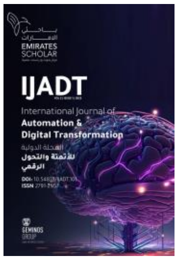

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Confirmatory Exploration of innovation in virtual exchanges through a study on Virtual Agents

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Abstract

The use of Conversational Agents for consumer services continues to grow, and the service industry is no exception. Carried out among 340 Moroccan consumers, this study shows the importance of perceived anthropomorphism, social presence, perceived trust, social influence, perceived cost, and facilitating conditions of a conversational agent in increasing adoption intention using the UTAUT model. The expected effort had no effect. This research confirms the moderating role of age on the relationship between social influence and intention to use, while gender and level of education had no moderating effect. The technology acceptance model tested is a powerful tool for understanding why people do or do not use conversational agents. It can explain nearly 75,8% of the variance in behavioral intention.

Various recommendations are put forward to optimize the design and successful implementation of chatbots, enabling them to take their rightful place among digital tools

Keywords: Conversational agent, UTAUT model, Moroccan consumers, adoption, services, PLS-SEM

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1. Introduction

Artificial intelligence is at the root of a new revolution. Artificial intelligence has been the subject of much debate for several years now (Desbiolles, 2019). The automation of information processing has made AI more powerful, more useful, and more ubiquitous. The evolution of AI in the field of speech understanding has fostered the emergence of conversational agents (Lahoual and Fréjus, 2018). Conversational agents represent a global market whose revenues are expected to increase tenfold by 2027 (Liu, 2020). They enable the collection of large amounts of data in addition to improving customer service and assisting human agents (Adnan and al., 2021). In the current context, companies in the service sector need to reinvent themselves to get through the crisis (Ioannides and Gyimóthy, 2020). Thanks to artificial intelligence (AI), chatbots are profoundly changing the customer experience (Sidaoui and al., 2020), and their development is therefore becoming an object for further research.

This new technology represents a new modality compared to the existing, customers can ask various questions through messaging applications such as Facebook Messenger, WhatsApp, Skype, WeChat, kik...etc (Dubois and al., 2019). Several works have shown that their presence promotes the feeling of trust towards a given site (Huang and al., 2021). However, several virtual agents have failed due to a lack of design and/or trust-enhancing features, according to the same source. Thus, according to the work of Cherif (2016), these features, namely technical and anthropomorphic, have a positive effect on social presence, trust and intention to use. However, innovation and consumer adoption remain serious hurdles to overcome (Ambawat & Wadera, 2019). Intention-to-use and adoption of conversational agents remain rarely used, especially in Moroccan academic literature. Little research (Luger and Sellen, 2016); (Fitzpatrick ans al., 2017) focuses on what constitutes an optimal user experience with AVs, as (Følstad and Brandtzaeg, 2020) testify. The adoption of chatbot technology is an emerging research topic in all fields (Pillai and Sivathanu, 2020). We can therefore ask the question about the different factors that influence consumers towards the adoption and use of conversational agents in the Moroccan services field?

The main aim of this study is therefore to evaluate the expected effort and social influence on chatbot use intention, which are the basic variables of the model used (UTAUT). This study will be supplemented by other variables. Through empirical research, the variables perceived trust, perceived anthropomorphism, perceived cost and social presence are expected to influence attitudes towards the use of this intelligence. The research also verifies the moderating role of age, gender and level of experience on the model's relationships.

The next sections deal first with the literature review, the conceptual framework (the extended UTAUT model) and the resulting hypotheses. The recommended methodology and results follow. The article concludes with a discussion of the main findings, highlighting the implications, limitations and future avenue of this research.

2. Literature Review

2.1. State of the art on conversational agents

The literature on conversational agents has developed considerably in recent years. Numerous terms have thus appeared: virtual agent, intelligent agent, chatbots, recommendation agent, interface agent, embodied conversational agent, avatar (Lemoine and Cherif, 2012; Diederich and al., 2022). The revolution around conversational agents lead us to believe that we are in the presence of a new technology. In reality, however, this technology has been finding its answers since the launch of Alain Turing's famous test, also called the "imitation game" (Turing, 2004). In the past, conversational agents were considered as an ambitious technology but were not very effective. Today, with the development of artificial intelligence, especially machine learning and deep learning, conversational agents are positioned to revolutionize many fields such as medicine, transportation, finance and marketing (Adamopoulou and Moussiades, 2020).

Lemoine (2015) have made them "associated with characters animating the virtual interface and performing several tasks requiring interaction with the consumer". For these authors, conversational agents are capable of understanding and responding to this interaction in an autonomous way. They range from a simple interaction, e.g. giving information about the weather forecast, to a deeper interaction, e.g.

delivering orders, booking hotel rooms or adjusting a rule or bill (Kasilingam, 2020).

Conversational agents are one of the technologies that could revolutionize e-commerce, especially the so-called conversational one (Kasilingam, 2020a). According to this author, these agents can replace mobile applications. Indeed, they integrate Today, several messaging applications such as WhatsApp, Facebook Messenger, Skype. For Cherif (2016), these virtual agents can be defined as "interactive messages powered by artificial intelligence". So, for Dubois and al. (2019) these agents are defined in several ways but they all describe the same phenomenon, it is the answer to the question "to what extent are conversational agents driven by artificial intelligence?", which is the main difference between these concepts.

For Chaumartin and al. (2020b), there are three types of virtual agents. Firstly, "virtual customer assistants", assist human agents via chat or voice. Secondly, "virtual enterprise assistants" are used internally in the company as automated assistance to employees. Lastly, "virtual personal assistants" are intended for the general public, accessible via a voice interface, e.g. Microsoft (Cortana), Appel (Siri), Google Home, or Alexa at Amazon. According to the work of Viot & Bressolles (2012), conversational agents in the marketing field carry out several missions, from navigational assistance to advice and purchase, to the issue of loyalty. However, Cherif (2016b), proposes a distinction between these agents according to their most novel functionalities, namely the capacity for collaboration, conversation, animation, availability, and ubiquity.

As conversational agents are beginning to occupy a prominent place in different domains, a different research approach is needed to measure the degree of adoption by Moroccan consumers, which is why we propose the UTAUT model as a model of choice for this type of study.

2.2. The UTAUT model

In information systems research, individual adoption of information technologies remains among the most advanced streams (Benbasat and al., 2007; Harnischmacher and al., 2020) Several theoretical models have tried to explain technology adoption (Mehra and al., 2022). Based on certain determinants to be identified, the objective is to understand the reaction and behavior of individuals to the use of technologies. Among these, we can cite the theories of reasoned action TAR, planned behavior TCP, the Technology Acceptance Model TAM and the diffusion of innovations theory TDI (Sebei, 2018). We have favored the UTAUT model of Venkatesh et al. (2003) called in French the unified theory of acceptance and use of technology because it remains the most complete model among the eight theories that have tried to explain the acceptance and adoption of technology (Cheikho, 2015).

This author considers UTAUT to be the most meaningful and important unified model in the field of technology adoption research, with great conceptual strength. Expected performance, expected effort, social influence, and finally facilitating conditions constitute the four fundamental determinants of technological intention and use.

Venkatesh and al. (2003) identify four moderating variables (age, gender, experience and willingness to use) that act on all four determinants, and which have an effect on the acceptance and use of ICT.

The theoretical model of Venkatesh and al (2003) was able to explain the variance in intention in a meaningful way. By moving from UTAUT1 to UTAUT2 in 2012 In this model, three variables were added, namely hedonic motivation, habit and price, allowing an improvement in the variance explained for intention from 56% to 74% and from 40% to 50% for (Chang, 2012). According to the same author, it remains the most explanatory model of individual technology adoption, despite some rare criticisms concerning the precision of the intention to use. Moreover, in the Moroccan context, very few studies have focused on the UTAUT model, especially in the context of our research. Most studies focus on the European or Asian market. The figure below illustrates UTAUT use of innovation technologies.

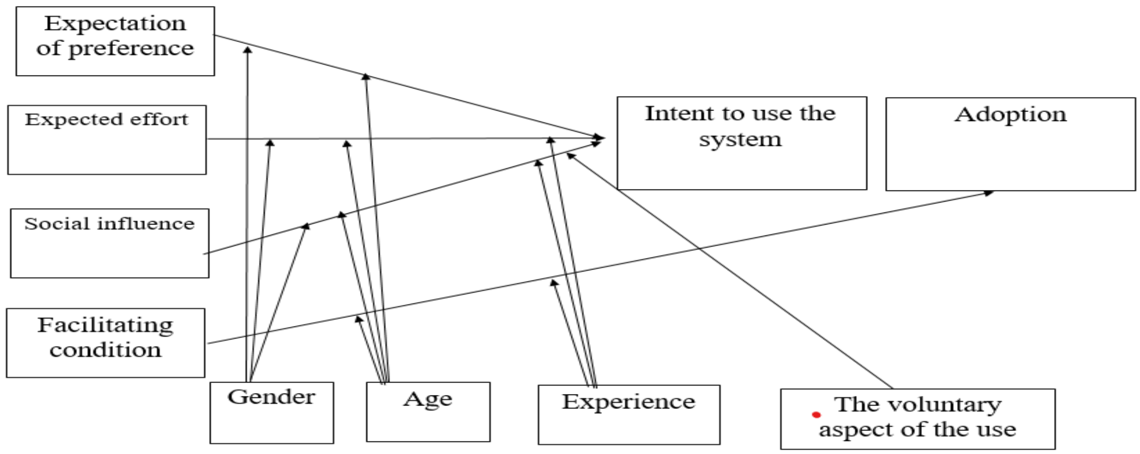

Figure 1: Model UTAUT

Source: Venkatesh and al. (2003)

3. Research Premises

3.1. Presentation of the modified model and research

In the case of our study, we have simplified the UTAUT model as several studies have used the model. The aim is to retain variables that are considered appropriate for our work.

Four additional variables inspired by the literature on conversational agents are included in the initial model. These are the anthropomorphic variables, perceived social presence, perceived cost, and perceived trust.

The anthropomorphic variables and their relationship with trust and social presence are inspired by the Cherif and Lemoin (2012) model, as well as the work of Lahoual and Fréjus (2018). The perceived cost is inspired by the model (Cheikho, 2015), which studied the acceptance and use of mobile banking in France. The modified model will remove expected performance as this is assessed within organizations and not at the individual level. Following numerous research studies in the field of information systems and technology adoption (Igbaria, 1993), the two demographic variables, namely gender and age, have always been a subject of discussion, so we retain these two variables alongside the respondents' level of education. On the other hand, we eliminate experience and willingness to use because the observation will be made in a single moment and willingness to use is impossible in our framework (Cheikho , 2015).

Anthropomorphic characteristics of conversational agent:

"Anthropomorphism is the attribution of human characteristics to non-human objects" (Cherif and Lemoine, 2019a). From this definition, it can be said that connected objects including conversational agents can have purely human functionality, such as voice recognition, animation, facial and gestural expressions and human voice. The latter was the subject of the work of Cherif and Lemoine (2012). Indeed, a Chatbot with a human voice has a more positive impact on a given site than a Chatbot with a synthetic voice. The behavioral reaction of an Internet user is in favor of a sufficiently anthropomorphized virtual advisor (Lemoine and Cherif, 2012).

For Lahoual and Fréjus (2018) "speech remains an intuitive, invisible and fast form of interaction to perform a variety of tasks using voice commands". According to the two authors, voice assistants such as Alexa, Google home, Cortana and others promote immediacy, ease and comfort of use. A stronger feeling towards a virtual agent designed with anthropomorphic features (Burgoon et al., 2000). In the same vein, Qiu & Benbasat (2009) propose to increase the resemblance to humans in order to make the anthropomorphism of these agents more credible. For many researchers ((Ben Mimoun and al., 2017);

(Cherif and Lemoine, 2019b); (Qiu and Benbasat, 2010)), the use of a virtual advisor is able to simulate a social presence on the internet.

H1: Perceived anthropomorphism has a positive effect on the social presence of conversational agents.

Perceived social presence:

According to social response theory, people can treat a computer as a social actor (Moon, 2000). Indeed, according to the results put forward by (Lemoine & Zafri, 2017), the perceived social presence is stronger on a site with the presence of a Chatbot, the latter is a social component of the site's universe according to the same source. (Gambino et al., 2020) found that humans often unconsciously apply social rules when interacting with machines that have a name and a profile photo.

Focusing mainly on Chatbots as a social component of the site's atmosphere, several authors have shown that their presence favorably influences the perceived credibility, integrity and benevolence of the site as well as dimensions of perceived trust (Jacquinot and Pellissier-Tanon, 2018). We therefore formulate the following hypothesis:

H2: The social presence of conversational agents has a positive effect on the confidence of Moroccan consumers.

Social presence:

Social representation is often favored because it is better perceived and easily understood by consumers. Indeed, the use of multimodal communication (facial expressions, gestures, posture) and the conversational habits of face-to-face interaction enrich the consumer's interactive experience (Araujo, 2018). The intention to use the technology, in this case, the intention to use the virtual agent, appears to be a reaction resulting from social presence. Thus, the work of Mimoun & Poncin (2015), shows that social presence has a positive influence on behavioral intentions. We therefore propose the following hypothesis:

H3: The social presence of conversational agents positively influences the behavioral intentions of Moroccan consumers.

Perceived transaction cost:

The literature review on information system adoption shows that financial resources are perceived as a significant antecedent of the behavioral intention to use an information system (Venkatesh and al.,2012). The cost of use appears in the literature as an important factor in making the difference between the framework of use and adoption at the level of consumers and organizations. At the consumer level, price can have a significant impact on consumer use of technology (Venkatesh and al., 2012; Hanafizadeh and al., 2014). According to the studies put forward by Venkatesh and al. (2012), financial resources are considered to be an important antecedent of a user's behavioral intention in the context of information system adoption. In our case, the cost of a financial transaction for an individual remains a determining factor for the adoption and acceptance of the electronic channel (Hanafizadeh and al., 2014).

H4: Perceived cost hurts Moroccan consumers' current intention to use conversational agents.

Expected effort:

It represents in this research the degree of ease associated with the use of chatbots in the service domain. We have previously shown that it is similar to the perceived ease of use defined in the theory of acceptance and use of MAT technologies by Davis and al. (1989). In the literature on computer-human interaction, studies on customer-business relations in the virtual environment (e.g. e-commerce) emphasize ease of navigation and speed of response as functional factors necessary for creating useful commerce sites that can be used by customers (Bazi and al.,2020; Balakrishnan and al.,2022). In these studies, ease of use emerges as the fundamental characteristic in the effectiveness of a merchant site.

Drawing on work on the perceived ease of use of MATs, the user associates the degree of ease with using the system. We formulate the following hypothesis:

H5: The expected effort has a positive impact on the intention to use conversational agents on the part of Moroccan consumers.

Social influence:

This is the "degree to which an individual perceives that it is important for others to believe that he or she is using the new system" (Venkatesh and al., 2003). Social influence has been incorporated into the MAT model by several authors (Shum and al., 2018 ; Gursoy and al., 2019). These authors consider that social influences are a determining factor in usage behavior. The influence of family, friends and hierarchy on user behavior is mentioned. This recognition can create a powerful social impact on customers in the service domain, leading to a positive attitude (Mogaji and al., 2021).We propose the hypothesis that the influence on user behavior will be significant :

H6: Social influence has a positive impact on the intention to use conversational agents.

Perceived trust:

This determinant is fundamental in physical relationships and becomes equally important in the virtual world. According to the work of Cherif (2016), trust in the virtual advisor, inspired by the Mayer, Davis and Schoorman model of trust, is presented in three dimensions, namely credibility, integrity and benevolence, which have a direct impact on the behavior of users. According to the two authors, credibility refers to a competence and expertise enabling a task to be carried out in accordance with standards. Perceived credibility depends essentially on the anthropomorphic characteristics of a virtual agent, such as dress, voice and gestures. The second dimension is integrity, according to the work of (Malle and Ullman, 2021), it corresponds to the reliability and honesty of promises. According to the work of Lemoine and Cherif (Lemoine and Cherif 2012), the perceived integrity is influenced by the discourse that he holds to the Internet users. The last dimension is called benevolence, "it deals with the conviction and belief of a trustor in the benevolence of the trusted person" (Sebei,2018). According to several works (Komiak and Benbasat, 2004); (Qiu and Benbasat, 2005); (Simpson, 2007) ;(Fernandez-Gago et al., 2017) trust in Chatbots act positively on the direct use of these agents. We formulate the following hypothesis:

H7: Trust in conversational agents positively influences their adoption by Moroccan consumers.

Enabling conditions:

According to the work of Venkatesh and al (2003), "the extent to which a person believes that an organizational and technical infrastructure exists to support their use of a system". The facilitating condition appears to be a better predictor of the use of services offered online, especially the time-saving aspect because the Internet is accessible 24/7 (Hossain and al., 2017). In the adoption of e-commerce, (Verkijika, 2018) has pointed out that the facilitating condition is the most influential variable on this adoption.

Saving time appears to be an important aspect of the facilitating conditions of electronic service (Hamari and al., 2016). AMBARWATI and al. (2020) in their study found that the facilitating condition has a positive influence on online consumer behavior.

In research on the adoption of information technologies, this determinant positively influences the use of Chatbots. In our study, this factor is considered as a perception that allows access to resources and knowledge to use online services in a flexible way.

H8: Enabling conditions have a positive impact on the adoption of conversational agents.

Intention to use:

According to Fishbien and Ajzen, intention to use plays an intermediary role between attitude and behavior. It has a sense of wish and desire, a willingness to perform a behavior, often materializing as "I intend to", "I feel like", "I will". According to several studies, the intention to use has a positive influence on the use of a system (Venkatesh and al., 2003). We propose the following hypothesis:

H9: Intention to use has a positive effect on the current adoption of conversational agents by Moroccan consumers.

The influence of moderating variables:

This involves studying the moderate effect of age, gender and education on the set of determinants on the one hand and the intention and current use of Chatbots on the other. The two socio-demographic variables remain an issue when it comes to technology adoption (Igbaria, 1993).

- Gender: (Kasilingam, 2020b)argues that technology has a weak influence on women compared to men. When it comes to studying trust and other proposed variables in online shopping, gender becomes a main determinant says the same author, so it is necessary to understand women's and men's behavior when using Chatbots. In our study,

gender moderates the relationships in the variablesH3 to H8.

- Age: young people are quick to familiarize themselves with new technologies, and are willing to accept any innovation (Kwateng and al., 2018). Conversely, older people are more concerned about any digital use, and would perceive great difficulty in interacting with these tools and would be less willing to accept changes unlike the former (Chawla and Joshi, 2017). In our study, age moderates the relationships in variables H3 to H8.

- Level of experience (education): Consumer behavior is often influenced by the level of education in various technological fields as reported by (Phellas and al., 2011). According to the work of (Mahwadha, 2019), users who do not have a high level of education would require a high level of usability. The author supports the idea that the level of education as well as the elements of trust increase the chance of adopting a technology. In our study, the level of experience moderates the relationships in variables H7 to H8.

Based on the above assumptions, the following figure proposes the model for this research:

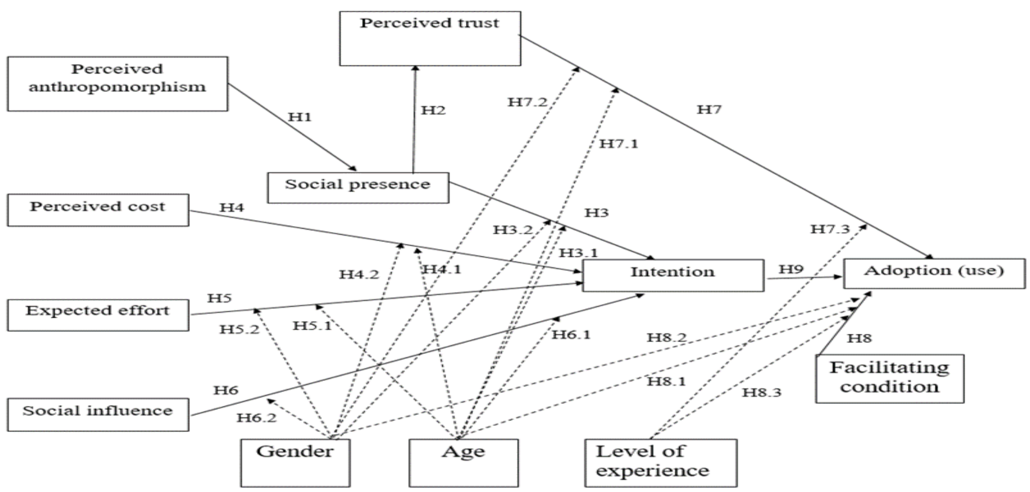

Figure 2: The proposed model

4. Research Methodology

4.1. Research Context

This study focuses on the factors that influence Moroccans' acceptance of conversational agents in the context of services. As previously mentioned, they represent an interesting market for this form of artificial intelligence (Følstad and Brandtzaeg, 2020; (Arnold, 2018). In a service context, this clientele is above all looking for a memorable experience during interaction (Veiga et al., 2017). To test the hypotheses developed, we opted for the deductive-hypothetical approach, based on a quantitative survey. Indeed, we experimented with 980 Internet users who make up a group on Facebook dedicated essentially to shopping via chatbots. The data was collected between July and August 2023.

Consequently, the use of digital channels was strongly recommended for all services. The questionnaire was distributed online via the aforementioned platform. 370 questionnaires were collected. The data were evaluated for multivariate outliers using a Mahalanobis distance test (Tabachnick and Fidell, 2007). Twenty multivariate outliers were identified and removed, leaving a final sample of 340 questionnaires.

The present study follows a two-stage approach to the analysis of the data obtained, including the evaluation of measurement and structural models using partial least squares and structural equation modeling (PLS-SEM) (Ringle and al., 2020).

4.2. Measurement and Research Instrument

All the measures in this study were applied according to measures already validated in the work of Venkatesh and al. (2003) with the addition of four variables developed in the literature review. In addition, it was essential to have the items of the scales validated by experts in the field: an expert in artificial intelligence, and three doctoral students who have certified studies on the behavior of cyber consumers. A pre-test of the measures was applied to 7 randomly selected individuals. It should be noted that all the scales were translated and validated by a translation expert. All the concepts that make up our questionnaire are presented in the following table:

Built	**Items**	**Coding**	**Sources**
Moderating variables	-What gender are you? -What age group do you belong to? -What is your level of education?	Age Gender Level of study	Venkatesh and al. (2003), Cheikho (2015) Mogaji and al. (2021)
Enabling conditions	-My Internet connection is very good for using conversational agents. -I have the knowledge and skills to use conversational agents.	C.F1 C.F2	Venkatesh and al. (2003), Davis (1989) Sanny and al. (2020)
B N Social influence	-people important to me think I should use the conversational agent -My opinion leader thinks I should use the conversational agent	I.F1 I.F2	Venkatesh and al. (2003), Mogagi et al. (2021)
Expected effort	-learning to buy via a virtual agent is easy for me - it is easy for me to find a website via a virtual agentthrough which I can buy the product /services I want	-E.A 1 -E.A 2	Venkatesh and al. (2003), Cherif (2012). Melián et al. (2021)
Social presence	-I felt human warmth on this site via a virtual agent -I felt a human contact on this site via a virtual agent -I felt sociability on this site via an agentvirtual	-PS1 -PS2 -PS3	Qiu and Benbasat (2009), Cherif (2016), Bressolles, Durrieu and Viot (2011), Mimoun and Poncin (2017)
Perceived trust	-The virtual advisor put my interest's first - The virtual advisor is honest	-CONF .P1 -CONF.P2	Qiu and Benbasat (2009) Wang and Benbasat (2005) Şbei (2018).
Perceived anthropomorphism	-a virtual agent must be smiling - a virtual agent must have a nice looking body - I like the virtual agent to have an attractive face	-AN . P 1 -AN .P2 -AN .P3	Cherif (2016),
Perceived cost	-The use of virtual agents would cost a lot. - There are financial barriers to using virtual agents(e.g. paying for the handset and call time). - The cost of using virtual agents is higher than using other digital channels	-C.P 1 -C.P2 -C.P3	Cheikho (2015), Hanafizadeh and al.(2014)
Intent to use	-I intend to use virtual agents for my current purchases - I plan to continue using virtual agentsfor the coming months	-I.U1 -I.U2	Cherif (2016), Sbei (2018), Venkatesh and.al(2003),

Adoption (Use)	-I am satisfied with my relationship with the virtualagents - I am satisfied with the way the virtual agents handlemy requests - I strongly recommend the use of conversational agents to others.	-Use1 -Use2 -Use3	Venkatesh and al. (2003), Cherif (2016*)*, Cherif and Lemoine (2012)

Table 1: Research items

4.3. Data Collection and Sample

Descriptive statistics were used to describe the demographic characteristics of survey respondents. Table 2 illustrates the demographic profile of respondents in terms of gender, age and level of education.

Respondent Characteristics	Frequency (n=340)	Percentages
SEX Men Women Total	 181 159 340	 53% 47%
Age 24 and under 25-50 50 and over Total	 68 238 34 340	 20% 70% 10%
Education Baccalaureate and less Higher education Total	 68 272 340	 20% 80%

Table 2: Demographic profile of the chatbot usage survey sample

The results show a slight majority of male users (53%), and that the largest proportion (51.6%) of respondents by age group are in the under-5 category. 80% of respondents have completed higher education. This information can be useful for tailoring chatbots to different demographic groups.

5. Analysis and results

5.1. Research model evaluation

The structural equation analysis method was chosen to evaluate our research model. This is because they offer a large flexibility in the interpretation and explanation between theory and data (Marcoulides, 1998). The choice of the Smart PLS software is justified as a continuation (El Ghazouli and el Khalkhali, 2019):

- The choice of the smart PLS technique corresponds to our research context "the adoption of virtual agents by Moroccan consumers";
- The model is exploratory; it finds its answers from the UTAUT model. By looking for the different determinants that influence the intention and adoption of virtual agents by Moroccan consumers;
- The PLS approach is highly valued by researchers who opt for the UTAUT model.

The evaluation of a PLS model requires careful consideration of two main methodological elements:

1. Evaluation of the measurement model.
2. Evaluation of the structural model.

5.1.1. Measurement model evaluation:

In order to evaluate the measurement model, the following criteria will be used: internal consistency reliability, convergent validity of the measures, and discriminant validity.

Internal consistency reliability:

Cronbach's alpha and composite reliability are the two measures used to verify internal consistency reliability (Hair and al., 2017). The range of these indicators must be between 0 and 1.

According to the researchers, the correlation coefficient must be greater than or equal to 0.7, to say that there is a good level of reliability.

The table below shows the values obtained through the Smart PLS software for the two indicators studied.

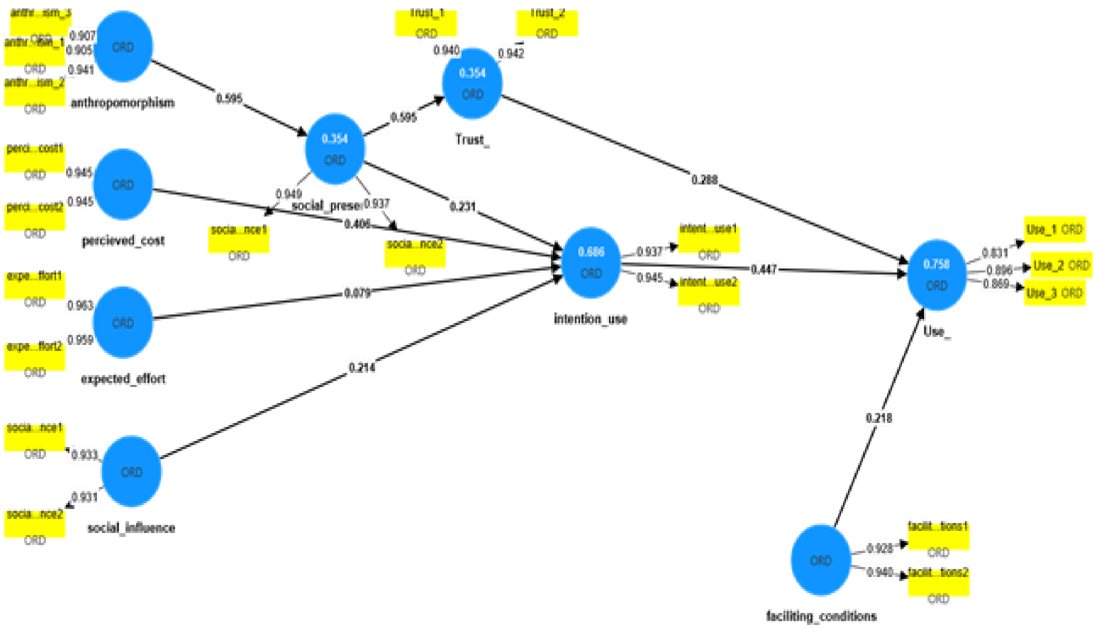

Figure 3: The "adoption" model in Smart PLS software presenting the results of the PLS algorithm technique

A number of use full pieces of information can be drawn from the figure, which will be used in the tables that follow

	Cronbach's alpha	Composite Reliability
Trust_	0,870	0,871
Use_	0,833	0,837
Anthropomorphism	0,906	0,906
Expected_effort	0,917	0,919
Faciliting_conditions	0,854	0,858
Intention_use	0,871	0,874
Percieved_cost	0,881	0,881
Social_influence	0,848	0,848
Social_presence	0,876	0,883

Table 3: Cronbach's Alpha and composite reliability values obtained

According to Table 3, Cronbach's alpha and composite reliability are both greater than 0.7. are considered acceptable, indicating a good level of internal consistency for the scales or constructs being measured. These coefficients suggest that the items within each construct are reliably measuring the underlying concept. The slight variations between Cronbach's alpha and Composite Reliability are normal, and the overall pattern in table indicates a reasonable level of reliability for your measures.

Convergent validity:

The convergent validity of the measures is based on the analysis of the correlations of the measures with the respective constructs. Indeed, for convergent validity to exist, the average variance must be greater than or equal to 0.5 (Hair & Alamer, 2022).

The table below summarizes the result found on smart PLS:

	Average variance extracted (AVE)
Trust_	0,885
Use_	0,750
Anthropomorphism	0,842
Expected_effort	0,923
Faciliting_conditions	0,872
Intention_use	0,886
percieved_cost	0,894
social_influence	0,868
social_presence	0,890

Table 4: AVE values

According to table 4, constructs with AVE values close to or above 0.5 (Trust, Anthropomorphism, Expected Effort, Facilitating Conditions, Intention to Use, Perceived Cost and Social Presence) suggest that a substantial amount of variance in the items is being explained by the underlying construct. The "Use" construct has an AVE of 0.750, which is still acceptable, but it is relatively lower compared to the others. It's important to assess if this value meets your study's criteria for convergent validity.

In summary, the AVE values in table generally suggest good convergent validity for the constructs, indicating that the measurement items effectively capture the variance in the underlying constructs they are intended to measure.

Discriminant validity:

"Discriminant validity represents the extent to which measures of one construct differ from measures of another construct in the model" (February,2011). Discriminant validity of constructs according to the researchers involves a comparison between the correlation of constructs and the square roots of AVEs.

To confirm this validity, the variance shared between constructs must be less than the variance that the construct shares with its indicators.

	Trust_	**Use_**	**Anthro**	**exp_ effort**	**fac_ conditions**	**int_use**	**cost**	**S_ influence**	**S_ presence**
Trust_	0,941								
Use_	0,860	0,865							
Anthro	0,589	0,707	0,917						
Exp_effort	0,721	0,794	0,635	0,961					
fac_conditions	0,842	0,899	0,601	0,814	0,934				
int_use	0,858	0,855	0,663	0,753	0,863	0,941			
cost	0,803	0,860	0,661	0,818	0,878	0,898	0,945		
S_influence	0,798	0,825	0,687	0,762	0,779	0,824	0,875	0,932	
S_presence	0,679	0,858	0,665	0,733	0,803	0,790	0,793	0,680	0,43

Table 5: Estimated discriminant validity of the study variables

The table 5 reveals that the "square root of AVE" amounts are higher than the correlations of the construct with the other constructs. This implies that each measure generates results distinct from those of the other constructs, thus guaranteeing its discriminant validity.

5.1.2. Evaluation of the structural model

In order to test the overall quality of our model, we propose an evaluation on the basis of the predictive relevance of the latent variables, and the test of the hypotheses (Mourre, 2005).

Predictive relevance of latent variables:

According to (Bagozzi and Yi, 2012) the indicator R2, the coefficient Q2, and the fit indicator GoF (Goodness of fit) are the basic elements to check the predictive power of the latent variables studied.

The coefficient of determination R2.

The usefulness of calculating R2 exists in understanding the involvement of each explanatory variable in predicting the dependent variable (Hair and al., 2017).

According to the work of (Croutsche, 2002):

- If the R2 >0.1, it means that the model is significant;
- If the R2 is between 0.05 and 0.5 the model is tangent;
- If the R2 <0.05, it means that the model is not significant.

	R-square	**R-square adjusted**
Trust_	0,354	0,351
Use_	0,758	0,755
Intention_se	0,686	0,681
Social_presence	0,354	0,352

Table 6: Value of the coefficient of determination R^2

According to Smart PLS calculations (Table 6), all the dependent variables present interesting percentages, especially intention to use and use, which present high percentages (68.6% and 75.8%). This confirms the explanatory power of our model.

The Stone-Geisser Q coefficient2:

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Also called the redundancy index in cross-validation, this coefficient makes it possible to check

the coefficients obtained and the parameters calculated and how they reproduce themselves in the model studied, it measures the quality of each structural equation. Indeed, the calculation is done by the Blindfolding procedure. And if the Q2 is positive, it confirms the predictive validity of the model (Hair and al., 2017).

	Q^2predict
Trust_	0,240
Use_	0,650
Intention use	0,650
Social présence	0,343

Table 7: Stone-Geisser Q coefficient ²

According to table 7, Q2 is positive for all dependent variables, so the result is satisfactory. This confirms the predictive quality of our model.

The GoF "Goodness of fit" index:

This index combines both the structural and measurement models (Iacobucci, 2010). It is equal to the geometric mean of the community mean and the mean of R2:

$$GoF = \sqrt{Community * R^2}$$

The quality of the model to the data is considered good when the index is close to 1. According to the work of several researchers (Wetzels and al., 2009) :

- If the GOF<0.1, there is no predictive power;
- If the GOF>0.36, there is strong predictive power.

$GoF = \sqrt{0.758 \times 0.8728} = 0.813377$

According to the calculations, our model argues for a good level of fit of the overall model.

5.1.3. Testing research hypotheses without moderating variables

"Hypothesis testing consists of evaluating the direct effects between latent variables linked by a causal relationship"(Mourre,2016). Indeed, Student's t values can be presented as follows (Hair and al.,2017): 1.65 (significance level = 10%), 1.96 (significance level = 5%) and 2.57 (significance level = 1%).

In order to test the hypotheses, we mobilize the PLS approach, which is presented in two techniques: The Jackknife technique or the Bootstrap technique. We engage the latter, namely Bootstra. In our research, we validated any hypothesis with a student's t greater than 1.96 at the 5% error level. The table below shows the different results.

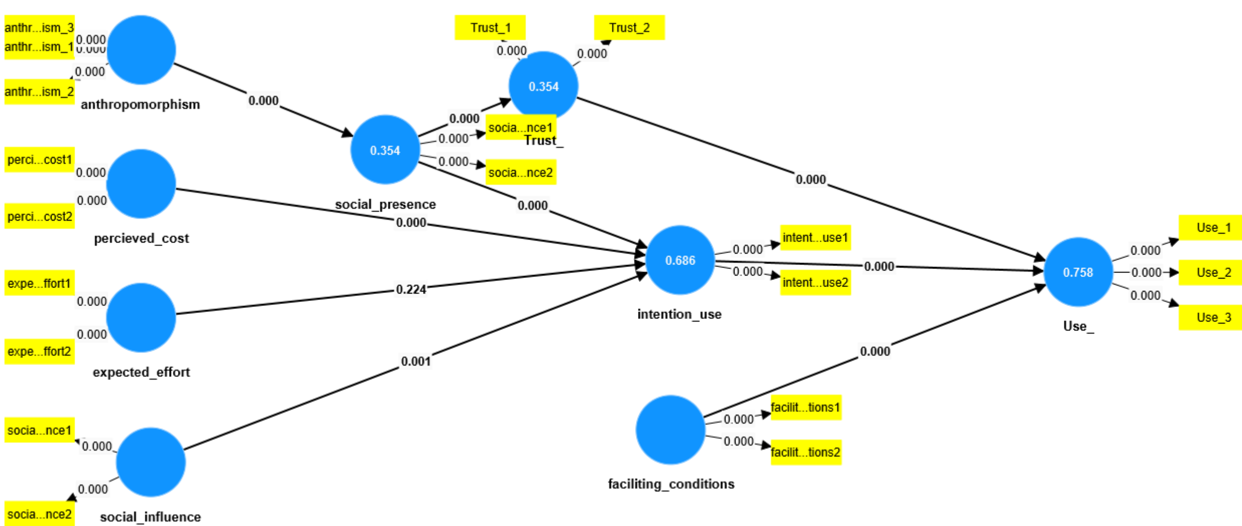

Figure 4: The "adoption" model in Smart PLS software presenting the results of the bootstrap technique

Table 8 shows the results of the model presented in Figure 4. It can be seen that perceived cost, social presence and social influence have a significant impact on behavioral intention ($p < 0.05$), while expected effort does not. On the other hand, facilitating conditions, perceived confidence and intention to use have a significant effect on use. Anthropomorphism also had a significant effect on social presence.

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Decision**
Trust_ -> Use_	0,288	0,290	0,063	4,584	0,000	Validated
Anthropomorphisme -> social présence	0,595	0,595	0,057	10,529	0,000	Validated
Expected_effort -> intention use	0,079	0,081	0,065	1,217	0,224	Rejected
Faciliting conditions -> Use_	0,218	0,217	0,053	4,132	0,000	Validated
Intention use -> Use_	0,447	0,446	0,059	7,624	0,000	Validated
Percieved cost -> intention use	0,406	0,402	0,078	5,238	0,000	Validated
Social influence -> intention use	0,214	0,216	0,065	3,283	0,001	Validated
Social présence -> Trust_	0,595	0,596	0,052	11,331	0,000	Validated
Social présence -> intention use	0,231	0,231	0,065	3,530	0,000	Validated

Table 8: Status of hypothesis validation using the Bootstrap method

	Original sample (O)	**Sample mean (M)**	**2.5%**	**97.5%**
Trust_ -> Use_	0,288	0,290	0,171	0,416
Anthropomorphisme -> social présence	0,595	0,595	0,477	0,699
Expected effort -> intention use	0,079	0,081	-0,039	0,217
Faciliting conditions -> Use_	0,218	0,217	0,116	0,319
Intention use -> Use_	0,447	0,446	0,327	0,557
Percieved cost -> intention use	0,406	0,402	0,245	0,551
Social influence -> intention use	0,214	0,216	0,092	0,348
Social présence -> Trust_	0,595	0,596	0,487	0,693
Social présence -> intention use	0,231	0,231	0,105	0,363

Table 9: Confidence Intervals

This table 9 provides information on confidence intervals for the estimated coefficients in a structural equation model. Confidence intervals provide a range within which we are reasonably sure that the true population parameter. The narrower intervals suggest more accurate estimates for all relationships except the Expected effort -> Intent to use relationship. Indeed, the 95% confidence interval is [-0.039, 0.217], indicating that the true coefficient is negative.

The table 10 gives an overview of the total indirect effects of certain variables on others in your structural equation model. T-statistics and p-values are used to determine whether these indirect effects are statistically significant. The validated hypotheses imply that there is evidence of the presence of these indirect effects for all relationships except the "expected effort -> Use" relationship. The original coefficient is 0.035. The T-statistic is 1.208, with a p-value of 0.227, indicating that the total indirect effect of expected effort on use is not statistically significant. The hypothesis is therefore rejected.

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Decision**
Anthropomorphisme -> Trust_	0,354	0,355	0,051	6,930	0,000	Validated
Anthropomorphisme -> Use_	0,163	0,165	0,036	4,562	0,000	Validated
Anthropomorphisme -> intention use	0,137	0,138	0,042	3,238	0,001	Validated
Expected effort -> Use_	0,035	0,036	0,029	1,208	0,227	Rejected
Percieved cost -> Use_	0,182	0,178	0,038	4,749	0,000	Validated
Social influence -> Use_	0,096	0,097	0,035	2,765	0,006	Validated
Social presence -> Use_	0,274	0,277	0,050	5,468	0,000	Validated

Table 10: Validation status of hypotheses with an indirect effect using the Bootstrap method

5.1.4. Verification of research hypotheses with moderating variables

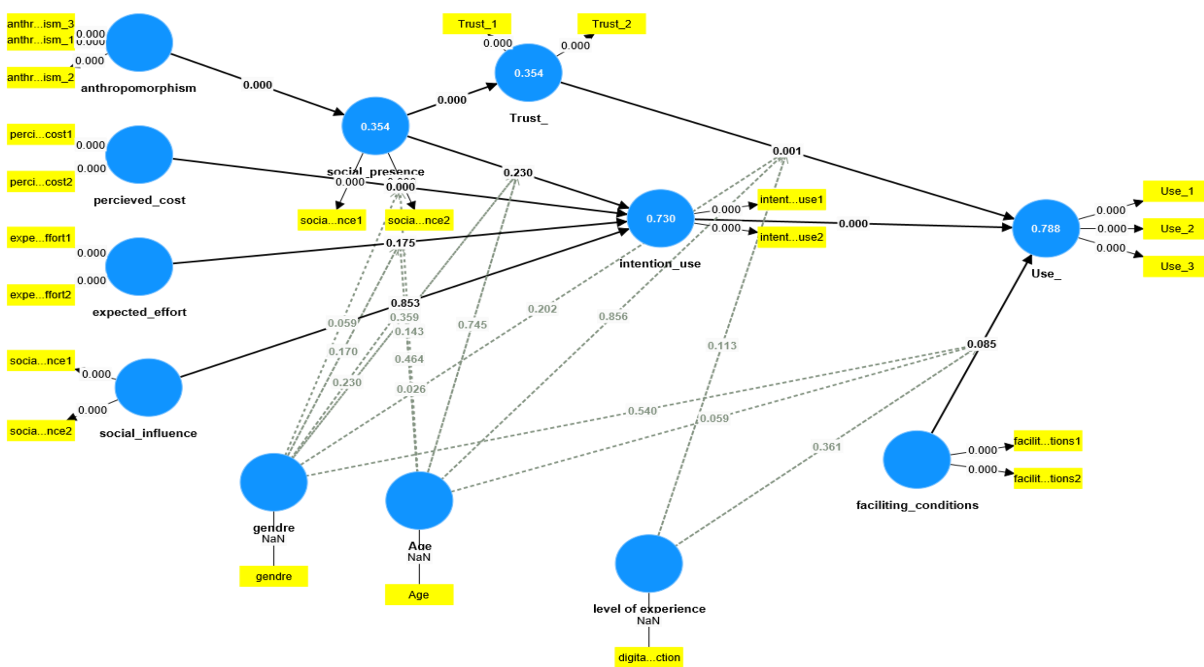

Figure 5: Moderator variables in the model

The table 11 provides information on the moderating effects of gender, age and level of experience on various relationships. T-statistics and p-values are used to determine whether these moderating effects are statistically significant. A statistically significant moderating effect suggests that the relationship between the independent and dependent variables varies with the level of the moderating variable. Non-significant effects suggest that the moderator variable does not significantly influence the relationship. In our case, gender and level of experience had no moderating effect on the variables. Age, on the other hand, had a moderating effect on a single relationship between social influence and intention to use.

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Decision**
Gendre x social_influence -> intention_use	0,179	0,202	0,149	1,202	0,230	Rejected
Gendre x expected_effort -> intention_use	-0,165	-0,170	0,121	1,373	0,170	Rejected
Gendre x percieved_cost -> intention_use	-0,314	-0,328	0,166	1,891	0,059	Rejected
Gendre x social_presence -> intention_use	0,123	0,113	0,134	0,917	0,359	Rejected
Gendre x Trust_ -> Use_	-0,140	-0,137	0,109	1,276	0,202	Rejected
Gendre x faciliting_conditions -> Use_	0,061	0,052	0,099	0,613	0,540	Rejected
Age x social_influence -> intention_use	0,157	0,174	0,070	2,225	0,026	Validated
Age x expected_effort -> intention_use	0,045	0,046	0,062	0,732	0,464	Rejected
Age x percieved_cost -> intention_use	-0,117	-0,123	0,080	1,466	0,143	Rejected
Age x social_presence -> intention_use	-0,019	-0,017	0,059	0,325	0,745	Rejected
Age x Trust_ -> Use_	-0,011	-0,012	0,062	0,181	0,856	Rejected
Age x faciliting_conditions -> Use_	0,100	0,104	0,053	1,892	0,059	Rejected
Level of experience x Trust_ -> Use_	-0,089	-0,091	0,056	1,586	0,113	Rejected
Level of experience x faciliting_conditions -> Use_	0,047	0,048	0,052	0,913	0,361	Rejected

Table 11: The results of the test of the moderating effect of gender, age, level of experience

6. Discussion and conclusion

6.1. Discussion

The adoption of Chatbots by citizens has long been a discussion of many researchers around the world. It is a challenge and a crucial issue for companies that want to implement and develop this project. In our study the majority of the variables seem to have an influence on the decision taken to adopt Chatbots by Moroccan citizens. After analyzing the different data, we proceed to the following interpretations:

H1: Perceived anthropomorphism has a positive effect on the social presence of conversational agents:

This hypothesis is tested by three questions to assess the effect of Chatbots' anthropomorphism on their social presence in front of Moroccan consumers. The result is truly significant ($t=10.529$, $p=0.000<0.05$). This is consistent with previous findings on the adoption of virtual agents in various fields (Sunder and al.,2019; Sheehan and al., 2020).

H2: The social presence of conversational agents has a positive effect on the confidence of Moroccan consumers. And H3: The social presence of conversational agents positively influences the behavioral intentions of Moroccan consumers.

This hypothesis was evaluated using three items to assess the effect of the social presence of virtual agents on the confidence of Moroccan consumers. The result was significant, with a positive effect on confidence when the virtual agent plays a social role in relation to requesters. This role was confirmed by the mediating role played by social presence between the anthropomorphism attributed to virtual agents and the trust felt by Moroccan consumers ($t=11.331$; $p= 0.000<0.005$). Furthermore, the direct effect of social presence on adoption intention was well validated (3.530; $p=0.000<0.005$). These results confirm several research studies, for example, (De Visser et al., 2016) assert that if a virtual agent is meticulously anthropomorphized and has a real social presence, people will trust this artificial intelligence more. Furthermore, (Balakrishnan and Dwivedi, 2021), suggest that the use of text-to-speech with human cues directly increases social approval.

H4: Perceived cost has a negative effect on Moroccan consumers' current intention to use conversational agents.

Perceived costs: According to the analysis of the results, the cost of using virtual agents has an impact on their adoption, and the hypothesis was validated (t=2.060, p=0.040<0.05). This shows the absence of financial barriers that could influence the intention to adopt virtual agents, particularly in terms of purchase. This result confirms previous work (Ben mimoun and al.,2017). There is a positive mediating effect of adoption intention between perceived cost and virtual agent adoption.

H5: The expected effort has a positive impact on the intention to use conversational agents on the part of Moroccan consumers.

Expected effort: several studies confirm the role of expected effort (Følstad and Brandtzæg, 2017). Indeed, the items chosen examined the judgment that the consumer may make about the effort provided at the time of the virtual interaction. Contrary to our expectations, the result of this hypothesis showed no effect of the variable on adoption intention (t=1.217, p=0.224). It is possible that the contradictory results are due to the diversity of consumer cultures or to the slow acceptance of artificial intelligence by Moroccan consumers in the service sector.

H6: Social influence has a positive impact on the intention to use conversational agents.

Social influences: According to the work of venkatech and al. (2003), the variable social influence is an antecedent of adoption intention. Indeed, in our study, the link between the two is validated. Our hypothesis of a stronger positive effect is validated (t=3.283, p=0.001). This result is in line with several studies (Sripalawat and al., 2011); (Gursoy and al., 2019b)) that indicate that IS can have an effect on people's willingness to exploit online services. In the present case, we aim to understand how much individuals value the influence of personal surroundings when using an AI (Verma and Sinha, 2018).

H7: Trust in conversational agents positively influences their adoption by Moroccan consumers.

Perceived trust: The items chosen enabled us to study trust at two levels: trust in virtual agents and trust in a platform. The result showed a positive relationship between trust and the adoption of virtual agents (t=4.584, p=0.000<0.05), and as trust plays a mediating role, it must be said that to increase consumer trust in these agents, companies must invest in the anthropomorphism and social presence of virtual agents. Finally, the study confirms a positive mediating effect of trust between social presence and adoption of a conversational agent. These results confirm several research studies (Janani and al., 2022; (Talwar et al., 2020), which consider trust to be an essential element in the adoption of a new technology.

H8: Enabling conditions have a positive impact on the adoption of conversational agents.

The relationship between facilitating conditions and Chatbot adoption is significant (t=4 .132, p=0.004<0.05). Indeed, the more Moroccan consumers have access to resources, knowledge and support, the more positive their adoption of Chatbots will be. This result confirms previous research on adoption (Sanny and al.,2020; cheikho, 2015; Venkatesh et al., 2003).

Moderating variables:

We included the moderating variables gender, age and level of education to determine their impact on all the variables. Contrary to our expectations, only age had a moderating effect on the relationship between social influence and intention to use. This result is consistent with that reported in multiple research studies (Venkatesh and al., 2003; (Riffai and al., 2012); (Garg, 2022). Age is an essential moderating variable when it comes to the use of artificial intelligence. As age progresses, doubts and worries become a fundamental element in acceptance. In our case, age influences social relationships when it comes to accepting chatbots in the service sector. On the other hand, and contrary to many (Venkatesh and al. 2003; Natarajan and al. 2017; Shannon, 2019), gender had no moderating effect. For the moderator "level of education", the results are surprising compared to previous research (Coeurderoy and al., 2014) which considers that "level of education" has a direct influence on the adoption of modern technology. These results can be understood by the very nature of the technology. Chatbots, for example, may be simple and intuitive enough to use, so that "education level" has no influence on their adoption.

6.2. Conclusion

6.2.1. Theocraticals Contribution

The aim of this work is to strengthen the marketing literature and determine the set of variables that promote this man-machine interaction. However, the chosen model was empirically tested on 340 Moroccan consumers. Using the PLS approach, the model was able to explain 75.8% of the variance in the adoption of virtual agents by Moroccan consumers. The results of the modified model confirm the structuring role of facilitating conditions and social influence, but the expected effort was not approved by our sample. This is explained by the strong entry of adoptive variables in the context studied, namely perceived trust, perceived cost, social presence and the anthropomorphism of virtual agents. Contrary to our expectations, the moderating effect of gender and level of education had no influence on the various variables. On the other hand, the mediating effect of perceived trust and social presence and intention were approved.

6.2.2. Managerial Implications

From a managerial point of view, our results should encourage platform managers in the development of Chatbots, which appear to be essential marketing tools for customer relationship management.

However, a set of tips can be recommended on a managerial level. The results can be a roadmap to convince managers, marketing and website managers of the usefulness of using virtual agents. Perhaps the cost of their installation is still a barrier for some managers who still doubt the relevance of such technological investment. It can be said that the result of this research may shed light on the advantages offered by conversational agent and reduce the mistrust of their use. In addition, managers in the service sector need to focus on the influence of their customers' entourage on the adoption or non-adoption of this artificial intelligence. Our results reveal the importance of the influence of the personal and professional environment.

6.2.3. Limitation of study/ Future directions of research

Despite these various interests, our research has some limitations. The first concerns the choice of platform (Facebook Messenger) on which we worked. In order to increase the external validity of our research, it will be necessary, in the future, to integrate other platforms that are currently using chatbots in mass, such as WhatsApp, Amazon and others. The second limitation concerns the lack of distinction between so-called intelligent and non- intelligent chatbots in our survey. It seems desirable, in future work, to test the degree of influence of each type of conversational agent.

Among the possible future research perspectives, it seems necessary to us to question the interactions between Chatbots and cyber consumers. Indeed, if the understanding of the adoption of virtual agents is essential, it is necessary to keep in mind that they are only one of the elements likely to be mobilized by the managers. In other words, it could be useful for both researchers and practitioners in marketing, to take an interest in the technical characteristics of chatbots (the speed of responses, the degree of interactivity of chatbots, the ability of chatbots to recognize Internet users during future connections, the language used by the chatbot, etc.).

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