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Factors Promoting Healthcare Chatbot Adoption Based on Technology Acceptance Model

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Abstract

Chatbots have been increasingly adopted in multiple contexts, including healthcare. This study aims to identify the factors influencing the acceptance of chatbots by healthcare users. For that purpose, it adopted a quantitative approach; a correlational scope; and confirmatory factor analyses using SPSS software to examine a sample of 259 surveys answered by chatbot users. The hypotheses in the model proposed here were tested using Somers' D coefficient. The results indicate an association between two factors: problem-solving and access to updated information. There are other significant relationships between usage knowledge, access to updated information, problem-solving, and perceived humanness. These findings can be used by healthcare managers, policy-makers, and practitioners to increase adoption of chatbots in the future.

Keywords: Chatbot; Conversational Agent; Artificial Intelligence; Technology Adoption Model; Healthcare.

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1 Introduction

Societies are currently experiencing the fast development and mediation of digital technologies. These technologies have changed the way we interact, supporting communication processes and improving the effectiveness and quality of human activities (Hosszu & Botezatu, 2020). Companies use Artificial Intelligence (AI) tools—such as chatbots—to improve their brand positioning and recall, their customer relationships, and the personalized modification of the product or service they offer (Rana et al., 2021). Especially in the last decade, there has been growing interest around the application of these computer tools to facilitate human-computer interactions using written language (Rapp et al., 2021).

In the recent COVID-19 pandemic, new demands were placed on health services due to social distance and restrictions on traditional face-to-face services. In addition, the said pandemic increased people's need for information, which led to the spread of disinformation and misinformation which increased anxiety and confusion (Amiri & Karahanna, 2022). In this context of increased demand for healthcare services, internet addiction, and people avoiding going to the hospital

(Nain, 2018), AI has been widely implemented, and the use of different technology resources for healthcare processes was promoted. In healthcare, chatbots are important to support activities related to diagnosis, detection, symptom management, gathering information, and medical history, among others (Boucher et al., 2021). However, there is a lack of knowledge about the factors that influence human acceptance of chatbot technologies (Følstad et al., 2018).

Chatbots, aslo referred to as conversational agents, are now popular and innovative methods of reaching out with information. They can impart knowledge, share experiences, and encourage people to participate in different scenarios (Roman et al., 2020). According to Biduski et al. (2020), a positive experience of the use of digital applications in environments related to healthcare practices is an essential condition for the motivation to accept and adopt this kind of technologies. Given the above, it is essential to analyze the factors that influence people to accept chatbots while addressing the personal and mental barriers that prevent them from using these services.

This study aims to identify the factors influencing the acceptance of chatbots by healthcare users by revealing the main antecedents and variables related to said acceptance.

The structure of this paper is as follows: Section 1 discusses essential aspects related to the evolution of chatbots. Section 2 introduces the main concepts related to chatbots, their relevance, and usage in healthcare services. It also addresses some of the main factors in the Technology Acceptance Model (TAM) and explains their relevance in the evaluation of the acceptance of chatbots by healthcare users. Section 3 details the methodology adopted here, describing the approach, scope, method, population, and analyzed sample, as well as the instruments implemented to code and analyze the data. Section 4 describes the main findings of this study; the reliability of the instruments employed to measure the different variables and constructs related to the model; and the hypothesis testing. Section 5 discusses the results of this study, comparing them with those of similar publications in the literature. Finally, Section 6 draws the main conclusions supported by the results and the literature review.

2 Theoretical framework

2.1 Chatbots and their importance

Due to the widespread use of the internet and rise in mobile device ownership, chatbots have become increasingly prominent in various environments for interaction (Malik et al., 2021). Additionaly, they are progressively accepted in today's society (Cheng & Jiang, 2020). According to Li et al. (2021), this has been a consequence of advances in AI in which chatbots have been integrated to multiple user-focused applications. This strong digitization has transformed knowledge and the forms of human interaction (Ellis & Tucker, 2020).

Chung and Park (2019) define a chatbot as a platform created to produce intelligent conversations based on the interaction with individuals interested in a field or topic via a chatting interface. It can be facilitated by linkages with the major social network service messengers (Facebook and Twitter, among others), through which individuals can receive various health services.

Chatbots have become increasingly popular because they can fulfill multiple tasks for organizations by facilitating their interaction with customers using natural language. To achieve this, conversations are simulated using various characters, interactive games, or even virtual animators (Wan Hamzah et al., 2021). In addition, they can aid in enhancing various corporate processes (Luo et al., 2022).

According to Lei et al. (2021), consumers still prefer interacting with human agents because they build more trust via direct contact. However, to provide higher quality services and increase process efficiency, it is important to adequately combine companies' digital technologies (chatbots) with their human talent.

2.2 Chatbots in healthcare and telehealth services

Virtual assistants have constantly evolved—from using basic components (menus and buttons), including keywords, to being context-based by means of machine learning and AI to gather and analyze training patterns which enable chatbots to offer better answers to concrete user questions. More specifically, these assistants have become a transformative element in companies in the healthcare sector (Kandpal et al., 2020).

As a result of the growing concerns about health, lifecare, and disease, users have demanded more emphasis on adequate prevention and health management as essential parts of human life. This has resulted in additional, novel, and smart services to assist them (Chung & Park, 2019). According to Joerin et al. (2020), the healthcare sector worldwide is increasingly interested in and demanding service alternatives in the form of more accessible, flexible, and scalable solutions. This has encouraged the (AI-based) development of various tools that can truly improve individuals' → the quality of life and wellbeing → well-being of individuals. In this context, the integration of chatbots into healthcare service provision is increasingly generalized (Liao & He, 2020).

Nowadays, chatbots have great potential mental health, chronic conditions, pain-related disease, and cancer research (Chavez-Yenter et al., 2021). In addition, the COVID-19 pandemic and the resulting lockdowns around the world have posed enormous challenges for healthcare services in terms of providing adequate and timely care. In this regard, technologies such as virtual assistants can be a solution to the limitations of healthcare environments (as useful tools to reduce the burden of different diseases) and support the creation of patient-centered healthcare systems (Darwish et al., 2021).

It should also be mentioned that in the era of knowledge demands speed in health services and patient consultations, which is reflected in the high volume of data processed in the interactions between chatbot and humans. Thus, as the amount of data and the complexity of medical records increase, AI helps healthcare providers and users by employing data mining and innovating multiple services (preemptive diagnosis, customized procedures, prevention and management of chronic diseases, and use and effects of medicine). Via smart portable devices, AI also enables users to check their health status, obtain information in real time, make a doctor's appointment, identify symptomatologies, and read complementary suggestions—all of this is in line with the advances of the Fourth Industrial Revolution (Bates, 2019; Chung & Park, 2019).

It is clear that virtual assistants can facilitate user access to telehealth, make services more efficient, reduce costs, and (at the same time) favor the creation of significant experiences for users. Nevertheless, chatbots still have restrictions in terms of data recognition and analysis, as well as the identification of symptoms or signals in diseases that demand in-person examination by hospital staff (Bates, 2019).

In the scenario of the COVID-19 pandemic, chatbots have been incorporated as a solution to support the dissemination of up-to-date information, promoting adequate behaviors in healthcare and reducing the negative psychological effects of isolation and fear. In these cases, chatbots should be adequately designed and applied to obtain more effective results (Miner et al., 2020). Gabrielli et al. (2021) suggest that integrating chatbots into smart devices has facilitated digital mediations , characterizing them as a social phenomenon linked to mental health conditions. This shows substantial potential for their utilization in particular medical situations, where they are expedient for preventive measures and cost savings.

Furthermore, chatbots have supported the collection and analysis of data about different medical conditions (e.g., obesity and overweight, some of the main health-related problems around the globe) and connected stakeholders with information about different medical topics thanks to mobile technologies (Asensio-Cuesta et al., 2021).

Still, chatbots should improve their user interaction with more personalized designs and contents (Williams et al., 2021). Likewise, to enjoy their benefits, those who provide AI-based services should create solid, clear patterns of ethical behavior that follow the global regulations on the protection to the personal data privacy and security (Joerin et al., 2020). Because of the latter, they are elements considered critical in the adoption and use of chatbots. Computer security in digital media or cybersecurity remains a sensitive and determining factor in the adoption of technological tools, due to the perceived risk in the disclosure of personal information (Lappeman et al., 2022). Therefore, despite the great advantages of bots in providing accurate and fast information to those who consult through this medium, they also represent great risks to information security, as they can be trained to perform malicious and criminal tasks, such as promoting cyber-attacks, fraud, theft, sending spam and spreading viruses, among others. In accordance with Joyanes (2017) today there is a need for both companies and public entities to establish ethical and regulatory limits regarding the programming and functions of chatbots, to reduce the risk to the users of health systems.

2.3 Model and hypotheses proposed in this study

Numerous studies have investigated technology adoption due to the widespread usage in various sectors, products, and services (Faqih, 2022). The most commonly researched model in this field is the Technology Adoption Model (TAM) proposed by Davis (1989), who posited that the determinants of the intention to use new technologies are perceived usefulness and ease-of-use. However, this model has been updated to reflect advances in technology development, for instance, the increased sophistication of intelligent machines that are capable of performing assigned tasks with a high degree of autonomy. With respect to autonomous robots, Shamout et al. (2022, p.578) identified three categories of factors that affect the adoption of this technology: technological factors such as relative advantage, complexity, and cost; organizational factors including management and financial support, as well as employee competence; and environmental factors such as competitive and customer pressure, and vendor support.

Other authors have studied the adoption of technologies applied to healthcare services. For instance, Schmitz et al. (2022), based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), identified the factors that influence the acceptance of telemedicine among users, i.e., effort expectancy, performance expectancy, facilitating conditions, social influences, habit, perceived security, perceived product advantage, and usage intention. However, few studies have addressed the use of chatbots in healthcare. By the way, there is a study by Bharti et al. (2020) which analyzes the development and inclusion of a conversational bot in order to provide information, support, instructions, recommendations, among other services, for the health care of patients with chronic conditions in the context of the COVID-19 pandemic in order to reduce the limitations of accessibility to health coverage issues for the population, based on the use of AI technologies. Also, other authors have explored the implementation and possible challenges in the use of chatbots supported by artificial intelligence in the diagnosis and identification, behavior modification and symptomatology management in patients with mental illness, showing their applicability and effectiveness (Boucher et al. 2021). In the same way, authors such as Nain (2018), Rosruen and Samanchuen, (2019) and Car et al. (2020) have studied the development of medical communication systems that use artificial algorithms to examine user consultations and answer them, thus providing adequate guidelines for a good and healthy lifestyle. These systems are implemented so that individuals do not need to visit a hospital to self-diagnose their health status.

Huang et al. (2022) found that the intention to use chatbots in healthcare (in the context of weight control) was mediated by factors such as gender and experience. Mokmin and Ibrahim (2021) established that the acceptance of this technology is determined by perceived benefit (in this case, basic healthcare knowledge and early health advice if users do not feel good) and five variables: performance expectancy, effort expectancy, attitude, self-efficiency, and behavioral intention.

Based on the above, this study can propose hypotheses and variables. The variable usage knowledge refers to an individual's level of knowledge of a technology (chatbots in this case), which indicates a better performance in its use (Berrin Arzu, 2021). The literature has proved that usage knowledge has a positive effect on technology adoption in several contexts. In particular, having skills to use a chatbot helps users to employ it effectively (Chatterjee et al., 2021; Marikyan et al., 2022). AI-based chatbots provide access to information, education and orientation related to their interests, enabling organizations to provide various services remotely and free of charge in response to the different needs of the users of these intelligent systems (Bharti et al., 2020). Therefore, knowing how to use a chatbot is related to being able to access current information about a service. Thus, this study formulates the first hypothesis:

H1: Usage knowledge positively affects access to updated information.

Perceived humanness is a measure of how well a chatbot is able to pass as a human while it interacts with a user (Ramachandran, 2019). It is relevant because the communication and compatibility between the user and the virtual assistant results in a better understanding of the problem (Bonales et al., 2021). Furthermore, the fact that users can access updated information via rule-based bots makes a significant contribution to their continuance intention towards chatbot usage and their adoption. According to Nguyen et al. (2021), chatbots are programmed to have customized human-like conversations and provide high-quality information, which also depends on the update of the latter achieved by chatbot learning. Therefore, this study proposes a second hypothesis:

H2: Perceived humanness positively affects access to updated information.

Abd-Alrazaq et al. (2020) argue that a chatbot should be evaluated based on its performance and responses that solve users' problems or answer their questions. This should enable their acceptance and application in business. Likewise, chatbots should be able train and re-train themselves to become remote intelligent assistants that provide updated, specific information (Joshi, 2021). Consequently, conversational agents enhance dialogic learning as they are based on a communicative exchange between the bot and the user (Sandu & Gide, 2019). During their constant response to queries, chatbots can store information that feeds the existing database, making them increasingly effective and improving their performance. Based on this, the third hypothesis is presented:

H3: Problem-solving positively affects access to updated information.

Maigua-Guanoluisa and Medina-Chicaiza (2021) confirmed that, still today, the use of chatbots in healthcare is limited due to a lack of knowledge of their operation and the services they can offer. Mokmin and Ibrahim (2021) found that the adoption of new technologies among users requires enough time, good infrastructure, and knowledge of the platforms so that they can be properly used. As mentioned above, people interact with chatbots to answer their questions, solve problems, or simply to ask a common question about a service (Sheehan et al., 2020). This emphasizes technological competency and literacy. This helps them to express their questions more effectively and to better understand the provided solution. Such communication increases the intention to adopt virtual assistants. Therefore, it is included in the following hypothesis:

H4: Usage knowledge positively affects problem-solving.

Chatbots ask questions to understand the user's query and questions (Bharti et al., 2020). Therefore, another aspect that could influence problem-solving by virtual assistants is that they could bombard users with consecutive questions, which can be overwhelming (Joshi, 2021). The emulated language in a conversation with a virtual assistant is relevant for the adoption of this technology. In the healthcare context, Laumer et al. (2019) proved that the capacity of a chatbot to provide clear, human-like information about health issues can significantly affect users' acceptance of it. Sheehan et al. (2020) found that, in customer service, the greater a user's need for human interaction, the stronger the adoption of a technology tool if its service is anthropomorphic. Therefore, the following hypothesis is proposed:

H5: Problem-solving positively affects perceived humanness.

Finally, if the user does not know how to properly use the virtual agent, and the chatbot does not have a high conversational capability either, the user will not be provided a good experience (Ramachandran, 2019). In that sense, it is easier to have good communication with people if they feel comfortable when they are assisted by a human being (Cordeiro & Batista, 2020). This is what is known as captivating consumers, and it leads to a better adoption of a technology. Based on the above, the sixth hypothesis is formulated:

H6: Usage knowledge positively affects perceived humanness.

Figure 1 shows the proposed model, the factors in it, and the hypotheses presented above.

3 Methodology

This study aims to identify the factors influencing the acceptance of chatbots by healthcare users. For that purpose, it adopted a quantitative non-experimental, causal-correlational approach. The main source of information was a set of 259 questionnaires answered in person in the second quarter of 2022 by healthcare users in Medellín, Colombia, who were users of some of the chatbots: EPS Sura Virtual Healthcare (called "Tibot"), Salud Total ChatBot (called "Pablo") and EPS Sanitas (called "Ana María"). The completed questionnaires to be investigated were selected by non-probability convenience sampling (Otzen & Manterola, 2017b). The main inclusion criterion for participants was to be a college student who had used a virtual assistant to access healthcare services.

An expert validated the instrument, designed in Spanish, to ensure that the proposed items were accurate and consistent with the intended dimensions and constructs to be measured. A pilot test using 10 questionnaires was also conducted to confirm that they provided clear and easy-to-understand information. The instrument addressed the four constructs, namely, usage knowledge, perceived humanness, access to updated information, and problem-solving, developed in this study based on the literature review presented above. The questionnaire comprised 22 items:

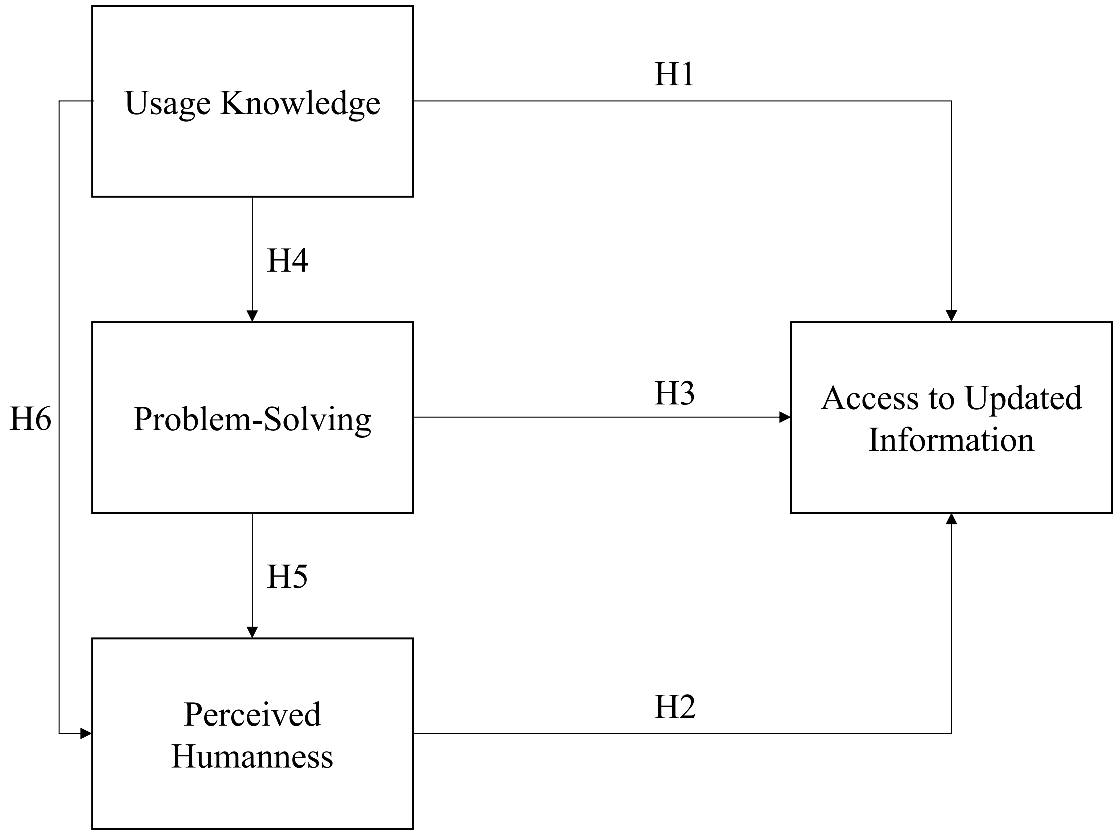

Figure 1. Model proposed in this study

Thirteen statements with a Likert scale, one closed-ended question, and eight multiple-choice questions.

Most participants were men (52%, compared to women, 47%), and 1% selected "don't know/no opinion" in the gender question. Most participants (81%) were between 11 and 40, while the rest were 41 and older. In terms of educational attainment, 44% had graduated from high school, 36% from associate degree programs, and 13% from undergraduate programs. Among the participants, 43% worked and studied, 25% only worked, and 19% only studied. It was found that 83% of the participants did not know what a chatbot is. Then, they received an explanation of what it is and were asked how important chatbots were for them. They responded as follows: important (39%), very important (25%), and indifferent (25%). They were also asked about the type of services they would access using chatbots. Although most of them responded "All kinds of services" (updating personal data, vaccination, information about an HMO, appointments, procedures, complaints, and claims), they emphasized making appointments, accessing information about an HMO, and procedures.

After the data were collected, they were processed using confirmatory factor analysis, conducting reliability and validity tests to verify that the constructs in the instrument did indeed measure the proposed factors. In other words, Cronbach's alpha was used to evaluate the internal consistency and validate the constructs as explained in the next subsection.

3.1 Confirmatory Factor Analysis (CFA)

CFA is a research technique used to test a model built a priori by a researcher and determine the correlations between its composing elements (Gómez-Molina et al., 2019). If deemed necessary, the number of factors in CFA can be reduced. In this research project, CFA was employed to investigate the explanatory power of the proposed model, which represents the acceptance of chatbots by healthcare users. Therefore, the validity and reliability of each variable were established since a questionnaire can be reliable but not valid (although it must be reliable if it is valid).

According to Clark and Watson (2019), although there is a vast amount of literature about instrument validation, three types can be differentiated. First, validity can be assessed by measuring content, since it provides evidence of the extent to which the items of an instrument represent the concept being assessed (Padilla & Akers, 2021). According to Almanasreh et al. (2018), This assessment can be issued by experts who analyze and categorize the items according to the phenomenon under study. Second, criterion validity, likewise used to assess questionnaire validity, quantifies the relationship between an instrument and external variables, known as criteria or factors, to which it is expected to relate. Third, Lacave et al. (2016) argue that, construct validity extends the evaluation of an instrument by confirming whether the relationships between variables establish a dimensional structure in the questionnaire. This allows the interpretation of the results in other study populations.

3.2 Data analysis

The data were previously tabulated to conduct the statistical analysis. For that purpose, Statistical Package for the Social Sciences (SPSS) was implemented because it is one of the most commonly used statistical software suites in social sciences. In addition, SPSS stands out for its ease of use and reputation in the field of correlational statistical analysis, both in the context of univariate, bivariate and multivariate analyses (Ong & Puteh, 2017). In this study, SPSS software (version 22.0) for Windows was used to process the data.

Table 1. Factor loadings

Factor	Item	Factor loading	Average factor loading
Usage Knowledge	UK1	0.737	0.776
	UK2	0.823	
	UK3	0.768	
Perceived Humanness	PH1	0.767	0.767
	PH2	0.767	
Access to Updated Information	AUI1	0.864	0.845
	AUI2	0.800	
	AUI3	0.872	
Problem-Solving	PS1	0.813	0.808
	PS2	0.807	
	PS3	0.805	

In this process, the variables underwent analysis where they were adjusted based on typology, nature of the data, reduction of dimensionality, and categorical transformation. The initial step involved analyzing the factor loadings. This process is executed to validate the significance of the factor loadings and, as a result, ensure that the relevant indicators load well onto their respective factors (Chu, 2008). Thus, the goodness of fit of the factor analysis structure is evaluated to obtain a simple structure (Fleming & Merino Soto, 2005). The literature has studied the right value to consider a factor loading to be significant. According to Otzen and Manterola (2017), 0.5 could be considered adequate, and from 0.71 to 1 it would be ideal. Table 1 presents the factor loadings of the proposed chatbot adoption model. The results are adequate because all the loadings are above 0.71.

The Kaiser–Meyer–Olkin (KMO) test was conducted to verify the convergent validity that evaluates the partial correlations between the variables (see Table 2). Authors such as Bagozzi and Yi (1988) have established that KMO values equal to or greater than 0.5 indicate that the model is reliable. Bartlett's symmetry test confirmed this conclusion, which tests the null hypothesis that the correlation matrix of the variables is an identity matrix; in that case, the variables would not be related. It is impossible to reject the null hypothesis if the p-value of Bartlett's test is greater than 0.05. A dimensional structure or a factor analysis of the instrument would not make sense in that case.

Table 2. KMO values and Bartlett's test of sphericity

Factor	KMO	Barttlet's
Usage Knowledge	0.644	0.000
Perceived Humanness	0.500	0.000
Access to Updated Information	0.686	0.000
Problem-Solving	0.644	0.000

The discriminant validity of the model was evaluated as well. According to Farrell and Rudd (2009), discriminant validity refers to the discrimination of a factors from other variables, that is, the extent to which variable A discriminates from other variables (e.g., B, C, D, E...). This indicates that the factor or construct can explain a greater amount of variation in the items related to other constructs. The standard process to evaluate discriminant validity is carried out following the recommendations of Anderson and Gerbing (1988) with Spearman's rank correlation coefficient. This technique requires a confidence interval around the estimation of the correlation between factors, where a value of 1 is not included. This test aims to determine if the correlations between factors are significant to each other (Voorhees et al., 2016). Table 3 shows that the proposed model (which represents chatbot adoption by healthcare users) meets this criterion, since no correlation between the constructs was significant enough to include the value 1, therefore, the constructs discriminate among themselves.

Table 3. Discriminant validity of the model

Factor	Usage Knowledge	Perceived Humanness	Access to Updated Information	Problem-Solving
Usage Knowledge	1			
Perceived Humanness	[0.150; 0.371]	1		
Access to Updated Information	[0.151; 0.387]	[-0.171; 0.197]	1	
Problem-Solving	[0.118; 0.357]	[-0.083; 0.188]	[0.550; 0.725]	1

The results of the evaluation of the discriminant validity of the model, as shown in Table 3, indicate that the correlations between the factors are in accordance with the established criteria. Each factor is perfectly correlated with itself, as expected. In addition, the correlations between the different factors are within the predetermined intervals: "Usage Knowledge" shows significant correlations with "Perceived Humanness" (range: [0.150; 0.371]) and with "Access to Updated Information" (range: [0.151; 0.387]), as well as with "Problem Solving" (range: [0.118; 0.357]). "Perceived Humanness shows correlations within the established range with Access to Updated Information (range: [-0.171; 0.197]) and Problem-Solving (range: [-0.083; 0.188]). "Access to Updated Information has an in-range correlation with Problem-Solving (range: [0.550; 0.725]). Finally, Problem-Solving has a perfect correlation with itself. These results confirm the ability of the proposed model to discriminate between the different factors, thus supporting its discriminant validity.

Table 4. Reliability of the model

Factor	Cronbach's alpha
Usage Knowledge	0.818
Perceived Humanness	0.749
Access to Updated Information	0.895
Problem-Solving	0.862

Finally, the internal consistency of the proposed instrument is measured using Cronbach's alpha. Mathematically, reliability is defined as the ratio of the real score of variance to the total score of variance (Amirrudin et al., 2021). In the instrument, this is translated into the reliability of the measurement scale. Hence, reliability is defined as the extent to which an instrument composed of several items consistently measures a sample of a population. The reliability of the scale can be determined based on Cronbach's alpha (Ravinder & Saraswathi, 2020). The latter can be used to evaluate the magnitude of the correlation between items in an instrument, which would represent an average of the correlations between items. In other words, it is the measure of which factor is present in each item (Oviedo & Campo-Arias, 2005). Theoretically, Cronbach's alpha values close to 1 indicate great reliability of the instrument. Nevertheless, 0.7 has been established as the minimum allowable value (Amirrudin et al., 2021; Oviedo & Campo-Arias, 2005). Table 4 shows that each one of the factors examined here obtained values above the minimum limit.

4 Results

Somers' D was used to evaluate the hypotheses, i.e., the strength of the correlation between the factors usage knowledge, problem-solving, perceived humanness, and access to updated information. Somers' D can be employed to evaluate the association between ordinal variables. Somers' D (X | Y) is the difference between the corresponding conditional probabilities, assuming that a predictor variable X and a variable with an outcome Y are associated (Newson, 2010). Therefore, Somers' D can be used as an indicator of predictor performance, measuring the performance of X as a predictor of Y (Newson, 2006).

This measure is interpreted based on its proximity to a value of 1. Values close to 1 indicate a strong positive association; close to -1, a negative association; and close to 0, no association whatsoever. In general, values greater than 0.3 indicate a strong association (Sáenz Vela et al., 2018). Figure 2 shows the results of the hypothesis testing of the proposed chatbot adoption model.

Figure 2. Hypothesis testing results

The results obtained by the proposed chatbot adoption model present a relevant relationship between problem-solving and access to updated information. The other hypotheses in the model (i.e., the relationships between usage knowledge and access to updated information, problem-solving, and perceived humanness) show a moderate association, according to Sáenz Vela et al. (2018). In contrast, the relationships between problem-solving and perceived humanness and that between the latter and access to updated information were not relevant or minimal.

5 Discussion

A predominant component of technologies in Industry 4.0, AI represents an advance in the development and improvement of technology tools to provide healthcare services—which have been stimulated by the global popularization of digital technologies and the consequences of the most recent pandemic (Amiri & Karahanna, 2022; Boucher et al., 2021). Chatbots are a clear example of digital tools integrated into service provision as strategies for attractive and creative communication. They enable people to interact in customer service processes in multiple healthcare fields where they can be implemented (Roman et al., 2020).

AI acts as a mediator in the interaction between technology and human beings (Tanioka, 2017) so that the dynamics of the service are well received by users. Chatbots are considered helpful and a new way to access such services (Li et al., 2021). According to Luo et al. (2022), chatbots are still growing in popularity in different sectors, facilitating several types of activities for organizations and improving internal processes. Since the healthcare sector enjoys the advantages of this kind of AI technology, it is necessary to identify how interactions with chatbots are generated and what factors enable users to assimilate this technological integration.

According to users and their response, chatbots have been well received as conversational tools in the healthcare sector. Chavez-Yenter et al. (2021) found that approximately 70% of those who interacted with the chatbot in their study had a good experience with the service it provided. Another important aspect is the reliability of the information provided via chatbot. For example, Benate (2020) studied a tool that produced pre-diagnoses with 95% accuracy and had an 80% accuracy in the model that classified users' intentions regarding their communication with the tool.

To comprehend the factors that have an impact on chatbot usage, the six hypotheses in the proposed model were evaluated to demonstrate their association. The existing literature has verified these associations. For instance, Benate (2020) investigated chatbots' ease of use, response reliability, response speed, and usage experience. Response speed was the criterion with the best score in their validation. They also hold that it is necessary to work more on the interface to provide a better user experience.

The variable *natural language processing* is defined as a computer's capability to have a conversation via text messages and determine actions based on its understanding of the query (Fernandes, 2018). This aligns with Hypothesis 6 of this study, which demonstrated a moderate correlation between knowledge of usage and perceived humanness.

Usage knowledge presented a moderate relationship with problem-solving in the model proposed here. This relationship is also supported by the study conducted by Laumer et al. (2019), where perceived access to the health system was positively affected by technology-mediated access, especially in contexts where said access is complex. In addition, the adoption of conversational agents produces better results when users know more about their operation and advantages.

The hypothesis that achieved the best results in this study connects problem-solving with access to updated information. This is in agreement with Abd-Alrazaq et al. (2020), who emphasized chatbots' functionality and problem-solving. The intelligence that chatbots can develop is a characteristic that will enable them to be more accepted because, thanks to it, they can provide updated and current information and solve, in the best possible way, users' queries (Joshi, 2021). Kadariya et al. (2019) developed a chatbot focused on patient knowledge to provide customized information that resulted from the constant contact with users and learning about their needs. In their study, chatbots enjoyed good acceptance because user needs were met based on personalization and fast responses.

It was found that, accessing updated information improves the provision of healthcare services, and better chatbot usage promotes quick access to information and diagnoses (Pérez & Ramos, 2021). Similarly, Roman et al. (2020) found a relationship between usage knowledge and access to information. This is possible thanks to interactions over time that enable users to learn more about how to use this technology and the benefits it has to access information of interest in a fast and easy way. Their paper also conducted an analysis of study variables that included demographic aspects. This type of analysis could be the next step in similar studies. As pointed out by Kim et al. 2021, it is important to take into account other variables of the population (e.g., age, access to technology resources, or ICT skills) because they enable us to produce better chatbot designs, more focused on populational groups directly related to the use and benefits of chatbots in healthcare services.

This study can serve as a starting point to understand some of the factors that determine the acceptance of chatbots as useful digital tools in healthcare services, specifically from the perspective of users in a Latin American country with certain characteristics and challenges regarding healthcare provision. In addition, this article describes a wide range of application domains of chatbots in the healthcare sector: mental health (Boucher et al., 2021), pediatric services (Benate, 2020), urology (Pérez & Ramos, 2021), blood donation (Roman et al., 2020), and cancer (Chavez-Yenter et al., 2021), among others.

The advances of chatbots and conversational agents can improve service provision, reduce the gap between the supply of and demand for healthcare workers, and meet users' needs (Hernandez, 2019). Hence, healthcare services directors, managers, and institutions ought to be knowledgeable about the properties of this technology and the factors that facilitate its adoption.

Research in this field should advance in order to develop increasingly functional conversational agents and identify the factors that enable their incorporation in different contexts. These digital tools have a great potential to provide a good service and help organizations in their processes. Nevertheless, future research should establish the factors that enable their correct interaction with users, which will further increase their adoption as a service technology. Among the factors that could be considered are related to the protection of sensitive user data, the scope of AI, the personalization of content according to the needs of individuals, the possible limitations in knowledge in the use of digital technologies among the elderly, the increase in user confidence in these resources, among others.

6 Conclusions

Taking into consideration the challenges to come, the findings of this study can be used by healthcare managers, policymakers, and practitioners to guide a successful implementation of chatbots in the future. The results can be used to formulate strategies to improve the intention to use these tools in health care delivery. By helping specialists in the design of chatbots to recognize the advantages and opportunities for improvement of these technologies. This study also highlights that some chatbots have been adopted in various industries to replace people in customer service without reviewing whether they are effective or provide satisfactory customer service, so it is still in the early stages of training chatbots to obtain more detailed responses in terms of obtaining more accurate information

The results obtained here were compared with those of other studies, which showed that the hypotheses proposed above and the relationships found between the variables were supported. The strongest relationship established in this study was that between problem-solving and access to updated information, which is also supported by findings in other studies that have examined the problem-solving efficiency and continuous learning AI of chatbots. It also looks to establish strategies to improve the intention to use these tools in healthcare provision given the extensive use that is being given in this sector.

This approach to generating applicable knowledge will be addressed in future research, offering a concrete and insightful vision. In the Conclusions chapter, we highlight the vital importance of conducting an additional study specifically aimed at developing concrete strategies to strengthen the intention to use these tools in the field of health care delivery. This recommendation is a significant result of the current analysis, considering the wide scope with which these technologies are being implemented in said sector. This concrete proposal, supported by the analysis carried out, provides a concrete vision and knowledge that deserves to be deepened in future research.

Continuous research in the field of healthcare and AI technologies is necessary to (1) find promising solutions to provide care to users in different health sectors, (2) identify the factors of their adoption, (3) and collect more information that validates hypotheses and models that can be applied in future studies and different contexts. Future studies could propose new adoption models, explore new factors in this sector to expand the available knowledge about the adoption of chatbots in the health sector in different contexts, for example, emerging economies or developed countries and to be able to compare the perceptions of the users.

Future studies should explore the extent to which these identified adoption factors, such as perception of humanity and access to up-to-date information, can be adapted and optimized to effectively improve users' intention to use artificial intelligence-driven chatbots in different healthcare settings.

In addition, it will be important to explore possible differences in the perception and acceptance of chatbot technology among users in different socioeconomic and cultural contexts, thus contributing to a more complete understanding of the factors influencing adoption.

Similarly, exploring the long-term impact of chatbot adoption on patient satisfaction, treatment outcomes, and the overall healthcare experience is a valuable line of research. As the landscape of artificial intelligence technologies and the dynamics of healthcare evolve, continued research remains critical to unlocking the full potential of these innovations and their insights in healthcare.

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Biographies

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