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Abstract

The appearance of Artificial Intelligence implementations, such as text-based virtual assistants (chatbots) in education is relatively new. These implementations can be useful for helping teachers and students to solve both educational questions and routine tasks. This paper examines the factors that explain teachers' acceptance of chatbots through the dimensions of the Technology of Acceptance Model (perceived usefulness and perceived ease of use), its conversational design (use of social language and proactiveness), and the teachers' age and digital skills. The data collection process included a pretest and an online survey with four different types of chatbots. We analyze 225 responses of primary and secondary education teachers. The results show that the perceived easiness and perceived usefulness leads to greater acceptance of chatbots. As for the chatbots' features, formal language by a chatbot leads to a higher intention of using them. These results can help in chatbot design and communication decisions, improving the acceptance of the educational community.

Keywords: chatbot, education, teachers, TAM, proactiveness, social language, digital skills

Introduction

When people access some universities' web pages, they find a pop-up saying: "Hello! I am the virtual assistant of the University Information Service. I am here to help you". For example, this service is called Quizbot at the University of Stanford and Carol at the Complutense University of Madrid. Specifically, Quizbot and Carol are chatbot programs that integrate Artificial Intelligence, and they are capable of maintaining a level of conversation with people and save time and effort.

This illustration is an example of how information and communication technologies are transforming society. People no longer interact with each other, buy products or seek information, learn or study in the same way, and computer-mediated environments have become pervasive. In this ambiance, chatbots emerge as a software tool to maintain a text conversation with users on a particular topic or specific field.

Due to advances in language processing and artificial intelligence (AI), today's chatbots have sophisticated natural language processing tools that allow them to understand complex conversations and address user requests with depth, compassion, and even humor (Wilson et al., 2018). Moreover, chatbots can consistently talk in a friendly way because they do not have bad days and never get frustrated or tired like humans (Gao et al., 2018).

Chatbots or conversational agents help humans in customer service in many fields, from retail commerce, financial advice, healthcare to education and teaching, because they provide convenience and cost-efficiency. However, new challenges have also appeared. In particular, chatbots are still perceived as a machine and not human beings, and many individuals are reluctant to interact with them (Araujo, 2018; Go & Sundar, 2019). Human beings still prefer to have contact with real people, for example, when users know that they are interacting with a bot instead of a human, they perceive the agent as less knowledgeable and less empathetic and behave more abruptly (Luo et al., 2019).

Increasing the affective human-likeness similarity of agents can also improve their level of acceptance and use (Catrambone et al., 2002), as they are intended to interact with humans more naturally than in a traditional human-computer interaction (Bernard & Arnold, 2019). The humanity of agents can be suggested through visual attributes, identity and conversational attributes that mimic human language (Go & Sundar, 2019).

Since chatbots are relatively new, there is little research on their general acceptance (Rese et al., 2020) and even less on educational chatbots (Chen et al., 2020). Specifically, it is important to analyze how chatbots are accepted and valued by teachers, key participants in the educational process, including the factors that can increase or decrease the probability of acceptance of this technology.

Therefore, our first objective is to analyze teachers' intention to adopt virtual agents in an educational context from the perspective of a general technology adoption model (TAM) (Davis, 1989). Secondly, we also study how conversational attributes of the agents, social language and proactivity, affect this process. Finally, our third objective is to examine the additional effect of specific user characteristics on using the assistants (digital skills and age).

The creation of these assistants is a complex effort that requires research in various areas such as AI, computer animation, interface design, sociology, and psychology, among others.

Incorporating chatbots into the educational area during the last decade have implied an increase in interest in the characteristics that should be implemented for teaching and learning. Progress in the area can significantly benefit from a better understanding of the factors that guide this technology's adoption. We contribute to this area with a novel analysis of the determinants of the intention to use virtual text assistants in education, studying general perceptions about the assistants, their conversational features, and teachers' characteristics.

In the section below, we present the conceptual framework along with our hypotheses. Afterwards, we describe the research design used in this study. Then, we depict and discuss the results, and our conclusions are summarized.

Conceptual framework

Chatbots in the educational environment

The term chatbot combines two words: "chat" for conversation and "bot" for robot. This type of communication technology has received numerous names since its appearance. Luo et al. (2019) define chatbots as computer programs that simulate human conversations using natural languages through voice or text commands and serve as virtual assistants to users. Other interchangeable terms are dialog systems, conversational agents, digital agents, and virtual assistants. Here, we use this term for agents operating mainly through text since voice virtual assistants generally receive specific names such as Voice Activated Personal Agents or VAPAs (Easwara Moorthy & Vu, 2015).

Educational chatbots are those designed with a specific educational purpose (Bii, 2013). Their goals can be purely educational or oriented to administrative and supportive tasks. Administrative tasks involving automating the processes and administrative consultations include calendar management, reminders of assignments and deliveries, and frequently asked questions about admissions, registration, or technical problems with email or the virtual campus. Chatbots with educational intent show high potential as a teaching-learning tool in distance education (Heller et al., 2005) and favor the teaching and learning processes directly, acting as tutors that accompany the learning process. Bork (2001) notes how this interactive tutoring can make a change in the educational paradigm. These educational tasks include the facilitation and adaptation of content, such as knowing the difference between two concepts or practicing a language by chatting with a mobile phone (Fryer et al., 2019; Lu et al., 2006). Chatbots can create an individualized learning environment with the benefits of having a two-way, one-to-one conversation: immediate feedback and unlimited conversation time.

Nowadays, most text-based educational chatbots are implemented in mobile phone messaging services such as Facebook Messenger, WhatsApp, or Skype. Mobile phone messaging platforms are increasingly used as a communication channel and can reach 2.5 billion people (Clement, 2019). These platforms bring convenience to chatbots, decreasing the cost of starting using this technology, as there is no need to install a particular app on mobile devices (Baier et al., 2018). They also allow users to learn from anywhere and at any time and get quick responses. Smutny & Schreiberova (2020) have studied 47 educational chatbots available in Facebook Messenger platform based on attributes of the quality of teaching and accessibility, among others. However, their results show that chatbots are still in the early stages of becoming teaching assistants.

To date, research on the application of virtual assistants and their use in education is scarce, although the few existing studies show the benefits of chatbots. Goda et al. (2014) found higher quality debates when students have had a previous conversation about the topic with an online agent. Young Oh et al. (2020) showed that attitudes towards bullying problems were more positive after implementing a chatbot. Gulz (2004) established that educational chatbots provide increased motivation, greater fluency in the information and communication process, and gains in memory, understanding, and problem-solving. Finally, Veletsianos & Miller (2008) also concluded that there was substantial evidence of chatbots' positive effects as educational agents. However, the factors determining the acceptance of this technology have not been fully studied yet.

Factors in the adoption of chatbots for education- The Technology Acceptance Model

The Technology Acceptance Model (TAM) (Davis et al., 1989; Moussawi et al., 2020) is designed to explain the process of information technology acceptance and has been widely applied in different contexts for understanding users' behavior regarding the acceptance of new technology. TAM is tailored to information systems contexts, and it is the most recognized model by far in terms of research on user acceptance behavior (Liu et al., 2009). TAM is highly generalizable (Park, 2010), and it allows easy transfer and application to different contexts (Venkatesh, 2000).

TAM explains the users' behavioral intention with two factors: the perceived usefulness of the new technology and its perceived ease of use. *Perceived usefulness* refers to the degree to which people believe that using a particular system would enhance their job performance (Davis et al., 1989). *Perceived ease of use* applies to the degree to which potential users believe that using a particular system would be free of effort (Davis et al., 1989). Warshaw & Davis (1985) define users' *behavioral intention* as "the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior" (p. 214). The TAM's main idea is that the user's behavioral intention determines the acceptance of the technology by the user, which, in turn, is defined by the perceived usefulness and the perceived ease of use (Farahat, 2012). Chen et al. (2020) have successfully applied the TAM model to explore a new chatbot developed to learn Chinese vocabulary.

Therefore, according to TAM, we propose our first two hypotheses:

H1. Chatbot perceived usefulness is positively related to its usage intention, and

H2. Chatbot perceived effort is positively related to its usage intention.

The TAM model has been extended by adding different factors to fit different contexts better. For example, the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) includes, as additional determinants of behavioral intention, the facilitating conditions, social influence, and personal characteristics. Chen et al. (2020) added perceived enjoyment as a predictor of perceived ease of use, which means that if users enjoy using chatbots, they will probably perceive that they are easier to use, which will affect their adoption.

In the context of chatbots, two characteristics can also impact behavioral intentions: the type of social bond established with the chatbot and its level of intrusiveness. First, concerning social bonds, people's preference for communicating with each other results in rejecting many

new automatization technologies such as chatbots or shelf service technologies (Collier & Kimes, 2013; Lee & Lyu, 2016). Castelo et al. (2019) provide a review of human versus algorithmic advice preference, which supports greater preference of human advice for varied topics ranging from medical recommendations to the stock market. However, when a virtual agent shows signs of human identity, it is perceived as more anthropomorphic and is evaluated more favorably (Sundar et al., 2016; Xu & Lombard, 2017). The increase in anthropomorphism drives a positive effect in perceived social presence, an essential factor in human-computer interactions (Araujo, 2018) and a key predictor of positive attitudes and behaviors (Araujo, 2018; Bente et al., 2008).

Designers can improve customers' perceptions of the agents' anthropomorphic level through different types of social cues: visual attributes, such as the agent having the shape of a human figure, identity attributes such as personal names, and conversational features using language that mimic the human one (Go & Sundar, 2019). This paper will pay attention to the last type of social cue: conversational attributes because they present more challenges than visual and identity characteristics due to human language complexity. For that purpose, we use the computer-mediated communication (CMC) framework and the taxonomy of social attributes established by Feine et al., (2019) for conversational agents. In this framework, conversational attributes are considered "invisible cues."

In CMC, the perception of dialogue is fundamental in two-way communication (Seltzer & Mitrook, 2007). The parties will understand each other if they speak a similar language. A vital characteristic of this human communication is the style of language. Agents who use social language get better responses from consumers than when they use a functional language (Adam et al., 2020).

Emoticons are combinations of ASCII characters used to represent a particular emotional state such as happiness or sadness (Baron, 2003) and increase the perception of interpersonal relationships (Liebman & Gergle, 2016). Conversational agents can submit these textual or pictorial depictions of facial expressions to increase social language perception and obtain better responses (Liebman & Gergle, 2016). Using emoticons adds personality and makes the conversation more entertaining, visually appealing, and more enjoyable. Moreover, customers themselves use these emoticons when communicating with virtual agents. (Hill et al., 2015) analyzed communication changes when people communicate with an intelligent agent and with another human, and their results showed no statistically significant differences in the mean number of emoticons.

We establish our third hypothesis as:

H3. The chatbots' use of a social language style, including emoticons is positively related to its usage intention.

Another important element in the category of invisible social cues is the proactiveness in the conversation, that is, who takes the first turn in the discussion (Feine et al., 2019). Proactive assistants start the conversation, make themselves known, and do not wait for the user to take the initiative to request information. The effects of proactive assistants have been studied in various task settings, such as interactive learning, web searches, and educational software. Proactive help may cause some users to perceive chatbots as intrusive, annoying, distracting, and offensive rather than useful (Rickenberg & Reeves, 2000), and therefore, they are

perceived as less useful. Xiao et al. (2003) provided evidence from their text-editing assistant experiment. They found that although individuals feel that both reactive and proactive assistants are valuable, they perceive that the proactive assistant would not improve the result and would be intrusive. Therefore, we hypothesize that the reaction of users to an assistant may vary as a function of the assistant's initiative. An assistant who makes unsolicited suggestions could cause the user to feel discomfort, intrusion, and distraction and be less helpful compared to an assistant who responds only to user questions, which leads us to establish a fourth hypothesis:

H4. The proactiveness of the chatbot is negatively related to its usage intention.

Finally, we include two personal characteristics in our model of technology adoption: digital skills and age. The lack of digital skills is one of the teachers' common reasons for not using technology and a major barrier to technology integration (Snoeyink & Ertmer, 2001; Williams et al., 2000). In our case, teachers' particular backgrounds and experience will make them more or less comfortable interacting with an assistant. Chen & Wang (2018) confirmed that user experience and technical knowledge affect conversational agents' perceived usability. Specifically, technical knowledge seems to increase perceived usability for inexperienced users, which leads us to establish the fifth hypothesis as follows:

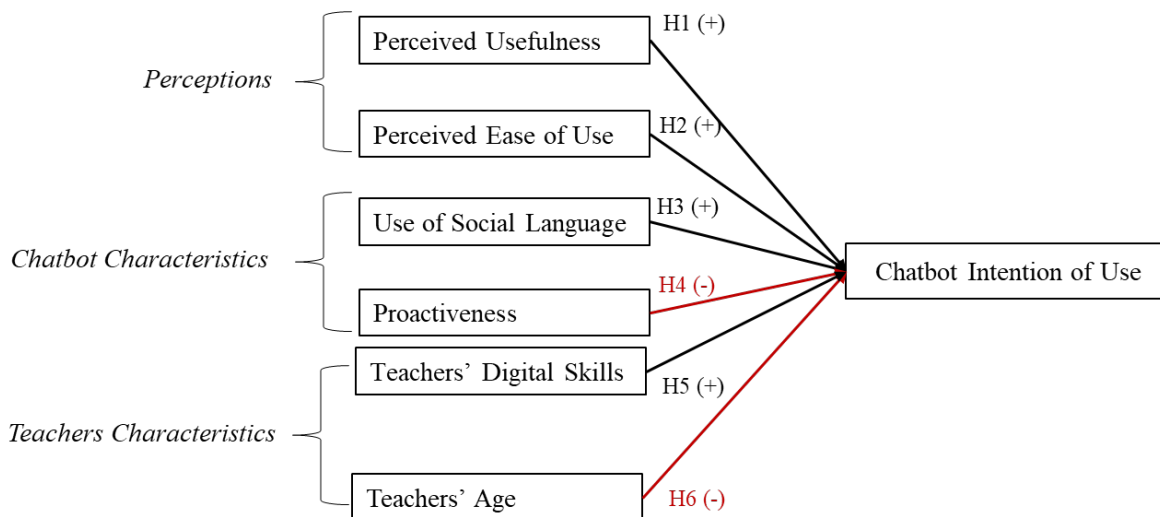
H5. The level of teachers' digital skills is positively related to the chatbots' usage intention.

The age of teachers is the last factor influencing the process included in our model of adoption. There is considerable evidence of differences by age in the degree of acceptance of the technology. Fernández-Cruz & Fernández-Díaz (2016) found that older teachers have much lower ICT profiles than younger ones. Younger teachers have more technical skills and integrate them more into their teaching practices (Russell et al., 2000; Suárez-Rodríguez et al., 2012). Therefore, as the last hypothesis, we propose the following:

H6. The teachers' age is negatively related to the chatbots' usage intention.

We illustrate the research model in Figure 1.

Figure 1. Conceptual Framework and Hypotheses



Research design

Sample

To test our hypotheses, we developed a questionnaire distributed during November 2019 in 28 primary and secondary education centers located in the Navarre region (Spain). In five of these centers, we contacted the management team asking for collaboration in the study, and they sent the questionnaire to the teachers through their center's email system. We complemented these data with additional ones collected directly from teachers through snowball sampling. We gathered a total of 225 valid responses. The participants have an average age of 43 years and 15 years working as a teacher. More than half (65%) were women.

Materials: chatbots

Our study used a 2x2 experiment: with two treatments:

- Social vs. functional language: we varied both the language and the use (or not) of emoticons.
- Proactive vs. reactive language: the chatbot initiates the conversation in the first case and the user in the second case.

The combination of these two treatments results in four types of chatbots.

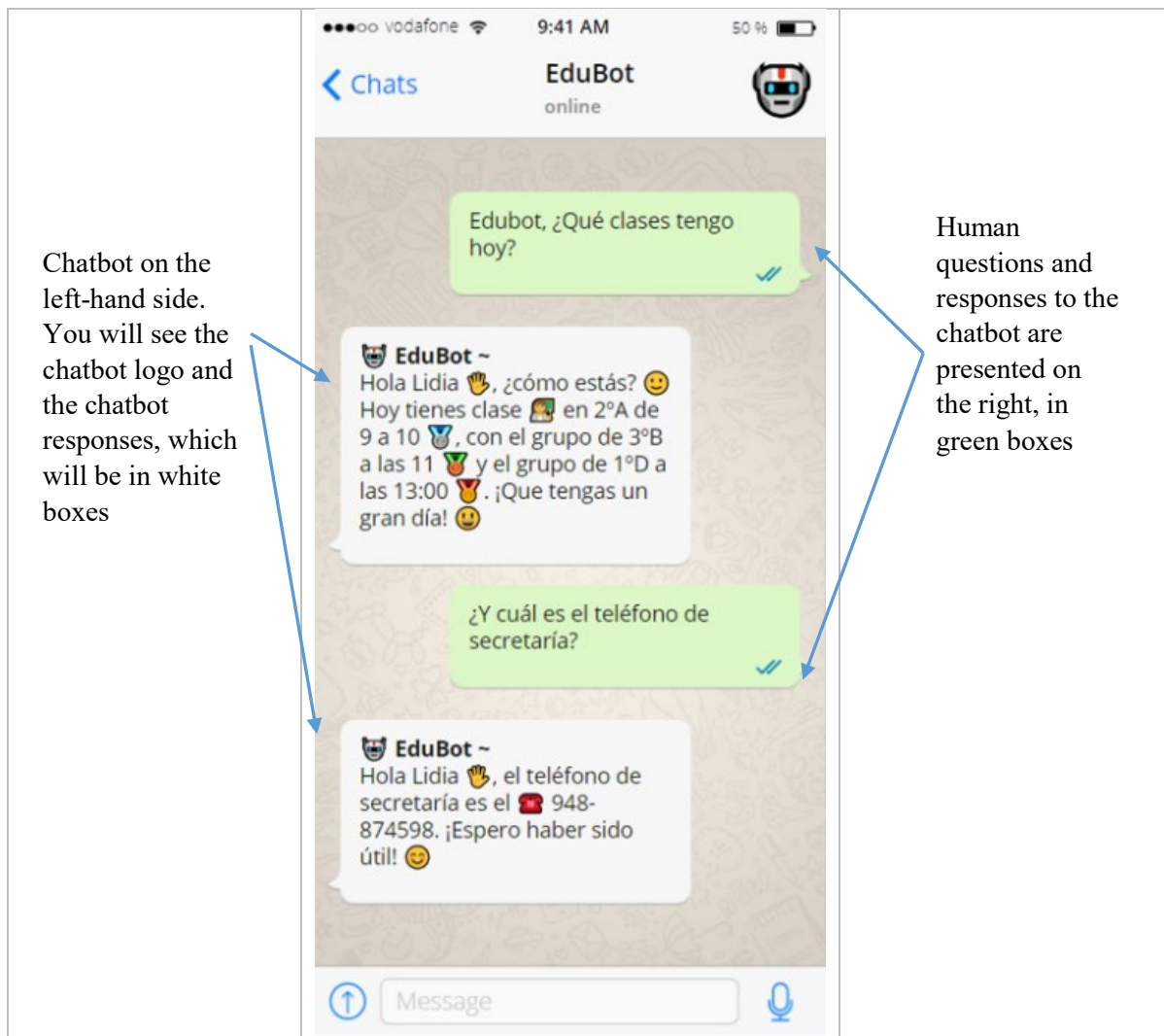
We implemented the experimental design by creating four simulated conversations with the chatbot in a *Whatsapp* interface, one for each of the four different types of chatbots. We chose the WhatsApp mobile application because it is one of the three most used globally, making it a familiar interface for the participants.

Each individual was randomly exposed to only one of these four designs. One example is shown in Figure 2, and the four possible screenshots are presented in Appendix 1. After being

exposed to the screenshot, the participants complete a series of statements about using the chatbots in the questionnaire.

Figure 2. Image provided to respondents as part of the conversation with a chatbot.

Screenshot 4: Example of conversation (social language, human first turn)



Transcript of screenshot 4 (the text was in Spanish in the original experiment):

- **Human:** Edubot What classes do I have today?
- **Chatbot:** Hello, Lidia 🙌, how are you? Today you have class 🧑🏫🏠 in 2°A from 9 to 10 AM 🕒, with the group of 3°B at 11 AM 🕒 and with the group of 1°D at 1:00 PM 🕒. Have a great day! 😊
- **Human:** And what is the main office number?
- **Chatbot:** Hello, Lidia 🙌. The main office number is 948-874598 📞 I hope I have been useful! 😊

Procedure

The *ad hoc* questionnaire was hosted by the *Qualtrics* survey service and accessible from different platforms (i.e., cellphone, tablet, or computer). In the questionnaire, respondents could visualize the screenshot of the chatbot conversation and a series of questions. As an

incentive, we stated that the five collaborator centers would receive a 120€ bonus to buy school supplies if the global center response rate reaches 90%. The data collection, including the conversation display and questionnaire completion, took approximately 15 minutes per person.

Method

This experiment enabled us to obtain questionnaire responses from each subject. The questionnaire included information regarding TAM items and digital skills and teachers' age. Finally, we included other subjects' characteristics, such as subjects taught and training cycle, and demographics for control purposes. Given our objectives, the metrics employed in this study about chatbots are as follows.

First, we use as metrics for usage intentions, perceive usefulness and perceive ease of use the original questionnaire items of the TAM model from Davis et al. (1989), adapted to the chatbot context:

- *Assistant usage intention*: The respondents were asked to indicate on a 1 to 7 scale their level of agreement (1-disagree strongly, 7-agree strongly) with one statement:
 - “I would like to use virtual assistants in the future in my teaching work.”
- *Perceived usefulness*: The respondents were asked to indicate on a scale of 1-7 their level of agreement (1-disagree strongly, 7-agree strongly) with four statements:
 - Utility: “I think that chatbots like this can be useful for my work.”
 - Performance: “Using chatbots like this would improve my performance.”
- *Perceived ease of use*: The respondents were asked to indicate on a scale of 1-7 their level of agreement (1-disagree strongly, 7-agree strongly) with four statements:
 - Easiness: “I find it easy to use chatbots like this.”
 - Mental effort: “Using chatbots like this would not require much mental effort on my part.”

Also, we include the following measures for teachers' characteristics.

- *Digital skills*: To assess the respondents' skills, we used the standardized scale of Digital Competence Framework for Educators (DigCompEdu) (Caena & Redecker, 2019; Redecker, 2017) that was used to evaluate educators in the European Union. As a global measure, the respondents were asked to indicate on a scale of 1-6 their self-assessed skill

level according to the DigiComp categories: newcomer, explorer, integrator, expert, leader or pioneer.

- *Age*: Each teacher had to indicate their age expressed in numerical value from 21 to 70 years.

Results

Table 1 shows the descriptive statistics for the variables involved in this study. First, regarding the attitudes toward chatbots, participants have a moderately high usage intention with a mean value of 4.2 out of 7. The indicators of perceived usefulness and ease of use also have similar mean values, with the highest one for perceived easiness (5.16/7) and the lowest one for the perceived impact on performance (3.98/7). Surprisingly, the perceived mental effort of using the chatbot presents a value relatively high (4.58/7) and also has the highest standard deviation of these variables, indicating a lower level of agreement between participants in this aspect.

The next two variables show the proportion of participants exposed to each experimental condition, and, as expected, they match the 50% fixed by the experimental design.

Finally, the last two rows are participants' characteristics: age in years and the self-declared digital competence level. On average, the respondents are 43 years old, with a minimum of 23 and a maximum of 65. This maximum value is consistent with its theoretical value, the age for retirement in Spain. Self-declared digital competence level has a mean value of 3 on a range from 1 to 6, which means that, on average, teachers considered themselves as an "integrator" regarding their digital skills.

Table 1. Descriptive Statistics

Variable	Mean	Min.	Max.	SD	N
Use Intentions	4.24	1	7	1.66	225
PU1. Perceive Utility	4.36	1	7	1.50	225
PU2. Perceive Impact on Performance	3.98	1	7	1.42	225
PEU1. Easiness	5.16	1	7	1.30	225
PEU2. Perceive Mental Effort	4.58	1	7	1.62	225
Bot with Social Language (dummy)	0.51	0	1	0.50	225
Proactive Bot (dummy)	0.50	0	1	0.50	225
Age (years)	43.09	23	65	9.92	225
Digital Skills	3.00	1	6	1.04	225

PU: Perceive usefulness. PEU: perceived ease of use.

We estimated a regression model (Wooldridge, 2006) with the R software (version 3.6.2). Our dependent variable is the chatbot usage intention and we have eight independent variables. The model results are presented in Table 2.

Table 2. Regression Model.

Variable	Estimate	Std. Error	Statistic	P value
Intercept	0.175	0.527	0.333	0.739
PU1. Perceive Utility	0.409	0.093	4.413	0.000
PU2. Perceive Impact on Performance	0.430	0.095	4.528	0.000
PEU1. Easiness	0.206	0.066	3.124	0.002
PEU2. Perceive Mental Effort	-0.010	0.054	-0.176	0.861
Bot with Social Language (dummy)	-0.320	0.146	-2.193	0.029
Proactive Bot (dummy)	-0.011	0.149	-0.075	0.940
Age (years)	-0.002	0.007	-0.214	0.831
Digital Skills	-0.073	0.076	-0.956	0.340
R Squared	0.610			
Adj R squared	0.595			
χ^2	39.165			
P value	0.000			
Degrees of freedom	8.000			

PU: Perceive utility. PEU: perceived ease of use

The last five rows in the table show the statistics for the goodness of fit of the model. The percentage of variance explained by the R² and adjusted R² show that the model has good explanatory power, with around 60% of the variance in the usage intentions explained by our model.

Considering our two indicators of usefulness, both are significant at the 1% level, with a positive sign, therefore, confirming our hypothesis 1: the perceived usefulness of chatbots increases the intention to use them. The effect is slightly higher for the perceived chatbots' impact on performance. Regarding the effect of the perceived ease of use, perceived easiness has, as expected, a significant positive parameter value. However, we do not find evidence of a significant negative impact of perceived mental effort, although the parameter sign is negative, as expected. We partially confirm hypothesis 2.

The next two rows show the effect of the two experimental conditions: social language and proactive versus reactive behavior. Contrary to our expectations, using social language with emoticons has a significant negative influence on the intention to use assistants. Therefore, we reject our hypothesis 3. Furthermore, the proactive conditioned effect has the predicted sign but is not significant, and consequently, we cannot confirm hypothesis 4. Finally, regarding the individual characteristics: digital skills and age, neither one significantly affects using a chatbot, and we cannot confirm hypotheses 5 and 6.

Conclusions, discussion and limitations

In this study, we empirically test the TAM model of technology acceptance (Davis, 1986) to explain teachers' usage intention of a chatbot in an educational context, including the effect of conversational design decisions and teachers' characteristics.

Our results confirm a positive and substantial impact of the perceived usefulness for using the chatbot on teachers' technology usage intention. Improving the performance and usefulness of chatbots is a critical determinant for teachers when considering adopting this technology for their jobs.

Furthermore, our results also show that chatbots' ease of use does relate to higher intention of use. On the contrary, low required mental effort does not have a significant relationship with the intention of use. We think that in an educational environment, mental effort is an endogenous constant for teachers. The evidence shows that users often adopt technology for pleasure (Toubia & Stephen, 2013). Researchers such as Fosso Wamba et al. (2017) noticed that enjoyment and playfulness emerged as constructs responsible for explaining usage intention in the Technology Acceptance Model. However, in our context, the chatbot is a tool for more efficient work, and mental effort is a part of the job. Therefore, it could take a secondary role in explaining their usage intention.

In hypothesis 3, we posit that there would be greater acceptance of virtual assistants that use social language versus assistants with a more functional one. However, the results show a negative impact of social language with emoticons. Therefore, the acceptance of chatbots with formal language assistant is higher than that for a social one. There are two possible alternative explanations for this unexpected result. First, in some cases, technology and anthropomorphism can be perceived as a threaten to humanity and generate strongly adverse emotional reactions, what has been called the Uncanny Valley theory (Wang et al., 2015). An increase in human similarity through a more social language could reduce the intention of adopting the chatbot. The second possible explanation may be due to the characteristics of our population for the study. Teachers may be more likely to use formal language and avoid the use of emoticons, and therefore, in this case, social language can increase the perceived distance with the chatbot. More research will be needed to investigate these two alternative explanations for our results.

Regarding the second variable of conversational design, the chatbot's proactivity, we do not find a significant effect. The effect is very close to zero, although it shows a negative sign. In this case, the participants do not perceive this chatbot as intrusive, maybe because of the professional nature of the interaction.

Finally, teachers' digital skills (H5) and age (H6) are not significant predictors of their usage intentions to use chatbots. Regardless of the existing evidence that younger teachers and more

digitally skilled ones more actively use IT in their practices, in our model, age and digital skills do not seem to influence their intention to use chatbots. Sánchez-Mena et al. (2019), in their research on teachers' intention to use videogames, also found that neither age nor gender moderate teachers' behavioral intention.

Given the results concerning both the conversational design and the teachers' characteristics, it will be convenient to replicate this research with students as a population to see the differential impact of the variables under study. Furthermore, other conversational cues, as the type of content (educational vs administrative) or language style, could be investigated.

Additionally, it would be interesting to examine how TAM factors might affect student learning outcomes. Barneche Naya & Hernández Ibáñez (2015) suggested that perceived usefulness and ease of use could influence learning outcomes. Recently, Chen et al. (2020) showed statistically significant improvement in learning achievement with the chatbot. These previous studies further advance the present investigation to analyze the correlations between TAM variables and the learning performance of students.

Our findings suggest that educational chatbot developers or teaching programs seeking to encourage the use of chatbots should highlight their utility at improving teachers' task performance. Teachers can find in chatbots an opportunity to increase efficiency and promote the tool as support when taking charge of certain instructions. Class time could be maximized by downloading certain tasks such as questions about homework submissions and information requests in digital assistants such as chatbots. Also, students could learn with chatbots in a personalized way and on-demand when there is no teacher available.

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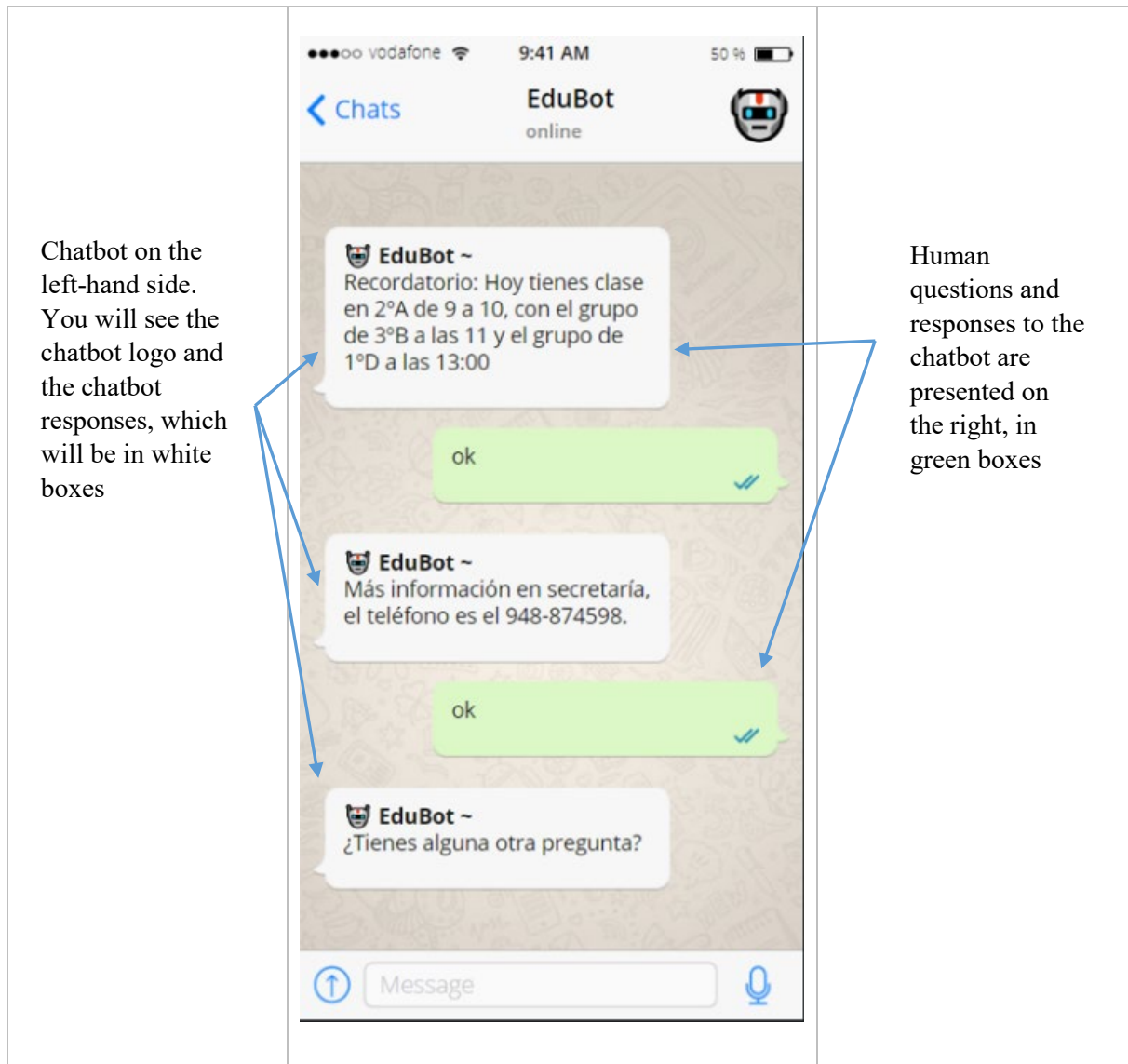
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Appendix

Detail of the four treatments

Screenshot 1: Example of conversation (no emoticons, human first turn)



Transcript of screenshot 1 (the text was in Spanish in the original experiment):

- **Chatbot:** Reminder: Today you have class in 2ºA from 9 to 10, with the group of 3ºB at 11 and the group of 1ºD at 1:00 PM
- **Human:** Ok
- **Chatbot:** More information at the main office, the phone number is 948-874598
- **Human:** Ok
- **Chatbot:** Do you have any other questions?

Screenshot 2: Example of conversation (no emoticons, human first turn)



Transcript of screenshot 2 (the text was in Spanish in the original experiment):

- **Human:** Edubot, what classes do I have today?
- **Chatbot:** Today you have class in 2ºA from 9 to 10, with the group of 3ºB at 11 and the group of 1ºD at 1:00 PM
- **Human:** And what is the main office number?
- **Chatbot:** The main office number is 948-874598

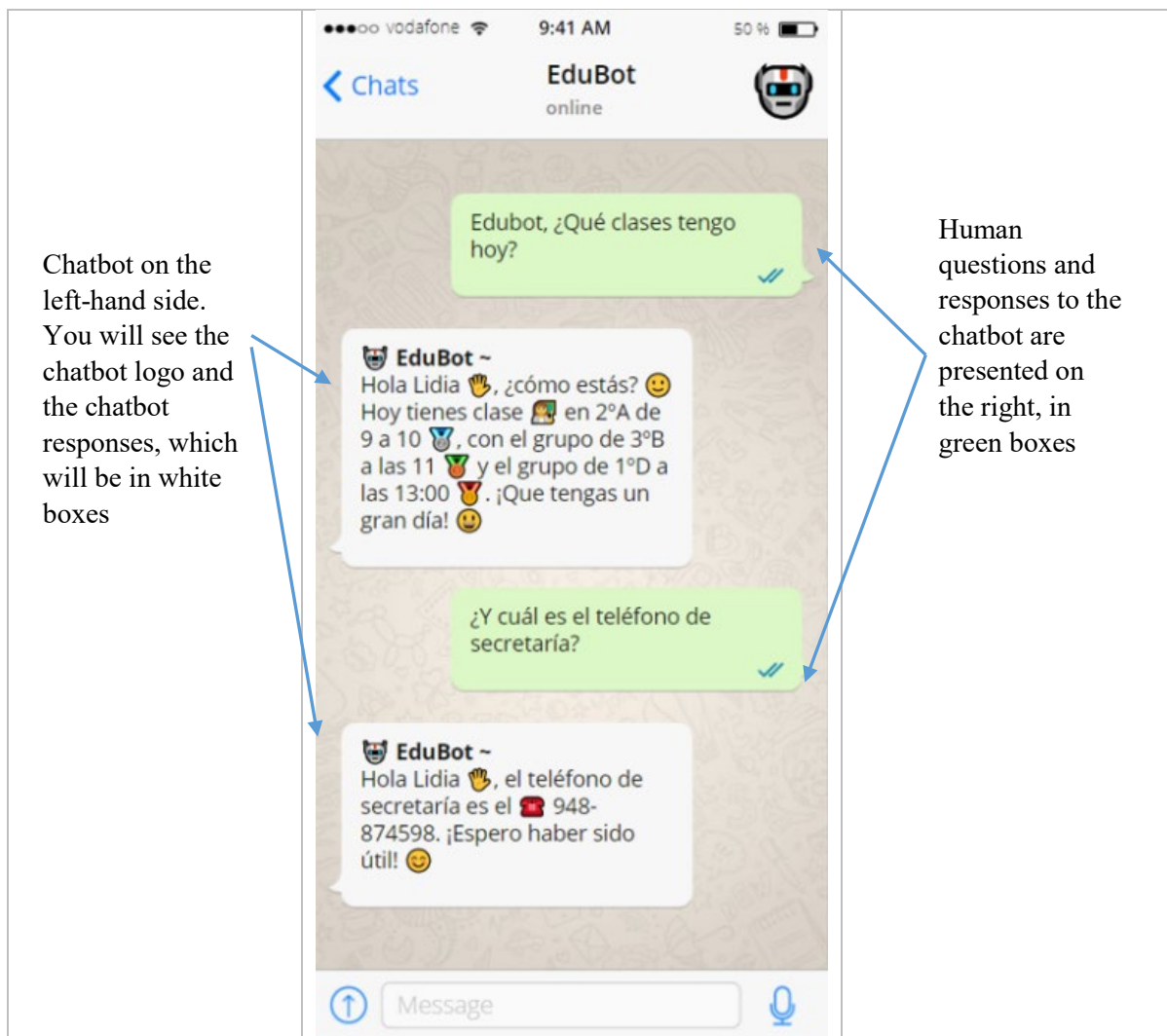
Screenshot 3: Example of conversation (emoticons, chatbot first turn)



Transcript of screenshot 3 (the text was in Spanish in the original experiment):

- **Chatbot:** Hello, Lidia 🙌, how are you? Remember, today you have class 🏫 in 2ºA from 9 to 10 🕒, with the group of 3ºB at 11 🕒 and with the group of 1ºD at 1:00 PM 🕒. Have a great day! 😊
- **Human:** Ok
- **Chatbot:** Hello, Lidia 🙌, remember! If you have any questions, the main office phone is 948-874598 📞 I hope I have been useful! 😊
- **Human:** Ok

Screenshot 4: Example of conversation (emoticons, human first turn)



Transcript of screenshot 4 (the text was in Spanish in the original experiment):

- **Human:** Edubot What classes do I have today?
- **Chatbot:** Hello, Lidia 🙌, how are you? Today you have class 🧑🎓 🏠 in 2ªA from 9 to 10 🕒, with the group of 3ºB at 11 🕒 and with the group of 1ºD at 1:00 PM 🕒. Have a great day! 😊
- **Human:** And what is the main office number?
- **Chatbot:** Hello, Lidia 🙌. The main office number is 948-874598 📞 I hope I have been useful! 😊