance, and whether humanisation can improve consumers' attitude toward covert information collection.

The present research has three aims. First, it analyses humanisation as a factor to improve users' attitude towards covert information collection by increasing trust and social presence and by reducing perceived surveillance. Second, it analyses the mediating role of trust in the relationship between humanisation and users' attitude towards covert information collection. Finally, it examines how social presence can reduce users' perceived surveillance. To achieve these objectives, 679 American smart home speaker users are surveyed, and their responses are analysed using structural equation modelling (SEM).

This article contributes to previous research in several ways. First, we contribute to interactive research by examining the antecedents of a new outcome variable: attitude towards covert information collection. Second, the article contributes to anthropomorphism and uncanny valley theory research by providing new evidence of how humanisation helps improve social presence and users' attitude towards covert information collection by these devices, and to reduce perceived surveillance. Finally, we contribute to extant research on interactive and smart products by providing empirical evidence of the important role that social presence plays in improving users' behaviour, particularly reducing users' perceived surveillance, improving users' attitude towards covert information collection and demonstrating that humanisation can generate trust in the service provider through social presence.

2. Conceptual development

2.1 Humanisation

Users who interact with devices that have anthropomorphic attributes may feel that they are interacting with another human being rather than a machine (Pitardi and Marriot, 2021). Regarding smart home speakers, research has mainly focused on conversational features, such as type of voice (Chen *et al*., 2022) or sense of humour (Go and Sundar, 2019; Kang and Kim, 2022). Two theories have been advanced to explain the effects that humanisation has on users' behaviours and emotions: realism maximisation theory (Groom *et al.,* 2009) and uncanny valley theory (Mori, 1970).

Realism maximisation theory states that human personality characteristics trigger positive emotional reactions in consumers as they perceive that they are interacting with another human being (Lee and Oh, 2021). Humanisation enables smart devices to generate higher levels of trust, feelings of familiarity and social presence (Foehr and Germelmann, 2020), and can even create an environment that generates high levels of user self-disclosure (Rhim *et al*., 2022).

On the other hand, uncanny valley theory, proposed by Mori (1970), has been used to explain the relationship between the degree of humanisation of an object and users' emotional response when using it. According to this theory, humanisation has a cubic effect on users' emotional response. Thus, low but increasing levels of humanisation can generate affinity towards the device, until a point of humanisation at which the device starts to be perceived as creepy and upsetting, leading to negative emotions of distress and eeriness (Mathur *et al.,* 2020). When humanisation is so high that consumers believe they are talking to a human being, the effect of humanisation on consumers' feelings becomes positive once more (Mathur *et al*., 2020). Although users may perceive some smart devices to be highly humanised, they will never mistake them for human beings as their physical aspect differs. Previous research has found that humanisation exerts such a quadratic effect on user behaviour, i.e., user perceived risks (Lavado-Nalvaiz *et al.,* 2022). This is because a voice that sounds human but is actually being generated by a computer may cause confusion over the humanness of the device and cause distrust towards it (Xie *et al*., 2020).

2.2 Social presence

With the increasing development of technology, PSR theory has been employed in various studies on the interaction between individuals and non-human entities (Han and Yang, 2018; Tsai *et al*., 2021). Heerink *et al*. (2010) conceptualised social presence as the degree to which a machine can make a human being feel as if they are interacting with another individual. In the present study, we define social presence as the feeling of human contact, human sociability and human sensitivity; in essence, the feeling of interacting with a real person when using a smart home speaker.

Smart home speakers can imitate human attributes, such as the ability to communicate verbally, by providing with human responses, such as jokes and original answers, or can even have a "human" name (Go and Sundar, 2019). Once the voice assistant is perceived as being close to human, users engage in interpersonal social interactions and develop a parasocial relationship with it (Han and Yang, 2018). Feelings of closeness, trust and friendliness then emerge, which in turn generates regularity in interaction (Ki *et al*., 2020) and a better attitude toward the device (Pitardi and Marriot, 2021). However, there is a need to further study social presence and how it is perceived by users in terms of their attitudes towards covert information collection and whether social presence can help reduce perceived surveillance.

2.3 Attitude towards covert information collection

Firms can adopt two types of information collection strategies. Overt information collection involves requesting the customer's permission to collect data, while covert information collection omits this request stage, or is based on a request made a long time ago, with the result that the customer is no longer aware that the company is collecting such information (Aguirre *et al.,* 2015; Libaque-Sáenz *et al.,* 2021). Previous research has found that covert strategies also increase the perceived risk regarding the use of information. Users feel a sense not only of invasion and loss of privacy but also of perceived control over their data (Libaque-Sáenz *et al*., 2021).

In this research, we focus on user's attitude towards covert information collection. The paper does not examine whether the firms are using covert information collection strategies, but the user's attitude toward that type of strategy. Following previous research on technology adoption and use, we define this attitude as the user's positive or negative beliefs about such type of information collection by the smart speaker (Bajaj and Nidumolu, 1998). Ho *et al*. (2022) studied the attitude towards non-conscious data collection among Generation Z. They found that 50% of consumers were not worried about covert data collection by firms, and thus concluded that users have a neutral attitude towards that collection strategy. A possible explanation for this result is that young consumers are resigned with respect to data sharing, and accept data collection as inevitable. Similarly, Lau *et al.* (2018) found that users of the devices do not feel uncomfortable with an "always listening" device because the recordings will not be of interest for the firm or because firms have already collected users' private information, so the new information collected is just a small addition. The present research augments previous studies by focusing on a concrete smart product and including not only age and sex variables, but also trust and humanisation, as antecedents of attitude towards covert information collection.

2.4 Perceived surveillance

Frick *et al*. (2021) defined surveillance effect as “people worry that their smart devices listen in on them and relevant ads are displayed in social media feeds or websites based on recent conversation topics”. Surveillance involves the acquisition of customers’ personal data by companies (Plangger and Montecchi, 2020). Smart home speakers need to continuously analyse audio signals as they wait to receive their activation messages (e.g., “OK Google” or “Hey Alexa”), and are technically capable of recording audio and transmitting it to a server (Frick *et al.,* 2021). Lau *et al*. (2018) made a qualitative research about the users’ perception of how smart speakers work. They found that users do not know if the device is recording or listening all the time. Some previous research based on interviews pointed out that consumers have fear about the data collected and that some turned off the device before having private conversations to avoid unwanted surveillance (Siddike *et al,*. 2018). They showed that users are afraid of being listened to, increasing user’s feelings of stress (Benlian *et al.,* 2019) and reducing the perceived value of smart home speakers and the intention to use them (Kowalczuk, 2018).

3. Hypothesis development

In this section, we develop our theoretical model and develop the research hypotheses. The model proposed and the hypotheses to be tested are shown in Figure 1.

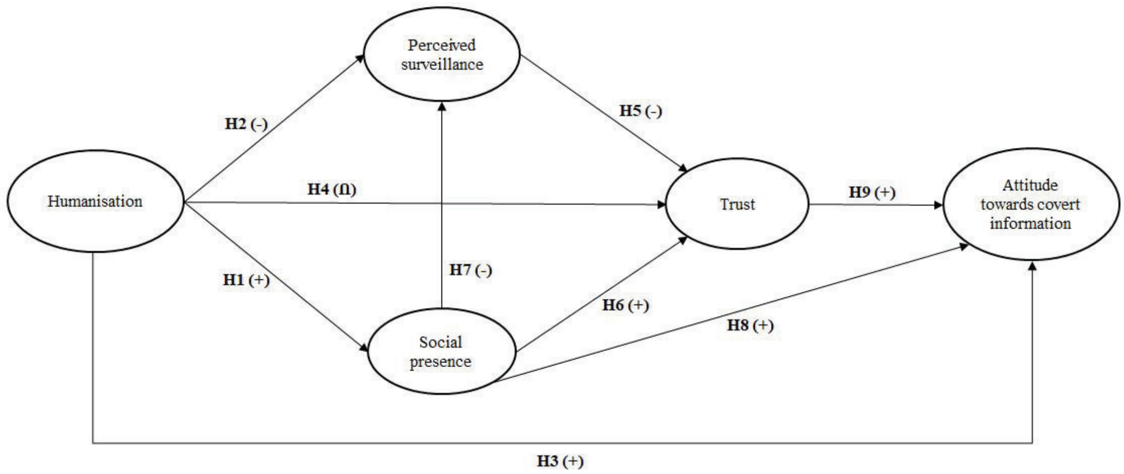

Figure 1. Theoretical model.

Previous research has considered how anthropomorphic design features of smart devices and robots affect users' perceptions of social presence (Rhim *et al.,* 2022: Toader *et al.,* 2019). When interacting with smart devices that have anthropomorphic features, such as humanlike voices and manners of responding, people may come to believe that they are interacting with another human being, enhancing feelings of social presence (Kang and Kim, 2022). According to PSR theory, if users interact and socialise with smart devices in a similar way as they would with humans they develop feelings of closeness and intimacy. Blut et al., (2021) proposed that by giving robots humanlike features, people perceived that they are connecting with another human being. Therefore, we propose:

H1. *Humanisation of smart home speakers has a positive effect on social presence.*

Anthropomorphism may reduce privacy concerns derived from consumers' perceived surveillance when using smart speakers. When technology possesses anthropomorphic characteristics, the sense of privacy invasion is reduced (Benlian *et al*., 2019). Recently, Lucia-Palacios and Pérez-López (2023) asserted that interactivity helps to decrease the perception of smart home speakers' intrusiveness. Interactivity involves bidirectional communication and responsiveness – two aspects of natural language and anthropomorphism included in smart home speakers. In addition, Blut et al., (2021) demonstrated that anthropomorphism has a positive effect on the perception of privacy security, suggesting that the more humanised a robot is, the safer the robot is considered to be in terms of privacy risks and privacy invasion. Thus, we propose:

H2. *Humanisation of smart home speakers has a negative effect on perceived surveillance.*

According to PSR theory, people are more likely to experience feelings of familiarity, intimacy and closeness when interacting with a device if it is perceived as having humanlike features (Blut *et al*., 2021; Poushneh 2021). Such features create a climate of comfort that leads users to relax and be less worried about the possibility of smart home speakers collecting information covertly. This can lead them to have a more favourable attitude toward this type of information collection. Furthermore, Melumad and Meyer (2020) stated that if devices are perceived as friends, users will voluntarily disclose information even without being subject to a prior request for permission. This is because a feeling of psychological comfort is created between user and device._Hence, we propose:

H3. *Humanisation of smart home speakers has a positive effect on attitude towards covert information collection.*

Under maximisation realism theory, providing a humanlike mind to an artificial device causes users to perceive it as a more competent agent (Waytz *et al.,* 2010). Indeed, trust improves when the intelligent agent applies humanlike characteristics, such as not interrupting during the interaction, being patient or even making jokes (Go and Sundar, 2019).

According to uncanny valley theory, humanisation can lead to increased trust feelings and social presence towards the device, brand or firm (Foehr and Germelmann, 2020; Poushneh, 2021). However, over-humanisation can raise major concerns, as users may be confused by an artificial voice that resembles that of a human, creating doubts about its humanity. These feelings can result in the user distrusting the smart home speaker, which also increases distrust of the provider behind the device (Xie *et al.,* 2020). Following recent findings in the field of smart speakers (Lavado-Nalvaiz et al., 2022), we follow this theory. Thus, we propose:

H4. *Humanisation of smart home speakers has an inverted U-shaped effect on trust.*

Privacy intrusion is annoying and irritating (Krafft *et al.,* 2017), and the problem is particularly salient when smart home speakers collect information without consumer awareness (Frick *et al.,* 2021; Jung *et al.,* 2021). Most of the time, users are unaware of the amount of personal information smart speakers are processing, and when they are doing so. These concerns make users feel that they have no control of what information is disclosed (Klumpe *et al*., 2020), in turn risking customer relationships and even generating feelings of distrust (Plangger and Montecchi, 2020). Thus, we propose:

H5. *Perceived surveillance has a negative effect on trust.*

Pitardi and Marriott (2021) demonstrated that social presence enhances consumer trust towards a device. However, it remains unclear whether social presence when interacting with a smart product can also create trust in the service provider. Moreover, some studies have shown that chatbots improve trust in affiliated websites. This is because they show signs of social presence, which is key in building trust in the avatar and consequently in the website (Foster *et al*., 2022). Parasocial interactions between the smart home speaker and the user enhance the user's trust (Hsieh and Lee, 2021). Based on this, we propose that the trust generated by the social presence of the device applies not only to the product but also to the brand or the service provider. Thus, we propose:

H6. *Social presence of smart home speakers has a positive effect on trust.*

When users interact with smart home speakers in the same way as they would with human beings, users experience feelings of closeness and intimacy towards the devices. Benlian *et al*. (2019) proposed that humanisation increases feelings of closeness with devices, such that users may be less concerned about the information they are providing to the device and the risks arising from that disclosure. Ki *et al*. (2020) showed that the social presence of smart home speakers influences users' self-disclosure, reducing privacy risks and perceptions of surveillance. Thus, we propose:

H7: *Social presence of smart home speakers has a negative effect on perceived surveillance.*

Tsai *et al.* (2021) suggested that the intuitive perception of being in the presence of another smart being triggers a sense of interpersonal interaction. When users perceive that they are dealing with a real person rather than with an electronic device, their perceived risk regarding the information that is disclosed is reduced (Ki *et al*. 2020; Melumad and Meyer, 2020). In fact, it is possible that even more information will be revealed because they see the speaker as a friend with whom they can socialise. As the device becomes more familiar with the user, these feelings of closeness and intimacy increase. Thus, users may show lower privacy concerns and a better attitude towards covert information collection. Therefore, we propose:

H8. *Social presence of smart home speakers has a positive effect on attitude towards covert information collection.*

Trust in the service provider can be defined as the degree to which a company can be trusted to protect users' personal information (Bawack *et al.,* 2021). Therefore, trust in the service provider will play a key role in making consumers feel more confident about sharing their personal information (Schaupp and Carter, 2010), and will positively influence users' attitude toward using artificial intelligence (AI) such as voice-based assistants (Hsieh and Lee 2021; Pitardi and Marriott 2021). Therefore, we propose:

H9. *Trust in the service provider has a positive effect on attitude towards covert information collection.*

4. Methodology

We conducted a survey via Amazon Mechanical Turk to collect data and test the proposed hypotheses. To participate in the study, respondents had to be over 18 years old and own a smart home speaker. Although 700 responses were initially obtained, some questionnaires were eliminated because respondents' answers followed a pattern or they answered one of the control questions incorrectly. The result was a total of 679 valid answers. The constructs and scales were presented randomly so participants could not to guess what our intentions were. The items of the selected variables are based on constructs used in previous research, all of which are reflective (Appendix I), and measured using a seven-point Likert scale (1 = "completely disagree" to 7 = "completely agree"). The independent variable, humanisation, is composed of five items based on previous research (Epley *et al*., 2007; Lu *et al.,* 2019). Social presence was measured using five items proposed by Pitardi and Marriott (2021). Perceived surveillance consisted of four items adapted from Jung *et al.* (2021). Trust in the service provider was adapted from Lee and Rha (2016). Finally, we adopted the attitude construct used by Lee (2012), which consists of four items taken from the definition of covert strategy proposed by Aguirre *et al.* (2015).

Additionally, we included control variables. Age was an open-ended response; education was formed of four levels; gender was a dummy variable (male = 1, female = 0); and frequency of use was also a categorical variable comprising five levels.

5. Results

5.1 Descriptive results

This section describes the characteristics of the sample of the present study (see Table I). Of the respondents, 55.52% were women; 56.55% were aged between 25 and 34; and 61.86% had a higher level of education (i.e., they held a bachelor's degree). In terms of average income level, 46.84% earned between $40,000 and $79,999 per year, which is considered a mid-level income. Finally, regarding the brand used, 65.87% used Alexa, 23.27% Google Home, 9.79% Home Pod (Apple) and 1.07% Cortana (Microsoft).

<Insert Table I here>

5.2 Measurement model validation

As we used latent variables in this study, it was necessary to confirm the unidimensionality of the constructs by conducting exploratory factor analysis. For this purpose, SPSS software was used, and five constructs were obtained. SEM and PLS combine two statistical methods: confirmatory factor analysis and path analysis. Confirmatory factor analysis aims to identify the validity of the latent variables. Path analysis is used to find the causal relationships among variables. Confirmatory factor analysis includes testing the internal consistency of the latent variables (using Cronbach's alpha, the composite reliability index, convergent validity analysis and discriminant validity analysis). SmartPLS4 was used to carry out this analysis.

Additionally, Harmon's one-factor test was performed on the entire sample in order to control for the possible existence of common method bias. The results showed that one factor explained 19.80% of the variance. When the rest of the factors of the model were incorporated, the variance explained increased to 78.32%, confirming that there was no common method bias. As for the factor loadings, all constructs were above 0.7 – the minimum acceptable value (Carmines and Zeller, 1979) (see Table II).

<Insert Table II here>

The internal consistency of the latent variables was then analysed. The Cronbach's alpha and composite reliability index were above the minimum standards, in this case 0.7 (Nunnally, 1978). All latent variables presented average variance extracted (AVE) values over 0.5 (Fornell and Larcker, 1981) and over 0.6 (Hair *et al.*, 2014), confirming the convergent validity of the measurement model. The discriminant validity of the model was also confirmed, since the heterotrait–monotrait (HTMT) ratios were below 0.85 (Henseler *et al.,* 2015), as shown in Table III.

<Insert Table III here>

5.3 Hypothesis testing

SmartPLS4 software was used to estimate the model, providing the path coefficients and their level of significance. The authors have examined the predictive performance of the model (Q^2), which is used as a goodness-of-fit criteria according to Stone (1974) and Geisser (1974). Positive values indicate good model performance. The results in our case showed that the Q^2 measures were adequate.

The results (see Figure 2) suggest that humanisation has a direct, positive and significant effect on social presence, which supports H1. As there is a negative and significant relationship between humanisation and perceived surveillance, H2 is also supported. Humanisation has a direct, positive and significant effect on attitude towards covert information collection, supporting H3. Regarding humanisation and trust, a significant quadratic effect of humanisation on trust exists ($b=0.185$, $p<0.05$). However, Figure 3 shows that humanisation has a U-shaped effect on trust, which does not support H4. Specifically, humanisation influences trust negatively when it is low; however, for greater levels of humanisation the effect becomes positive. Social presence has a positive and significant effect on trust, and perceived surveillance has a negative and significant effect on trust, supporting H5 and H6, respectively. The results show that social presence significantly and negatively affects perceived surveillance, which also supports H7. Additionally, social presence and trust have positive effects on having a positive attitude towards covert information collection, supporting H8 and H9.

Regarding the control variables, only level of education shows a positive and significant effect on attitude towards covert information collection. This means that those with a higher level of education have a better attitude towards covert information collection.

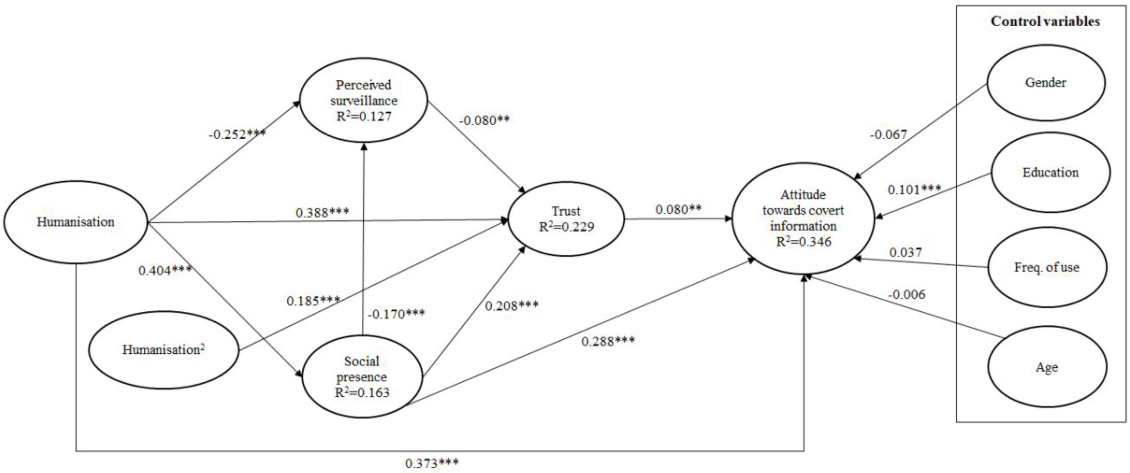

Figure 2. Structural model results

Note: ****significant at 1%; **significant at 5%; *significant at 10%*

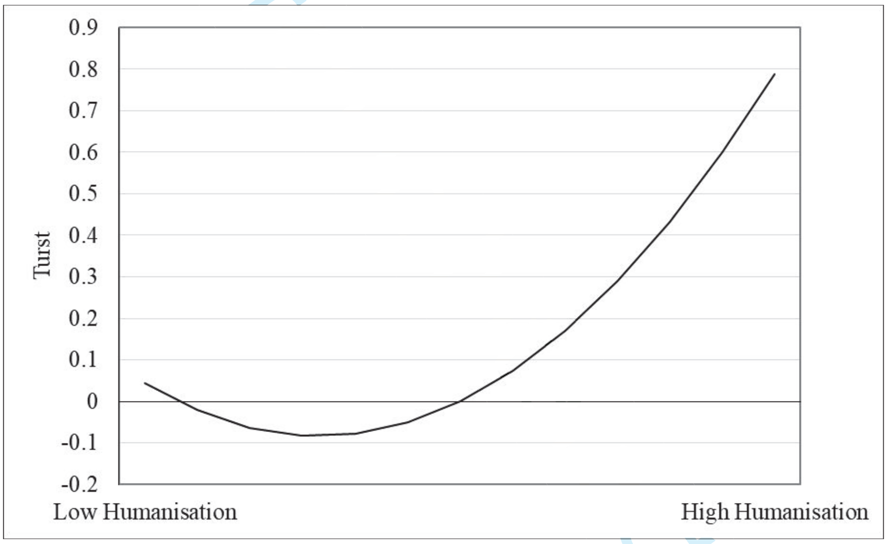

Figure 3. Quadratic effect of humanisation on trust

Although no mediation hypothesis has been proposed in this paper, we consider instructive to point out the existing mediating effects (Table IV). The results indicate that both social presence and perceived surveillance partially mediate the relationship between humanisation and trust in the service provider. Trust is also found to play a mediating role between humanisation and attitudes towards covert information collection. However, it should be noted that social presence has the greatest mediating effect between these two variables.

<Insert Table IV here>

6. Discussion, managerial implications, limitations and further research

6.1 Discussion

The results show that humanisation is positively related to social presence, confirming the findings of previous studies (Toader *et al*., 2019; Kang and Kim, 2022; Rhim *et al.,* 2022) and in line with PSR theory. This implies that providing smart home speakers with a humanlike tone of voice, NLP ability or personality increases users' feelings that they are in relationship with another person rather than with an artificial device. Furthermore, in line with previous authors (Benlian *et al*., 2019), we confirm that humanisation helps to reduce perceived surveillance while simultaneously improving users' attitude towards information collection.

Our results show that humanisation has a U-shaped effect on trust in the service provider. This implies that low levels of humanisation have a negative influence on trust, up to a point at which when humanisation increases, trust increases. It should be noted that the negative effect is very small and only happens for low levels of humanisation, while the positive effect is much more notable. This leads us to suggest that higher levels of humanisation are more beneficial, which contradicts our expectations. We can prose several possible explanations for this surprising effect. First, previous research has shown that, depending on the humanisation features, the results may be contradictory. The features presented by smart home speakers typically offer few options to include humanlike characteristics, and they will never be mistaken for humans in terms of anthropomorphic appearance (Lavado-Nalvaiz *et al.,* 2022). A second explanation is that consumers may have gained familiarity with smart home speakers. As a result, greater familiarity with these devices may involve that medium levels of humanisation are less likely to create feelings of eeriness and discomfort, which may explain why the humanisation-trust link does not follow an inverted U-shaped effect (Zlotowski *et al.,* 2015). Nevertheless, Reis *et al.* (2011) stated that for familiarity to improve the effects of humanisation on likeability, previous interactions should be pleasant. Furthermore, we find that frequency of use of smart home speakers is not relevant to explain attitude towards covert information collection. Thus, the role of familiarity with these devices is still not clear and future research could focus on studying how it can affect trust and attitude toward information collection. Third, the user's personal characteristics can modify how they react to humanisation in smart devices, since sensitivity toward privacy risks varies across generations (Van Schaik *et al.,* 2017). So, the effect of familiarity is still controversial. Therefore, further research should try to explain the role of humanisation on trust in the context of smart home speakers by investigating these personal characteristics.

As proposed, perceived surveillance reduces trust in the provider. This is consistent with previous research (Bawack *et al.,* 2021; Krafft *et al*., 2017), and demonstrates that concerns related to privacy cause a decrease in trust. Regarding the role of social presence, our results show that this construct is positively related to trust in the provider. This also aligns with previous findings that smart devices that exhibit humanlike behaviours generate an affinity between people and these devices, building a trusting relationship in this context (Han and Yang, 2018; Pitardi and Marriott, 2021).

Our findings also show that social presence is negatively related to perceived surveillance, indicating that when users perceive that they receive social support from smart home speakers, perceptions of surveillance can be reduced (Ki *et al.,* 2020). Furthermore, we confirm that social presence helps to improve users' attitude towards information collection, in accordance with previous studies (Melumad and Meyer, 2020). Our study also confirms that the influence of humanisation on attitude towards covert information collection is more important through social presence than through trust. For all these reasons, social presence acquires an important role in our model. This is in accordance with previous studies on this topic (Poushneh, 2021), and suggests that social presence feelings may lead users to be less concerned about the information the device is collecting from them and may also reduce those negative feelings of distrust.

Finally, the results show that, per previous studies (Pitardi and Marriott, 2021), trust in the service provider plays an important role as it is positively related to users' attitude towards covert information collection. We demonstrate that if users trust the service provider with respect to how their personal information is handled, used and stored, their attitude towards the collection of this information will be positive, even if users may think that the information is collected covertly.

Regarding control variables, people with lower levels of education may have difficulties understanding the technical aspects behind this information collection and storage strategy, resulting in greater concern about the misuse of their personal data and possible breaches of their privacy (Boerman *et al.*, 2021).

6.2 Theoretical implications

Our research contributes to the literature on interactive and smart products by considering the antecedents of a relevant consumer outcome: attitude towards covert information collection. Asking users' permission to collect personal information at each interaction, and thereby interrupting the flow of the conversation, can create a negative customer experience. Although some research has examined intrusiveness (Benlian *et al.,* 2019; Lucia-Palacios and Pérez-López, 2021), little attention has been paid to perceived surveillance and even less to the perception or the attitude towards covert information collection. In line with this contribution, our results reveal the important role of humanisation and social presence in improving users' attitude towards covert information collection – which, to our knowledge, has not been previously analysed. Furthermore, both variables reduce users' perceived surveillance and increase trust in the service provider. Our results contribute to PSR theory by showing that social presence and humanisation reduce some of the risks commonly associated with smart home speakers, such as the feeling of being under surveillance. Little research (Benlian *et al*., 2019; Lavado-Nalvaiz *et al*., 2022) has studied the effects of humanisation on negative aspects, such as intrusiveness and privacy risks.

Our findings offer further evidence on the effect of humanisation on trust in the context of smart home speakers. Our research examines the role of humanisation in building a relationship of trust with the service provider, and shows that humanisation has a U-shaped effect, suggesting that the more humanisation, the better. This result does not support either realism maximisation theory or uncanny valley theory. Therefore, more research is needed to offer additional insights. Nevertheless, this study provides new results with respect to the link between humanisation and trust in the service provider, since extant studies have only analysed trust in the humanised object, and not in the service provider.

6.3 Managerial implications

The results of this research show different ways in which marketers and companies can improve users' attitude toward covert information. However, there should be a balance between what is ethical and what the company wants to achieve. Collecting as much information as possible is essential to provide a better service, but, at the same time, ethical business practices must be used to set certain limits. Our study demonstrates the importance of trust in the service provider in improving users' attitude towards covert data collection. Trust can be enhanced in different ways. Intrusive ads should be reduced to reduce perceived surveillance and a recommendation for designers is to include an option to remind the user that the speaker is on. Informing and being more transparent can help to increase trust.

Similarly, when designing their interfaces, developers of smart home speakers must take into account the degree of humanisation they want to achieve, either through voice or conversation, to ensure greater naturalness when communication is taking place. By incorporating this aspect, social presence will increase and users will perceive that they are interacting with something similar to a human being, which will generate feelings of closeness and reduce perceived surveillance. Therefore, managers should focus on including capabilities that help to increase social presence, mitigating surveillance and improving users' attitude toward covert information collection.

These managerial suggestions can be extended to other contexts. For example, consumers are also using voice assistants to search for products online (Gao and Liu, 2022), and on websites in the form of front-line voice bots (Buhalis *et al.*, 2022). All new cars are equipped with voice control systems, which may give rise to the same privacy concerns as with smart home assistants as it is an intimate space. During conversations with voice assistants, consumers may reveal important information for companies, such as brand judgements and emotions about certain brands or products that can be recorded. This is extremely important with the emergence of new IA bots like ChatGPT, Bing or Bard that are used in the business context.

6.4 Research limitations and future research suggestions

Although this research makes broad theoretical contributions, as well as practical contributions for providers of this technology, it is subject to certain limitations that offer opportunities for future research. This study explained humanisation using a latent variable, so future research could analyse the humanisation variable at different levels, from low to high degrees.

It would be interesting to extend this research to different cultural contexts. Cultural background is an important element to take into account, as some countries are more accustomed than others to using, or are more willing to adopt, new smart technologies. .

Furthermore, this study shows that education influences on attitude towards covert information collection. Future research could assess whether education influences users' tolerance of the privacy risk they are willing to take. Similarly, future research could replicate our model and analyse how the results vary according to age distribution.

Regarding the control variable gender, we decided to use a binary measure (male/female). However, societal norms on this are changing. Cartwright and Nancarrow (2022) suggested that, although at present the number of respondents who identify as belonging to the non-binary category is very low, it can be expected to increase as this identity becomes more accepted in society. Therefore, future research might leave the question open to respondents.

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Appendix I. Measures

Latent variable	Items
Humanisation	HUM1:My smart home speaker has intentions.
	HUM2:My smart home speaker has a mind of its own.
	HUM3:My smart home speaker has consciousness.
	HUM4:My smart home speaker has its own free will.
	HUM5:My smart home speaker experiences emotions.
Social presence	SOCPRES1:When I interact with my smart home speaker I feel there is a sense of personalness.
	SOCPRES2:When I interact with my smart home speaker I feel there is a sense of human contact.
	SOCPRES3:When I interact with my smart home speaker I feel like if I am dealing with a real person.
	SOCPRES4:When I interact with my smart home speaker I feel there is a sense of sociability.
	SOCPRES5:When I interact with my smart home speaker I feel there is a sense of human sensitivity.
Perceived surveillance	SURV1:I personally believe I am being surveilled by my smart home speaker.
	SURV2:I feel my behavior was being observed by my smart home speaker.
	SURV3:I feel I am exposed to monitoring by my smart home speaker.
	SURV4:While I'm using my smart home speaker my behavior has to be kept under guard.
Trust	TRUST1:Smart speakers providers are trustworthy.
	TRUST2:Smart speakers providers treat my personal information fairly and honestly.
	TRUST3:I trust that smart speakers providers have my best interests in mind when dealing with my information.
	TRUST4:I can trust the privacy policy of smart speakers providers.
Attitude towards covert information collection	COVERT1:I think using covert strategies like covert data collection is a good information collection system.
	COVERT2:The fact that my smart home speaker collects data without my awareness / without my knowledge makes me feel good.
	COVERT3:I prefer the speaker does not constantly request permission to collect data.
	COVERT4:I like the idea that the smart home speaker is capturing information even though I am not actively using it.

Table I. Sample characteristics

Gender(%)		Education(%)		Frequency(%)		Brand(%)		Income $ (%)		Age(%)	
F	55.52	N	1.03	N	0.44	Alexa	65.87	<20,000	5.30	18–24	3.09
M	44.48	C	7.36	AN	1.62	Cortana	1.07	20,000–39,999	11.93	25–34	56.55
		B	61.86	S	17.38	Google	23.27	40,000–59,999	24.45	35–44	23.71
		M/PHD	29.75	AED	50.66	HomePod	9.79	60,000–79,999	22.39	45–54	10.75
				ED	29.99			80,000–99,999	23.56	55–64	4.27
								>100,000	12.08	>65	1.62
								Not disclosed	0.29		

Note: F=Female; M=Male; N=None; C=College; B=Bachelor's; M/PHD=Master's/PhD; N=Never; AN=Almost never; S=Sometimes; AED=Almost every day; ED=Every day.

Table II. Items and measurement model

	Loadings	Cronbach's alpha	Composite reliability	AVE
Humanisation		0.963	0.971	0.871
HUMAN1	0.910			
HUMAN2	0.938			
HUMAN3	0.944			
HUMAN4	0.940			
HUMAN5	0.935			
Social presence		0.888	0.918	0.691
SOCPR1	0.748			
SOCPR2	0.854			
SOCPR3	0.862			
SOCPR4	0.847			
SOCPR5	0.842			
Surveillance		0.859	0.905	0.704
SURV1	0.828			
SURV2	0.833			
SURV3	0.877			
SURV4	0.816			
Trust		0.902	0.932	0.773
TRUST1	0.891			
TRUST2	0.882			
TRUST3	0.876			
TRUST4	0.867			
Att covert information collection		0.946	0.961	0.861
COVERT1	0.939			
COVERT2	0.923			
COVERT3	0.918			
COVERT4	0.932			

Table III. Discriminant validity

	COVERT	HUMAN	SOCPRES	SURV	TRUST
COVERT	**0.928**	0.545	0.501	-0.268	0.357
HUMAN	0.572	**0.933**	0.412	-0.483	0.395
SOCPRES	0.541	0.440	**0.832**	-0.112	0.367
SURV	0.297	0.529	0.133	**0.839**	-0.292
TRUST	0.385	0.424	0.408	0.330	**0.879**

Note: Square roots of AVE appear in bold. Below the bold diagonal appear correlations between variables. Above appear HTMT ratio values. COVERT=Attitude covert information collection; HUMAN=Humanisation; SOCPRES=Social presence; SURV=Perceived surveillance; TRUST=trust.

Table IV. Mediating effects .

Specific indirect effects	Point estimate	t-statistic	P-value	Lower	Upper
HUMAN -> TRUST -> COVERT	0.031	2.003	0.045	0.003	0.063
HUMAN -> SURV -> TRUST	0.020	1.868	0.062	0.001	0.044
HUMAN -> SOC PRES -> SURV	**-0.068**	**3.909**	**0.000**	**-0.106**	**-0.036**
HUMAN -> SOC PRES -> TRUST	**0.084**	**4.231**	**0.000**	**0.048**	**0.127**
HUMAN -> SOC PRES -> COVERT	**0.116**	**5.642**	**0.000**	**0.077**	**0.157**
HUMAN2 -> TRUST -> COVERT	0.015	1.728	0.084	0.001	0.035
HUMAN -> SURV -> TRUST -> COVERT	0.002	1.211	0.226	0.000	0.005
HUMAN -> SOC PRES -> TRUST -> COVERT	0.007	1.793	0.073	0.000	0.015
HUMAN -> SOC PRES -> SURV -> TRUST	0.005	1.675	0.094	0.000	0.013
HUMAN -> SOC PRES -> SURV -> TRUST -> COVERT	0.000	1.149	0.251	0.000	0.001
SOC PRES -> SURV -> TRUST	0.014	1.732	0.083	0.000	0.031
SOC PRES -> TRUST -> COVERT	**0.017**	**1.828**	**0.068**	**0.001**	**0.037**
SOC PRES -> SURV -> TRUST -> COVERT	0.001	1.168	0.243	0.000	0.003
SURV -> TRUST -> COVERT	-0.006	1.278	0.202	-0.018	0.000

Note:COVERT=Attitude towards covert information collection; HUMAN=Humanisation; HUMAN2=Humanisation quadratic effect; SOCPRES=Social presence; SURV=Perceived surveillance; TRUST=trust.