Relational cohesion between users and smart voice assistants

Abstract

Purpose: The present study examines users' affective relationships with smart voice assistants (SVAs), and aims to analyze how these relationships explain user engagement behaviors toward the brands of SVAs. Drawing on relational cohesion theory (RCT), it proposes that cohesion between users and SVAs influences brand engagement behaviors, that is, continuing purchasing other products of the brand, providing knowledge to the brand, and referring the brand.

Methodology: Data from a survey of 717 U.S. regular SVA users confirm the validity of the measurement scales and provide the input for the Covariance-Based Structural Equation Modeling (CB-SEM).

Findings: The results demonstrate that frequent user-SVA interactions evoke positive emotions, which encourage cohesive relationships. Pleasured-satisfaction and interest emerge as strong emotions. Moreover, relational cohesion between users and SVAs promotes engagement with the brand of the assistant.

Originality: This paper applies an interpersonal approach in a context that, to date, has been examined from a predominantly technological perspective. It shows that users develop positive emotions toward smart technologies through their interactions, and establishes the importance of building affective relationships. To the best of the authors' knowledge, this is the first study to analyze cohesion between users and smart technologies and to examine the effect of this cohesion on user engagement with the brand.

Paper type: Research paper.

Keywords: Smart voice assistants, Relational cohesion, Engagement behaviors, Positive emotions, Interactions.

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Introduction

The emergence and rise of smart technologies have created new forms of services that have transformed traditional offerings and the way that firms relate to their customers (Chouk and Mani, 2019; Ostrom *et al.*, 2015; Park *et al.*, 2016). These services, named smart services, integrate technology and data to anticipate and fulfill customer needs at specific times and/or locations, based on changing customer feedback and circumstances (Kabadayi *et al.*, 2019). So, technologies such as smartphones, artificial intelligence, robotics, text mining, Internet of Things (IoT), digital media, virtual reality (VR) and augmented reality (AR), give rise to new forms of encounters that condition the management of relationships (Čaić *et al.*, 2019; Huang and Rust, 2018; Gummerus *et al.*, 2017; Kunz *et al.*, 2019). Although smart services can take a big variety of forms, smart voice assistants (SVAs) are positioned as dominant services.

SVAs are software agents that rely on voice commands supported by artificial intelligence, natural language processing techniques and machine learning, to assimilate, understand and respond to users' demands (Hoy, 2018; Pal *et al.,* 2020). They have the capacity of acting like actual human assistants, offering professional, technical and social services that individuals require in their daily lives (Santos *et al.,* 2016; Yang and Lee, 2019). SVAs can provide users with requested information, such as weather updates or specific questions, and also perform several tasks for users, such as turning lights on/off, controlling networked devices, and placing online shopping orders, among others (Feine *et al.,* 2019; Liao *et al.,* 2019; Lopatovska *et al.,* 2018). Thus, SVAs emerge as sophisticated service platforms that have changed the way that consumers interact, decide and behave, so they should be studied keenly (DeKeyser *et* *al.,* 2019). Globally, the most popular SVAs and brands are Siri from Apple, Alexa from Amazon, Cortana from Microsoft and Google Assistant.

Although the literature related to SVAs is still young, two main categories can be placed. The first category is focused on technological attributes of SVAs and explores the effect of their voice, language, security and privacy, among others (Davenport *et al.*, 2020; Pagani *et al.*, 2019; Poushneh, 2021). The second category analyzes SVAs from the point of view of users, examining their perceptions, motivations, gratifications and behavioral intentions (e.g., McLean and Osei-Frimpong, 2019; Shin and Park, 2017). These categories have in common that they apply one-sided approaches that were initially elaborated to explore previous technologies. So, they take for granted that the findings obtained for "classic" technologies, as computers or the Internet, can be applied to address smart technologies. Nevertheless, in this new context, only few works have studied relationships between users and SVAs, taking into account that smart capabilities may change the rules of the game (e.g., Biele *et al.*, 2019; Pagani *et al.*, 2019).

In contrast to previous research, we argue that smart technologies are no longer mere tools that allow users to communicate with others and obtain information, but become main actors that interrelate with users in an interpersonal way. Specifically, we propose that SVAs introduce a new case of relationship marketing in services, so understanding interactions between parties is crucial to advance in research. During these interactions, SVAs apply cognitive capabilities to process information and accumulate knowledge, personalizing experiences, providing solutions, and creating value-in-use (Payne and Frow, 2017). Therefore, SVAs develop close communication processes with users, oriented to the generation of user retention, loyalty and long-term profitability (Gwinner *et al.,* 1998; Palmer and Bejou, 1994; Wuenderlich *et al.,* 2015).

The aim of the present paper is to study the affective nature of relationships that users may establish with SVAs (e.g., Siri, Alexa, or Cortana, for example) during their interactions. For that, the paper examines, first, what factors lead users to perceive relational cohesion with their SVA and, second, how this cohesion promotes user engagement behaviors toward the brand of the SVA (e.g., Apple, Amazon, Google, Microsoft, etc.). We draw on the relational cohesion theory (RCT) (Lawler and Yoon, 1996) and propose that the interaction frequency between users and SVAs generates users' positive emotions, that is, pleasured-satisfaction and interest, these emotions eliciting relational cohesion. Moreover, we explore if this relational cohesion between users and SVAs goes beyond the technology and triggers relational ties with the brand of the SVA, concretely, user engagement. Engaged users consider that the brand is responsible for the benefits that the SVA provides, so they seek to continue their relationships.

In summary, the current paper intends to answer the following research questions: 1) What are the key drivers that determine relational cohesion between users and SVAs? 2) What is the nature of the relationship between users and SVAs? And 3) How does the relational cohesion between users and SVAs (e.g., Siri, Alexa, or Cortana) condition user engagement behaviors toward the brand of the SVA (e.g., Apple, Amazon, or Microsoft)?

The contributions of this study are three-fold. First, this is one of the first manuscripts that explore relationship marketing between users and SVAs, focusing on interaction frequency, emotions and relational constructs, instead of emphasizing technological capabilities and cognitive criteria. So, this paper breaks with previous research on information technologies and defines foundations to explore smart technologies (De Keyser *et al.*, 2019). Second, this paper brings a new scope of application for the relational cohesion theory, exclusively employed in interpersonal contexts, and demonstrates its adequacy to examine affective relationships with SVAs. Thereby, it offers a pioneering study that validates this conceptual framework in a technological context, responding to prior calls concerning the need for empirical research on conversational agents (Fernandez and Oliveira, 2021). Finally, this paper reveals that relational cohesion between users and SVAs acts as a psychological mechanism that not only determines the future use of the technology (consequences in the product-level) but also provokes user engagement behaviors toward the brand of the SVA (consequences in the brand-level). In this way, if the user establishes a cohesive relationship with Siri, for example, will (s)he will develop engagement with Apple, showing intentions to buy other products of Apple, recommending it to his/her his friends and providing it with suggestions to improve the service.

The paper is structured as follows. The next section develops the background to the study, reviews prior research on SVAs and critically evaluates it. Following this, the hypotheses are developed and the theoretical model proposed. Thereafter, the methodology and analyses are presented, and the findings discussed. In the final section, the theoretical contributions and managerial implications based on these findings are discussed, concluding with limitations and future research directions.

Background

SVAs are defined as disembodied conversational agents that differ from previous technologies based on screens (visual and tactile) because they employ voice-based interfaces to communicate with users (audial) (Biele *et al.*, 2019; Pagani *et al.*, 2019). SVAs have the capacity of processing users' natural language, engaging users in human-like conversations that introduce new-found intimacy based on emotions and feelings, such as happiness, excitement, and cohesion (Belk, 2017; Feng *et al.*, 2017; Hoffman and Novak, 2018). So, SVAs infuse experiential service encounters that lead users to build interpersonal relationships with the technology, despite they know that are relating to a non-human (Han and Yan, 2018; De Keyser *et al.*, 2019; Xu, 2020).

SVA employment has increased significantly during the last years, being expected that in 2021 it reaches a "critical mass" (eMarketer, 2021). Recent reports have shown that there are today 3.25 thousand million SVAs worldwide, and the estimate is that there will be over 8 thousand million users by 2023 (Canalys, 2019). In fact, voice shopping sales are expected to increase, just in the US and UK, from US$2 billion in 2018 to an estimated US$40 billion-plus in 2022. Thus, SVAs are expected to give rise to new service and engagement platforms that can provide firms with unprecedented opportunities (Capgemini, 2019).

Existing research into SVAs can be placed on two main categories: (1) studies that apply a technology-based approach, and (2) studies that apply a user-based approach.

Research on the first category examines what technological attributes of SVAs optimize their employment, focusing on aspects such as voice, language, security and privacy, among others (Barcelos Silvia *et al.*, 2020; Davenport *et al.*, 2020; Poushneh, 2021). In traditional communication, the speaker's voice and language provide important information about her/him, such as emotions, credibility, reliability, and personality factors (Nass *et al.*, 1997; Till and Busler, 1998). Thereby, some studies establish that developing a unique pleasant voice for SVAs is crucial for them to be considered desirable social partners (Schuetzler *et al.*, 2018). On the other hand, the issues of security and privacy have been indicated as big challenges that voice assistant applications need to deal with (Barcelos Silvia *et al.*, 2020; Pal *et al.*, 2020). In this line, some studies identify the security flaws present in SVAs, proposing also measures to counteract them (Pal *et al.*, 2020).

The second (more developed) category of research analyzes how and why users employ SVAs, paying special attention to their perceptions, motivations, gratifications and behavioral intentions (e.g., McLean and Osei-Frimpong, 2019; Shin and Park, 2017). This research applies classic theoretical frameworks such as the technology acceptance model (Kowalczuk, 2018; Moriuchi, 2019; Sohn and Kwon, 2020), the uses and gratifications theory (McLean and Osei-Frimpong, 2019), the expectation confirmation theory (Brill *et al.*, 2019), and the unified theory of acceptance and use of technology (Moriuchi, 2020). Findings demonstrate that perceptions such as ease of use and usefulness enhance user engagement and loyalty (Moriuchi, 2019), whereas perceived confirmation of expectations enhances user satisfaction with SVAs (Brill *et al.*, 2019). Appendix A shows a compendium of the main publications on SVAs.

Despite the advances in knowledge that research on SVAs has achieved, there are still several gaps that should be addressed. First, previous studies are largely conceptual and apply theories that were elaborated to examine technologies lacking artificial intelligence (Lu *et al.*, 2020). Nevertheless, the emergence of smart technologies leads to a new reality. These technologies are capable of learning users' likes and favorite topics, requiring little effort and no need to type, read or hold a device (Fernandes and Oliveira, 2021). So, they have caused a disruption in the study of human-technology interactions that opens new lines of research near to socio-psychological theories.

Second, it is highlighted that studies on SVA apply one-sided approaches that focus their attention on the technology or on the user, but do not explore relationships that emerge between the two parties. In fact, these studies do not address the role of users’ emotions, assuming that they make their decisions applying eminently cognitive criteria. Nevertheless, when users interact with smart technologies they feel that are involved in affective relationships with the service (Feine *et al.*, 2019; Liao *et al.*, 2019). So, they can develop feelings that to date have been considered only in interpersonal contexts, such as satisfaction, attachment and passion, and establish long-term affiliations that go beyond human-computer interactions (Nass *et al.*, 1994; Xu, 2020). New studies should empirically examine these relationships, focusing on concepts as user’s emotions and affections that to date have hardly been treated.

Third, most studies examine consequences of user-SVA relationships related exclusively to the use of the SVA, ignoring other fundamental relational ties in service marketing research such as user loyalty, engagement and trust. In fact, as far as we know, very few publications have gone one step further from the technology and have tested consequences related to the brand of the SVA (see, as exceptions, McLean *et al.,* 2021; Pagani *et al.*, 2019; Poushneh, 2021).

The present paper tries to fill these gaps, adding significant contributions to the body of knowledge. It evaluates the importance of affective relationships that users can establish with SVAs. Specifically, it empirically studies a model based on relational cohesion theory (Lawler and Yoon, 1996), initially proposed to explore interpersonal relationships, and demonstrates that relational cohesion can also study users’ interactions with smart technologies. This cohesion channels the effect of positive emotions that users feel when they frequently interact with the SVA, leading them to develop engagement behaviors toward the brand of the SVA. Engaged users feel gratitude to the brand so they seek to maintain the relationship with the aim of receiving benefits again.

Theoretical framework and hypotheses

Relational cohesion theory is a tested framework that explains the process that determines individual commitment behaviors in a particular interpersonal relationship (Lawler and Thye, 1999; Lawler and Yoon, 1996; Thye *et al.* 2002). It stipulates that frequent exchanges between actors can elicit positive emotions (pleasure-based satisfaction and interest) which, in turn, generate subjective perceptions of unifying, cohesive relations (Lawler and Yoon, 1996; Michael and Pacherie, 2015). Relational cohesion is defined as the individual's perception that (s)he is part of a group, this relationship being a unifying element in the social situation (Lawler and Yoon, 1996). So, when individuals perceive relational cohesion, they exchange their doubts with the other party, search for suggestions about topics, tend to collaborate, and seek to carry out new joint activities. These interpersonal activities lead individuals to feel interdependence and to develop observable acts of commitment (Parks and Floyd, 1996). Thus, RCT proposes a sequence of from-exchange-to-emotion-to-cohesion that encapsulates the psychological mechanism that influences individuals' behavioral outcomes, that is, the tendency for actors to stay in the exchange relation, to contribute to new joint ventures, and to exchange token gifts (Lawler and Yoon, 1996; Salmela and Nagatsu, 2017; Zheng, 2020).

Relational cohesion theory has been only applied to study interpersonal relationships in different contexts. For example, Yoon and Lawler (2006) studies the relational cohesion model to analyze organizational commitment, while Huang *et al.* (2018) theorizes the process by which online relationships are formed between users of social networks. Nevertheless, to the authors' knowledge there is not yet any existing work testing the cohesive relationship that emerges between users and technologies after making frequent and successful interactions. In this way, we adapt RCT to study affective relationships between users and SVAs, considering an endogenous process formed by two phases. First, we examine interaction frequency and positive emotions (i.e., pleasure-based satisfaction and interest) that determine users' relational cohesion with their SVA. Second, we explore the impact of relational cohesion on user engagement behaviors toward the brand of the SVA: continuing purchasing other products of the brand, providing knowledge to the brand, and referring the brand.

Figure 1 shows a summary of the proposed model.

(Insert Figure 1)

Users' relational cohesion with their SVA: interaction frequency and positive emotions

The endogenous process proposed in RCT establishes that exchange frequency is the starting point of cohesion in a relationship. Exchanges refer to the process through which two or more parties in a relationship collaborate and make joint efforts to complete tasks and share mutual benefits (Lawler *et al.*, 2000). If these exchanges are successful, they provide positive feedback and encourage parties to repeat behavior, which may generate further positive feedback. In other words, attaining success in an exchange boosts parties to engage in new exchanges, promoting the frequency of positive experiences and making them feel happy and satisfied (Lizardo, 2007). Moreover, successful exchanges generate trust among parties, which motivates them to be cooperative and to search together for new achievements (Lawler *et al.*, 2000). In this way, the relationship that parties establish provokes positive emotions, such as pleasure-satisfaction and interest (Lawler *et al.*, 2000).

Pleasure-based satisfaction is defined as a backward-looking emotion that occurs after something is gained (Lawler and Yoon, 1993, 1996). It is based on real judgments derived from experiences and involves a greater degree of stability than assessments based on attitudes (Bhattacherjee, 2001). On the other hand, interest is defined as the feeling of eager to do and enjoy an activity or subject (Lawler *et al.*, 2000). It is a forward-looking emotion based on the awareness of potential satisfaction in anticipation of possible gains (Lawler and Yoon, 1993, 1996; Yoon and Lawler, 2006).

Based on these arguments, we define exchange frequency in the SVA context as the frequency of interactions that the user carries out to accomplish her/his objectives and to obtain benefits provided by the technology. Frequent and successful interactions reduce uncertainties in the relation and increase the user's knowledge about the technology, also boosting the SVA cognition. This cognition generates a greater personalization of the relationship and improves the quality of the service. Thereby, frequent and successful user-SVA interactions provide users with enriching experiences and evoke positive emotions, specifically pleasure-based satisfaction with and interest in this technology.

H1. Frequent users' interactions with SVAs improve their pleasure-based satisfaction.

H2. Frequent users' interactions with SVAs improve their interest.

Pleasure-based satisfaction refers to the strong feeling of happiness and enjoyment that users may experience after interacting with SVAs (Lawler *et al.*, 2000). So, if the performance of SVAs confirms users' expectations, they will be satisfied and will want to continue with the relationship. Satisfied users tend to be friendly and cooperative, share their personal information, and want to learn more about SVAs, trying to maximize benefits derived from using them. Therefore, users' pleasure-based satisfaction forms an emotional attachment with SVAs that leads them to build close relationships with the technology and to feel relational cohesion (Huang *et al.*, 2018; Kim and Gweon, 2016).

H3. Users' pleasure-based satisfaction emotions positively influence their relational cohesion with SVAs.

Interest refers to the enthusiasm and excitement that users feel about their interactions with SVAs. So, when users are interested in SVAs, they want to spend and enjoy their time with them (Lawler *et al.*, 2000). These feelings make users to experience enhanced engagement in joint tasks, which promotes repeated and successful interactions (Huang *et al.*, 2018). As a result, users become more attached to, and integrated in the relationships with, their SVA, which is essential for the development of relational cohesion.

H4. Users' interest emotions positively influence their relational cohesion with SVAs.

Users' relational cohesion with their SVA and engagement behaviors with the brand of the assistant

Customer engagement is defined as the customers' behavioral manifestations toward a brand or firm, resulting from motivational drivers (Van Doorn *et al.,* 2010). It encompasses a wide range of behaviors toward a firm, such as word-of-mouth (WOM) activity, recommendations, helping other customers, blogging, writing reviews, and even co-creation, which involves making suggestions to improve consumption experiences and coaching brands (Van Dorn *et al.*, 2010). Customer engagement is close to other classic concepts, such as satisfaction, attachment and loyalty, but it differs from them in that it has a behavioral focus, being one of their main consequences. In other words, high levels of satisfaction, attachment, and loyalty lead to high customer engagement (Anderson and Mittal, 2000; Schau *et al.*, 2009). An exhaustive review of the literature has shown that, although the definition and components of customer engagement can vary, most authors agree on the various ways that engaged customers contribute to firms (Kumar and Pansari, 2016).

For the purpose of this study, we propose that the effect of the relational cohesion perceived by users with their SVA influences user engagement with the brand of the SVA (Hatfield *et al.*, 2008). This perception implies users' feelings of interdependence and gratitude, generating behavioral intentions to maintain the relation with the brand because they consider that it is the source of their positive emotions. So, going beyond consequences related to the technology (product-level), we propose that users' relational cohesion with their SVA is reflected on their engagement with the brand of the assistant (brand-level). We follow the conceptualization of engagement of Kumar *et al.* (2010), because it is comprehensive and considers different behavioral consequences: continuing purchasing other products of the brand, providing knowledge to the brand, and referring the brand.

The users' relationship with their SVA provides them with benefits that they want to continue to maintain, considering that the money they spent on the smart service is well spent. Users are happy with the SVA, so they decide to continue to patronize the SVA brand, and express their intentions to continue buying other additional products, despite the availability of attractive alternatives offered by other brands. In this context, users' purchases relate not only to the simple undertaking of future transactions, but also their desire to share a long-term relationship with the SVA brand. Consequently, they directly contribute to company value and produce increments in revenue without any increase in the firm's marketing investment.

H5. Users' relational cohesion with SVAs positively influences their intentions to continue purchasing other products of the SVA brand.

Relational cohesion also generates cooperative interaction between the parties. They work together to pursue a common purpose and, consequently, share the success achieved (Hauert *et al.*, 2007). When users perceive that they are in a cohesive relationship with their SVA, they exchange and share information by using a specific dialogue, thus improving mutual understanding (Parks and Floyd, 1996). Moreover, users' perceptions of cohesion with their SVA make them feel that they belong to a brand community that supports the service. Consequently, they get involved and actively collaborate to improve the brand's performance by providing suggestions and feedback about their experiences and interactions with their SVA (Kumar and Pansari, 2016; Lawler and Yoon, 1996). Users thus add value by helping the SVA brand understand their preferences and by participating in the knowledge development process (Joshi and Sharma, 2004). SVA brand can use this knowledge to improve and/or create new smart services compatible with its SVA, providing additional value to the user (Kumar and Bhagwat, 2010).

H6. Users' relational cohesion with SVAs positively influences their intentions to contribute knowledge to the SVA brand.

Finally, relational cohesion involves the parties in a relationship where token gifts are exchanged (Lawyer and Yoon, 1996). In the user-SVA relationship, we link these gifts with the role that users play when they refer the SVA brand. Users that refer the brand may not make the most purchases, but they are more profitable than other, similarly-profiled users (Schmitt *et al.*, 2011). In this way, when users perceive relational cohesion with their SVA, they make positive referrals of the SVA brand and help it to reach other users who would not be attracted by traditional marketing channels, thus contributing to overall user engagement (Kumar *et al.*, 2010).

H7. Users' relational cohesion with SVAs positively influences their intentions to make referrals of the SVA brand.

Methodology

Sample

The target population of this study is formed by regular SVA users, who know this smart technology and make frequent and diverse employments. To obtain a representative sample of this population, researchers hired an international market research company, specialized in studies about online customer behavior, electronic commerce, and acceptance of new technologies, among others. This company works with several consumer panels and establishes long-term relationships with members. To be a member of one of these panels, consumers should answer surveys that address topics such as housing, banking and telecommunications. In this way, the company classifies consumers according to their habits, uses and consumptions, identifying different profiles. All panels are certified with the ISO 26362.

The market research company designed an online platform specifically for this project and elaborated email invitations to participate. These invitations were exclusively sent to a panel of U.S. users of telecommunications, with more than 6,900 members (3,286 women), who had stated that they knew and employed SVAs. Invitations included a one-time personal link, which prevented self-selection bias and duplications. Moreover, panel members did not know the aim of the study. The data were collected in November 2018.

In order to guarantee that participants were effectively regular users of SVAs, they had to answer a first filter question: Do you regularly use a smart voice assistant? Only those participants who answered “yes” could continue answering the survey. Later, they had to answer other questions related to SVA characteristics, types of services, brands and devices. Participants that answered these questions incorrectly, raising doubts about their real experience with SVAs, were removed from the study. All these questions guaranteed that participants were regular users and ensured the reliability of the responses. Finally, a total of 717 valid responses were obtained. Of the respondents, 78.9% were men, 40.2% were aged between 25 and 37, and 38.7% between 38 and 54 years. Regarding the education level, 58.8% had at least a university degree. Respondents interact with their SVA at least 10 hours in a week.

Measures

The information was obtained through a survey with closed questions. The research constructs were operationalized using items adopted from previous research (see Table I). The variables were measured using 7-point Likert-type scales, where 1 indicated complete disagreement with the statement, and 7 complete agreement. First, the survey included general questions about SVAs, the participant’s experience as user, frequency interactions, types of uses (s)he makes, and the brand that supports her/his SVA. Second, the survey asked about emotions that the participant feels during her/his interactions with the SVA and about the characteristics of their relationship. Then, the survey recalled the main existing SVA brands (e.g., Amazon, Apple, Google, Microsoft, Samsung, etc.) and asked the participant to mentally identify the brand of her/his SVA. Finally, the survey included questions related to the user engagement with the brand of the SVA.

Pre-tests of the questionnaire were carried out to correct possible defects and to identify doubts and problems that might arise during the information-gathering process. First, 10 marketing and business management professors were asked to assess the conceptual adequacy and formulation of the questions. Second, the survey was administered to 20 regular SVA users. These respondents had similar characteristics to the target population that was to be examined. Pre-tests requested the respondents to complete the questionnaire and provide feedback. As a result of the pre-tests some redundant questions were eliminated and some of the scales were adapted to facilitate understanding and to avoid erroneous interpretations.

(Insert Table I)

Check of common method variance

The data were obtained through a single collection method, therefore to prevent common method bias we followed Podsakoff *et al.* (2003)'s and MacKenzie and Podsakoff (2012)'s recommendations.

Firstly, during data collection, anonymity of participants' responses was guaranteed and the exact aim of the study was not disclosed, avoiding conditioning participants' responses.

Secondly, items related to the dependent variables were placed in the questionnaire after items that measured independent variables. In addition, the participants' access to their responses to previous questions was limited so that their subsequent responses were not determined by their previous answers.

Thirdly, the absence of common method bias in the data was statistically checked using the Harman's single factor test using confirmatory factor analysis as suggested by Malhotra *et al.* (2006), where all the manifest items are modeled as the indicators of a single factor that represent the method effect. The poor fit of the model (SB-$\chi2$ (324)=4,433.4; CFI=0.680; TLI=0.654; RMSEA [90%CI]= 0.133 [0.130;0.136]) revealed no substantial method bias. Fourthly, the single common method approach proposed by Podsakoff *et al.* (2003)[1] was implemented as Williams *et al.* (1989) and Facteau *et al.* (1995) suggested. We estimated, first, the 8 traits measurement model and, second, the 8 traits measurement model plus a single uncorrelated method factor. Although the second model fitted significantly better (SB-$\chi2$ (276)=575.47; CFI=0.977; TLI=0.971; RMSEA [90%CI]= 0.048 [0.042;0.053]), the variance accounted for the method factor was 12%, significantly lower than the 27% reported by Williams *et al.* (1989). So, it is reasonable to conclude that common method bias was not a serious problem in this study (Choi and Chen, 2007; Facteau *et al.,* 1995).

Analyses and results

Covariance-Based Structural Equation Modeling (CB-SEM) analysis was developed in two steps. First, the measurement model was estimated through confirmatory factor analysis (CFA) to test the psychometric properties of the scales (i.e., reliability and validity). Second, the structural model was estimated to test the hypotheses (EQS 6.1 software).

Confirmatory factor analysis

The results obtained in the estimation confirmed the goodness of fit of the factorial structure to the empirical data. The three types of fit criteria most widely used in the Structural Equation Modeling (SEM) literature were applied (Hair *et al.*, 2010): measure of absolute fit, measure of incremental fit, and measure of parsimonious fit. The results, summarized in Appendix B, confirmed that the BBNFI, BBNNFI, IFI, and

CFI statistics exceeded the optimal levels of 0.9. The RMSEA was lower than 0.08, and the normed $\chi 2$ had a value lower than the recommended 5.0.

The reliability of the scales was tested using the composite reliability coefficient (CRC) and average variance extracted (AVE). In all cases, the results exceeded the recommended limits of 0.7 (Bagozzi and Yi, 1988) and 0.5 (Fornell and Larcker, 1981), respectively. Therefore, the indicators showed high internal consistency.

As evidence of convergent validity, the results showed that all indicators were significant ($p<0.01$), had an explanatory coefficient (R^2) higher than 0.50 (Jöreskog and Sörbom, 1993), and their standardized factor loadings were higher than 0.70 (Bagozzi and Yi, 1988).

The discriminant validity of the measures was evaluated by calculating the 99 per cent confidence interval of the latent factor correlation matrix and verifying that 1.0 was not included in any of them (Anderson and Gerbing, 1988). Moreover, the square root of each construct AVE was higher than the correlation among factors, thus fulfilling the criterion established by Fornell and Larcker (1981). HTMT ratios (Henseler *et al.,* 2015) were also lower than the conservative 0.85 benchmark (Hair *et al.,* 2017) (see Appendix B).

The analyses allowed us to conclude that the measurement scales met the psychometric properties required in the literature and were, therefore, appropriate.

Structural model analysis

Thereafter, the proposed causal model was tested. The results indicated that the data were in accordance with the proposed conceptual model: RMSEA = .070; BBNFI = .894; BBNNFI = .905; CFI = .915; IFI = .915. The effect size in CB-SEM is given by testing the maximum likelihood hypothesis, that is, the chi-square statistic: SB-χ^2 = 1404.069, d.f. = 313, p = 0.000.

The results show that interaction frequency positively influences users' emotions, improving pleasure-based satisfaction (H1: β_1= 0.729; $p < 0.01$) and interest (H2: β_2= 0.631; $p < 0.01$) with SVAs. These emotions enhance relational cohesion with the SVA (H3: β_3= 0.535; $p < 0.01$ for satisfaction, and H4: β_4= 0.497; $p < 0.01$ for interest), obtaining a joint explanatory power of 0.798. Finally, relational cohesion determines user engagement behaviors toward the brand of the SVA, that is, user purchases (H5: β_5 = 0.713; $p < 0.01$), user knowledge (H6: β_6 = 0.727; $p < 0.01$) and user reference (H7: β_7 = 0.748; $p < 0.01$) (see Table II).

The model achieves explanatory powers of 0.508, 0.529 and 0.560, for user purchases, user knowledge and user reference, respectively. These values demonstrate the importance of obtaining relational cohesion between users and their SVA to promote their engagement behaviors toward the brand of the SVA.

(Insert Table II)

Discussion

The findings verify the adequacy of RCT to explore relationships between users and SVAs. They show that frequent interactions and positive emotions (pleasure-based satisfaction and interest) turn users-SVAs exchanges into affective relationships, similar to those established between humans. Thus, the more frequent the interactions are, the more positive users' emotions are, and the more cohesion they feel with the assistant.

Moreover, relational cohesion has a positive impact on the brand of the SVA. Thereby, the findings demonstrate that cohesion perceived by the user with the SVA not only conditions the future relationship with the technology but also generates user engagement behaviors towards the brand. The effect of relational cohesion on user reference of the brand is the most important, followed by user knowledge and future purchases that the user intends to make of other products of that brand. Therefore, the findings reveal that users with close relationships with their SVA generate direct value to the brand of the SVA, referring it to other users, contributing with feedback, and making new purchases.

Conclusions

Theoretical contributions

The present study makes three important contributions to the existing literature.

First, this is one of the first studies that examines relationship marketing between users and SVAs. It goes beyond the technological approach predominantly applied in research on smart technologies (Davenport *et al.,* 2020; Pagani *et al.,* 2019; Poushneh, 2021), and focuses its attention on user interactions, emotions and relational constructs. Our findings show that future studies should address not only users' perceptions about SVAs (Kowalczuk, 2018; Moriuchi, 2019; Yang and Lee, 2019), but also the nature of the relationships between them. They demonstrate that frequent interactions boost cohesive relationships, based on principles such as cooperation, collaboration and integration. Therefore, this paper breaks with previous studies on information technologies and opens new lines to explore smart technologies. These findings are consistent with research on relationship marketing in services, which demonstrates that the frequency of service encounters has a positive impact on the strength of relationships between providers and customers (Barnes, 1997; Berry, 1995; Ward and Dagger, 2007).

Second, this paper demonstrates the adequacy of relational cohesion theory to examine smart technologies, despite this theory had been exclusively applied to explore relationships between humans (Lawler and Thye, 1999; Lawler and Yoon, 1996; Thye *et al.,* 2002). This paper considers that special characteristics of smart technologies turn them into main actors and make users behave differently than with previous technologies. So, findings demonstrate that users feel satisfaction with and interest in SVAs just as they feel these positive emotions toward other people. In this way, the present study responds to prior calls for empirical research on conversational agents (De Keyser *et al.*, 2019; Fernandez and Oliveira, 2021). According to these findings, future research should examine conceptual models based on socio-psychological theories with the aim of capturing the relevance of subjective factors inherent to individuals.

Third, this study sheds conceptual light on the process that drives the user to develop engagement behaviors toward the brand of the SVA, establishing relational cohesion as an essential mechanism that channels the effect of antecedents. Previous studies have mostly examined outcomes of users' employment in the product-level such as future use of the technology (e.g., Fernandes and Oliveira, 2021; Pridmore and Mols, 2020), without taking into account that interactions can also generate consequences in the brand-level. Our findings show that relational cohesion leads successful interactions and positive emotions to improve the user engagement behaviors with the brand of the SVA. These findings are consistent with research on engagement conducted by Kumar *et al.* (2010) and Kumar and Pansari (2016) and demonstrate that cohesive relationships between users and SVAs do not only influence their private union but also incentivize referral of new users.

Managerial implications

Our findings provide specific, actionable insights for managers.

- Managers should encourage as many user-SVA interactions as possible.

According to our findings, interaction frequency is a key trigger for users to develop engagement with the brand of the SVA. For this reason, we recommend firms to gradually conquer different areas of user daily lives, advancing slowly and safely. Firstly, they should start transmitting the benefits that users can obtain from the employment of SVAs to perform easy tasks. Then, once users have acquired knowledge and familiarity, firms should promote the application of SVAs to carry out more complex activities. So, the more frequent interactions between SVAs and users are, the stronger their relationship.

- Managers should implement relational strategies oriented to generate cohesion between users and SVAs.

These strategies can channel the effects of users' interactions with their SVA and foster the establishment of affective relationships based on cohesion. In this way, users might perceive that their relationships with their SVA are genuine and different to their relationships with other technologies, due to the human-like conversations, based on machine learning, that they hold with them. Machine learning allows SVAs to understand users' likes, to anticipate their needs, and to offer personalized solutions. These aspects can foster users' feelings toward their SVA, minimize pain points and lead to engagement. Accordingly, the challenge for managers is to design smart services that take the initiative, provide unique experiences, and empower users by allowing them to define the kind of exchanges that they want to experience.

- Managers should boost user-SVA cohesion with the aim of obtaining value through user engagement with the brand of the assistant.

Findings demonstrate that users' cohesive relationships with SVAs make them to be engaged with the brand of the SVA. So, users create value for the firm by making new purchases and by developing non-financial behaviors. First, engaged users consider that the brand is responsible for the benefits that SVAs provide, so they seek to consume other products from the brand in order to continue receiving similar benefits. Second, engaged users provide feedback to the firm with ideas for improvements and new services. This feedback is derived from user personnel experiences with SVAs, is given constructively, and allows the firm to obtain knowledge from the direct consumption of its services. Third, engaged users exhibit referral and WOM behaviors, which generate and disseminate information that affects other users' purchase perceptions and decisions. In this way, engaged users increase companies' reputations and contribute to brand recognition. In general, relational cohesion provokes user engagement behaviors that promote the establishment of close relationships with current and potential users.

Limitations and future research lines

Although the findings of this study provide meaningful insights into the relationship between users, SVAs and brands of SVAs, several limitations should be taken into account for future research.

This study explores users' relational cohesion with their SVA and their engagement with the brand, but it did not differentiate between types of assistant. Future research might compare interaction frequency, user emotions and relational cohesion with smartphone-based SVAs, such as Siri and Google Assistant, and these same variables with in-home voice assistants, such as Amazon Echo and Google Home. User-SVA interactions in each case, and the kinds of relationship that are established, can vary, which might generate different levels of user engagement with the brand of the

SVA. Future research should also address users' perceptions and behavioral intentions towards brands employing SVAs to assist them in routine shopping.

Moreover, the data were collected from regular SVA users in the United States. Further research might test the proposed model in different countries to assess the influence of culture on user behavior. It would be interesting to compare user-SVA relationships in countries with different levels of expertise. Finally, future studies should undertake longitudinal analyses to test the evolution of relational cohesion between users and SVAs. Future studies should examine how positive emotions, relational cohesion and engagement change as the users employ the smart service over time, acquiring knowledge and skills.

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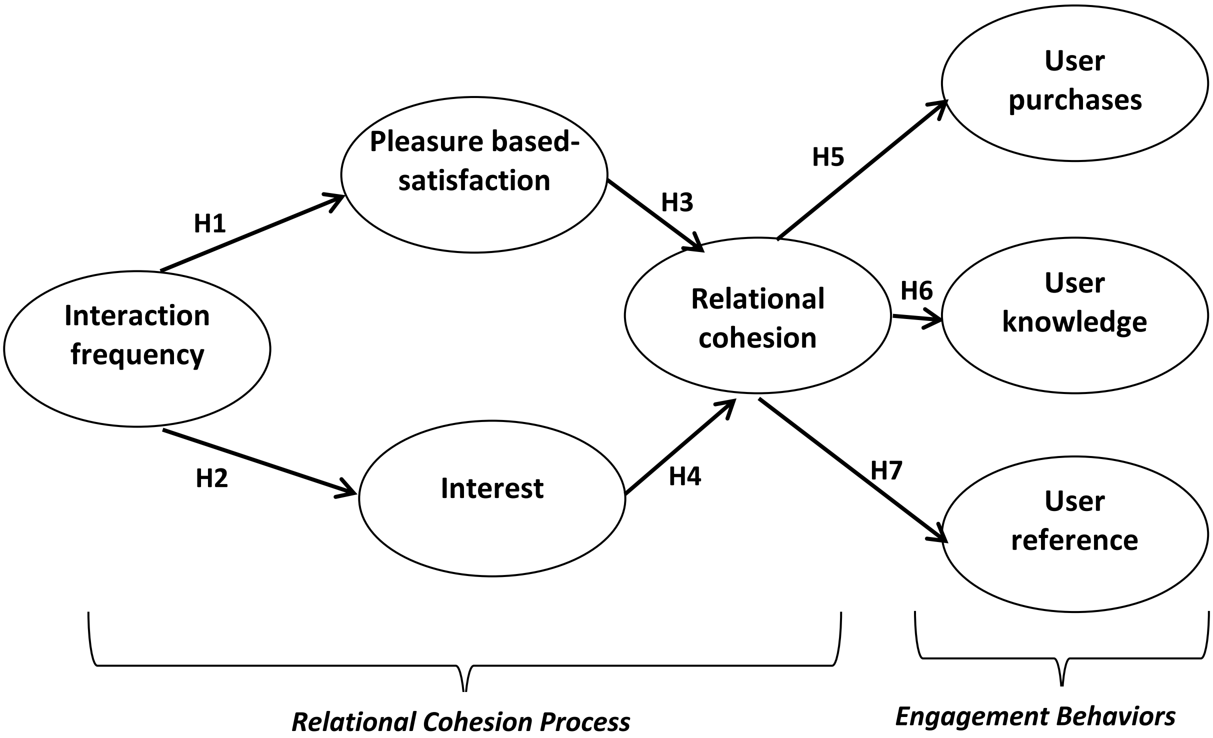

Figure 1 Proposed model

Table I Measurement scales.

CONSTRUCT **References**	**ITEMS**
INTERACTION FREQUENCY Huang *et al.* (2018)	I usually interact with my SVA several times a day I often ask my SVA questions My SVA always tries to resolve my doubts
POSITIVE EMOTIONS **Pleasure based-satisfaction** Lawler *et al.* (2000); Huang *et al.* (2018)	I feel pleased with my interactions with my SVA I feel happy with my interactions with my SVA I feel satisfied with my interactions with my SVA
POSITIVE EMOTIONS **Interest** Lawler, and Yoon (1996); Huang *et al.* (2018)	I feel interested with my interactions with my SVA I feel excited by my interactions with my SVA I feel enthusiastic with my interactions with my SVA
RELATIONAL COHESION Lawler *et al.* (2000); Huang *et al.* (2018)	**My relationship with my smart digital voice assistant is…** ....close …cooperative …integrative …solid …cohesive …convergent
USER ENGAGEMENT **User purchase** Kumar and Pansari (2016)	I will continue buying the products/services of this brand in the future My purchases with this brand make me content I get my money's worth when I purchase this brand Owning the products/services of this brand makes me happy
USER ENGAGEMENT **User knowledge** Kumar and Pansari (2016)	I usually provide feedback about my experiences with this service to the brand I usually provide suggestions for improving the performance of this brand I usually provide suggestions/feedback about other products/services of this brand I usually provide suggestions/feedback for developing new products/services for this brand
USER ENGAGEMENT **User reference** Kumar and Pansari (2016)	I recommend this brand because of the benefits that it provides Given that I use this brand, I recommend it to my friends and relatives I enjoy referring this brand to my friends and relatives because of the benefits it offers I promote this brand in my conversations because I feel that I am part of it

Table II Results.

Hypothesis	Relationship	Standardized coefficient	t-value (robust)	Results
H1	FREQ → SAT	0.729***	13.95	Supported
H2	FREQ → INT	0.631***	13.79	Supported
H3	SAT → RECH	0.535***	15.22	Supported
H4	INT → RECH	0.497***	12.76	Supported
H5	RECH → PUR	0.713***	15.10	Supported
H6	RECH → KNO	0.727***	20.36	Supported
H7	RECH → REF	0.748***	16.61	Supported

Note: *** $p < 0.01$

Appendix A. Studies on smart voice assistants

Study	Approach	Technology	Explanatory variables	Dependent variables	Findings
Fernandes and Oliveira (2021)	User-based	Digital voice assistants	Functional elements (perceived ease of use, perceived usefulness, subjective social norms); Social elements (perceived humanness, perceived social interactivity, perceived social presence); Relational elements (trust, rapport)	Acceptance	Functional, social and relational elements generate adoption. Experience and need for human interaction moderate the effect of these factors.
Poushneh (2021)	Technology-based	Voice assistants	Perceived auditory sense; Perceived auditory social interaction; Perceived auditory control; Surprise	Consumers' trust in voice assistants; Brand affect	Perceived auditory sense influences perceived auditory control through auditory social interactions with a voice assistant that lead to brand affect and consumers' trust in the voice assistant. Moreover, surprise acts as a repelling drive that attenuates the effect of perceived auditory control on brand affect.
Moriuchi (2020)	User-based	Voice assistants	Performance expectation; Effort expectation; Perceived risk; Social influence; Anthropomorphism; Engagement; Usage experience	Intention to re-use; Actual use	Anthropomorphism and engagement play mediating roles between usage experience with the voice assistant and re-use intentions. Intention to re-use has a positive effect on actual usage.
Pridmore and Mols (2020)	User-based	Household intelligent personal assistants	User expectations; Personal and social motivations; Structural circumstances; Integrated routines	Behavioral intentions; User behavior	Acceptance of the personal assistant does not imply to access to all data. Perceived usefulness and effort are antecedents of acceptance.
McLean and Osei-Frimpong (2019)	User-based	In-home voice assistants	Utilitarian benefits; Hedonic benefits; Symbolic benefits; Social benefits; Perceived privacy risk of in-home voice assistants	Usage of in-home voice assistants	Individuals are motivated by the (1) utilitarian benefits, (2) symbolic benefits and (3) social benefits provided by the voice assistant. Additionally, the research shows the role of perceived privacy risks in dampening and negatively influencing the use of in-home voice assistants.

Moriuchi (2019)	User-based	Voice assistants	Subjective norm; Perceived usefulness; Perceived ease of use; Localization; Consumer engagement; Attitude	Loyalty between consumers and voice assistants	Subjective norms influence perceived usefulness, ease of use and engagement; Perceived usefulness influences perceived ease of use, attitude and engagement; Perceived ease of use influences attitude; Attitude influences loyalty; Engagement influences loyalty.
Pagani *et al.* (2019)	Technology-based	Digital platforms	Interface response mode: Voice vs. Touch; Consumer privacy concern; Personal engagement	Brand trust	There is a three-way interaction such that the impact of privacy concern on the relationship between personal engagement and trust depends on the nature of the platform interaction (i.e., touch vs. combined touch and voice). Adding voice to the platform interface has the counterintuitive effect of reducing engagement toward that platform.
Yang and Lee (2019)	User-based	Virtual personal assistant	Perceived usefulness (portability, automation, content quality); Perceived enjoyment (content quality; visual attractiveness)	Behavioral intention	Perceived usefulness and enjoyment have a significant impact on usage intention. Content quality has the strongest impact on perceived usefulness. Visual attractiveness positively affects perceived enjoyment.
Kowalczuk (2018)	User-based	Smart speakers	Technology optimism; System diversity; System quality; Perceived enjoyment; Perceived usefulness; Perceived ease of use; Risk	Behavioral intention	Findings demonstrate that perceived ease of use, perceived usefulness, the quality and diversity of a system, perceived enjoyment, consumer's technology optimism and risk strongly affect the acceptance of smart speakers.

Appendix B. Confirmatory factor analysis

Table B.I Measurement model reliability and convergent validity.

Construct	Item	Factor loading	t-value	R^2	CRC	AVE
INTERACTION FREQUENCY	FREQ_1	0.826	23.550	0.683	.820	.603
	FREQ_2	0.789	18.749	0.623		
	FREQ_3	0.711	21.364	0.506		
PLEASURE BASED-SATISFACTION	SAT_1	0.913	21.908	0.834	.919	.790
	SAT_2	0.896	24.298	0.802		
	SAT_3	0.857	22.197	0.734		
INTEREST	INT_1	0.905	34.166	0.818	.899	.749
	INT_2	0.880	37.123	0.775		
	INT_3	0.808	25.608	0.653		
RELATIONAL COHESION	RECH_1	0.777	28.299	0.604	.955	.699
	RECH_2	0.823	22.887	0.677		
	RECH_3	0.854	25.924	0.729		
	RECH_4	0.887	27.893	0.787		
	RECH_5	0.852	25.884	0.725		
	RECH_6	0.846	26.064	0.715		
USER PURCHASES	PUR_1	0.894	21.284	0.799	.934	.779
	PUR_2	0.904	21.742	0.817		
	PUR_3	0.895	22.999	0.802		
	PUR_4	0.835	22.707	0.697		
USER KNOWLEDGE	KNO_1	0.888	36.252	0.789	.962	.863
	KNO_2	0.933	40.511	0.871		
	KNO_3	0.948	42.792	0.898		
	KNO_4	0.946	45.047	0.896		
USER REFERENCE	REF_1	0.872	22.101	0.761	.917	.736
	REF_2	0.896	23.435	0.804		
	REF_3	0.897	26.094	0.805		
	REF_4	0.758	23.749	0.575		
BBNFI= .916; TLI= .927; IFI= .937; CFI= .937; RMSEA= .061; SB $X^2(303)$= 113.55 p< 0.01						

Table B.II Measurement model discriminant validity

Panel a	F1	F2	F3	F4	F5	F6	F7
F1. Frequency	.78	.78	.69	.80	.77	.68	.72
F2. P. Satisfaction	.72	.89	.58	.80	.88	.53	.76
F3. Interest	.61	.50	.87	.79	.50	.79	.69
F4. Relation cohesion	.74	.76	.74	.84	.74	.76	.77
F5. User purchases	.70	.84	.42	.68	.88	.51	.87
F6. User knowledge	.65	.69	.63	.72	.81	.93	.69
F7. User reference	.61	.45	.73	.71	.43	.63	.86
Panel b	**F1**	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**
F1. Frequency	1.00						
F2. P. Satisfaction	.72	1.00					
F3. Interest	.66	.52	1.00				
F4. Relation cohesion	.77	.76	.76	1.00			
F5. User purchases	.71	.84	.47	.69	1.00		
F6. User knowledge	.64	.46	.74	.73	.46	1.00	
F7. User reference	.69	.70	.68	.75	.83	.67	1.00

Note (panel a): The diagonal represents the squared root of the average variance extracted. Below the diagonal, elements represent correlations among constructs. Upper triangle: upper limit of the 99% confidence interval for the estimation of the factor correlations

Note (panel b): HTMT ratios

[1] This method is recommended for situations in which predictor and criterion variables cannot be obtained from different sources and the sources of the method bias cannot be identified.