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Introduction

Digital humanities (DH) are a broad field of interdisciplinary research that aims to bring together research in technology and humanities (Walsh et al., 2021), since the latter does not have the tradition of investing in technological advances for their research. Thus, academic development with this focus is known as digital humanities (Luhmann & Burghardt, 2021).

Within DH, there are so-called chatbots, which are software tool that conducts conversations with a user, interacting through text or voice messages (Dennis et al., 2020). So-called conversational agents (CAs), often operationalized as chatbots, are becoming increasingly present in everyday life, both for personal and commercial purposes (Schuetzler et al., 2020).

With the development of the largest chatbot development support platform in 2019, Amazon Alexa reached over 100 thousand programs. Facebook Messenger has more than 300 thousand active chatbots on the platform, and many focus on health care and well-being (Zhang et al., 2020).

Skepticism and resistance to conversational agents highlight the biggest challenges in implementing the use of chatbots in everyday online interactions (Araujo, 2018). Some negative points of using chatbots are that customers may feel uncomfortable when being served by artificial intelligence, interacting on personal matters, or needing assistance to make a purchase. Furthermore, revealing that the conversation will be driven by a chatbot substantially reduces the duration of the interaction (Luo et al., 2019).

Chatbots can also be known as virtual assistants and are consistent in quality, as the responses to the same stimuli are always the same. New responses and functionality are being inserted according to new information inputs (Dennis et al., 2020). Other benefits are that chatbots do not have mood swings, bad days, or tiredness, among other human emotions that can harm customer service (Luo et al., 2019).

Chatbots have the power to relieve customer service centers, providing self-service and having the possibility to answer uninterruptedly, that is, 24/7, and reduce the costs of call center operations services (Dennis et al., 2020). The present research helps construct the constructs that directly impact the customer's perception about the use of chatbots and the decision-making of the choice of fundamental characteristics in developing this service.

The possibilities for using chatbots circulate in several areas, such as education, business, e-commerce, health, and entertainment. In addition, chatbots are starting to appear around mental health care; in rural areas, shift workers and others often have difficulty accessing the information on the subject. This artificial intelligence has been seen as a potential alternative for these people.

To make support more accessible and reduce barriers encountered when seeking help, technology-based solutions focused on mental health can play an essential role in the evolution of wellness care (Bakker et al., 2016; Simon & Ludman, 2009). These technologies are needed to help improve quality of life, ease the burden on health, community, and schools, and, most importantly, prevent mental health problems (Donker et al., 2013).

Chatbots can be useful tools for people facing mental health issues, especially for those who find it challenging to seek help due to stigma, which is more common among young people (Abd-alrazaq et al., 2019). Over the years, some research has suggested that chatbots can positively influence people's lives, especially those facing mental health issues (Khan et al., 2021; Nordheim et al., 2019; Toader et al., 2019; Zhang et al., 2020).

The objective of the interaction with this chatbot will be to inform and answer the main doubts about the theme of the campaign, which is focused on mental health care and suicide prevention.

The theme addressed in the chatbot interaction is “Yellow September”, a national campaign that aims to make people aware of suicide. The Brazilian Association of Psychiatry has organized the campaign in partnership with the Federal Council of Medicine since 2014.

According to the official website of the Yellow September campaign, around 12,000 suicides are recorded a year in Brazil and more than 800,000 worldwide. In the booklet published by the ABP and the CFM, in about 97% of the registered cases, the cause of suicide was related to a history of mental disorders, which can be treated, such as depression, substance abuse, and bipolar disorder (“A campanha Setembro Amarelo® salva vidas!”, 2017).

The World Health Organization (WHO) reported that the global suicide rate fell by 36% between 2000 and 2019, with the most expressive drops in Europe and Oceania, with reductions of 47% and 49%, respectively. In contrast, there was a 17% increase in suicides in the same period on the American continent (“Suicide prevention”, 2021).

Data from the Pan American Health Organization website states that 79% of suicides occur in low- and middle-income countries (“Suicídio”, 2017). The WHO published guidance in June 2021 to reduce the suicide rate by a third by 2030. This issue has become even more urgent with the COVID-19 pandemic, as some suicide risk factors have worsened. Those years: job loss, financial problems, and social isolation. The actions proposed by the WHO that will be carried out to contribute to the goal of reducing the number of suicides are limiting access to the most common means of suicide, such as highly toxic pesticides and firearms; early identification, assessment, and follow-up of anyone within the risk group; development of socio-emotional skills in adolescents and educating the media to report suicide responsibly (“Suicide prevention”, 2021).

The southeast region leads in an absolute number of annual suicides, with São Paulo being the state with the most suicides in 2019 and 2020 (IBGE, 2020). The dissemination of correct information and the recognition of risk factors is essential for suicide prevention, hence the importance of the campaign. In this way, the support of companies and the carrying out of actions and investment in the theme can help reduce the number of deaths every year. The user’s willingness to accept the information provided by the machines and follow the recommendations and benefit from the advantages of using a bot is influenced by the level of trust the user has in that chatbot (Hancock et al., 2011).

The article aims to identify if there is a difference between the groups that interacted with the non-humanized and humanized chatbot in the factors related to the chatbot of the Yellow September campaign in the user’s perception. And consequently, if these factors influence the perceived trust of the user.

Therefore, this study allows to helping decision-making about the application of chatbots in customer service. In addition, there is a social contribution linked to the research, informing participants about the campaign, and disseminating knowledge on the subject.

Theoretical Basis

Chatbots are an artificial intelligence tool with a wide range of field options. Artificial intelligence mimics human behavior and is developed and implemented with the customer as the center (Toader et al., 2019). The responses of social chatbots can be perceived as automatic and programmed by the user, making it difficult for them to perceive that they are being understood.

Although chatbots have the inherent characteristic of the bot’s lack of understanding with the user, since it is not a human, interactions with Artificial intelligence stimulate a more intimate disclosure of the interlocutor due to the lack of perceived judgment (Ho et al., 2018). Thus, it is necessary to experiment by comparing the perceptions of a chatbot with human characteristics in its essential characteristics (female chatbot, with profile picture and name) and a traditional chatbot (without human characteristics).

Anthropomorphism in Chatbots

Despite the growth in the use of chatbots, there is still a gap in studies focusing on the behavioral aspects of interactions with conversational people. Most of these studies emphasize the part of technological construction behind chatbots, intending to distinguish them from humans (Schuetzler et al., 2020).

In that direction, consumers generally prefer to communicate with humans and resist chatbot technology (Araujo, 2018), anthropomorphism attributes human characteristics, such as personality, language, and politeness, to non-human objects. Companies are making the technology more like humans changing how the user interacts with chatbots (Schuetzler et al., 2020).

Consumers with a high need for human interaction (NIHA) have greater adherence to anthropomorphic conversational agents. Consumers with a low need for human interaction (BNIH) do not have less adherence to anthropomorphic CAs (Sheehan et al., 2020). That is, anthropomorphism does not decrease the adoption of the use of chatbots or when users are generally less sociable people.

The look of the chatbot and the level of interactivity of the messages pay off when it comes to anthropomorphism (Go & Sundar, 2019). Thus, if the level of interactivity of messages is high and the look of the chatbot does not have as many human characteristics, one compensates the other and vice versa.

Although chatbots are increasingly common, there is still a gap in studies on performance in potential effects on business-related outcomes. Nevertheless, research shows that anthropomorphic agents that present social behavior significantly shapes the user's perception of trust in virtual assistants (Visser et al., 2016).

Natural Language Processing and Social Presence in Chatbots

Seeking anthropomorphism, Natural Language Processing (PLN) is a field of artificial intelligence that examines how computer systems interpret and control natural language, both in the question of text and in discourse. Chatbots use the Understanding of Natural Language (UNL), which is the ability to understand the context in which the interactions between humans and non-humans and interpret the user's intention)

Conversational agents use systems of dialogues in natural language with users through text, voice, or both. Communication capacity can vary between a more restricted language, where interaction occurs through bots, or without restrictions, where interaction flows freely through phrases, as in a conversation (Zhang et al., 2020).

The choice of language of a chatbot influences the attribution of human characteristics through anthropomorphism (Sheehan et al., 2020). The more natural the way a bot communicates is, the greater the similarity to human, positive evaluation of interaction, and perceived friendliness by the user.

The use of natural language is commonly used in the early stages of software development to describe scenarios, cases to narratives. However, natural language centered on the human, aiming at anthropomorphism, is more prone to error and imprecise when the number of specifications is very high. The quality of the ability to communicate with a chatbot and its language can be measured from a subjective evaluation of users about the coherence of the conversation, naturalness, and the fluidity of the interaction (Zhang et al., 2020).

With the progress of studies on Artificial Intelligence and knowledge of the importance of social relations for human development, the so-called social chatbot was developed. While the relationship of human and human trust is established when an affective bond is generated, in the relationship of humans with a social chatbot, it is necessary for both the development of the affective aspect and the practical aspect, that is, if the software used behind the chatbot is safe and respects the privacy laws (Skjuve et al., 2021).

Social presence refers to how much the user perceives the presence of an interlocutor in the interaction and how to present and available this interlocutor present (Calefato & Lanubile, 2007; Weidlich & Bastiaens, 2019). Some experiments previously demonstrated that chatbots called empathic can even help with the feeling of social exclusion and can help individuals combat the adverse effects of exclusion (Gennaro et al., 2020).

Studies suggest that the style of interaction in dialogue and the messaging interface may be sufficient to trigger the social presence (Araujo, 2018). With the possibility that chatbots must impute personalized information, there is a potential to overcome several traditional paradigms since they are built based on each user's characteristics and journeys. That is, the technologies of conversational agents have the power to create a relationship of empathy with the individual through conversations with natural language (Zhang et al., 2020).

The Theory of the Media Equation (Taddei & Contena, 2013) suggests that people treat machines as social entities and make social assignments like humans, even with the awareness that computers do not present and express emotions like humans. The social presence represents the feeling of the user being interacting with an interlocutor who is living in the same world and, in addition, is able to react to the questions asked by this user (Ho Moon et al., 2013; Kilteni et al., 2021).

Similarity to Human (SH)

The development of studies that study the relationship of humans with social chatbots (RHC) can be based, as a starting point, on studies of the relationship between humans and humans (RHH), since there are probably several similarities between these two relationships (Skjuve et al., 2021). Users are more likely to abstract errors and misunderstandings if the chatbot is more human-like than if the chatbot looks more like an automated machine (Van den Broeck et al., 2019). However, some others and experiences suggest that the reason for building trust is not the humanity of the chatbot but rather what occurs in the interaction between them (Ho et al., 2018).

Other experiments concluded that the user perceives the chatbot with a human photo called a "full-bodied chatbot" as more empathetic and supportive than the equivalent chatbots without an associated face (Gennaro et al. Moreover, in an online retail context, human-like characteristics as clues result in a greater perception of social presence on the site (L.C. Wang et al., 2007). Anthropomorphic agents represented by images and using a language more similar to humans make users feel more immersed in virtual interaction, reflecting on users' social responses (Bente et al., 2008).

Perceived Competence (PC)

Competence is the ability to achieve the desired results and adapt to any context. It is inappropriate to define competence as a one-dimensional characteristic, such as high competence vs. low competence (H. Wang & Liu, 2020). Research in psychology evaluated the competence of a multidimensional perspective (Schneider & Stern, 2010). A well-accepted theory analyzes competence in two dimensions: operational competence and conceptual competence (Canobi et al., 2003; Schneider & Stern, 2010.)

The attitude towards the brand that offers the chatbot greatly influences user satisfaction with a chatbot. Moreover, this attitude towards the brand responsible for the chatbot has a high relationship with the utility perceived by the user when using the chatbot (Van den Broeck et al., 2019). Regarding perceived competence, a false impersonation of a chatbot decreases user trust and satisfaction with the service (Honig & Oron-Gilad, 2018). In addition, there is evidence that perceived competence concerning the user's interlocutor is essential for a positive return of the consumer in online interactions (Toader et al., 2019).

Satisfaction (SA)

Several studies relate the high customer satisfaction of a company with better financial performance (Alkhan & Hassan, 2020; Qadir et al., 2021). Satisfaction is connected with the perception of the quality of the product or service provided, and the focus on quality is even more important than the marketing strategy (Munawar, 2020a, 2020b). In the service sector, the quality evaluated by the client is a critical indicator of a company's performance (Chaouch, 2016; Sufian, 2007). The quality of the service is measured by the difference between the service provided and the customer's previous expectations (Iqbal et al., 2021). Thus, companies that provide high-quality services have competitive advantages over their competitors and report obtaining more profit than in the industrial areas of the same conglomerate of the company (Ahmad et al., 2020; Taap et al., 2011).

Customer satisfaction is positively impacted by chatbots through their skills to improve customer service, given the flexibility of time and the potential to meet the needs of this customer at any time and place (Haan, 2018). The awareness of the product, that is, how much the customer knows about that particular product and the amount of information that the consumer has, also correlates with satisfaction (Khan et al., 2021; Munawar, 2020a, 2020b).

Trust (TR)

An essential aspect of the trust established between human beings is a characteristic called self-revelation, which concerns how much one reveals himself during a conversation. To establish trust between social chatbots and humans, there is greater tolerance for the lack of self-revelation because it is understood that a chatbot has greater limitations with this characteristic (Skjuve et al., 2021). In one study conducted, two groups talked to an online attendant, one a human and the other a chatbot, contemplating the same levels of trust and self-revelation in both groups (Ho et al., 2018). There is still a significant gap in studies that understand the variables that impact user trust in customer service chatbots. The existence of these studies is essential to identifying the needs and desires of users (Nordheim et al., 2019). In some specific cases, such as in agriculture, the use of Artificial Intelligence is compared to a black box, where the technology's accuracy is verified without delving into the way it was developed and how each choice was made. Thus, the user begins to trust this technology, knowing a permissible percentage of errors (Garcia-Magarino et al., 2019). The Theory of Social Information Processing suggests that users rely on the social cues given by the computer, such as language, interactivity, and the ability to express emotions (Taddei & Contena, 2013).

Expertise (EX)

The credibility given to chatbot is analyzed from some elements: honesty, expertise, predictability, and reputation. In addition, the experience and competence attributed to the system responsible for the construction of the social bot are analyzed. Expertise is the user's perception of the knowledge and mastery of the subject that the chatbot presents. The chatbot can also be considered with expertise when it correctly answers user questions and interprets messages as expected, so it is often considered the feature that most affects user trust levels (Nordheim et al., 2019).

People's vision of robots comes very much from the cinematic pattern of a smart, perfect, flawless machine. Many exploratory studies were carried out to understand how an error in a social chatbot impacts the user's perception of the robot (Toader et al., 2019). Studies have shown that the search for the chatbot for clarification and asking questions to the user to understand your request better is as effective as the total absence of error from the point of view of similarity to human (Sheehan et al., 2020).
After presenting the main constructs, a theoretical model proposed in Figure 1 was built followed by the formulation of hypotheses.

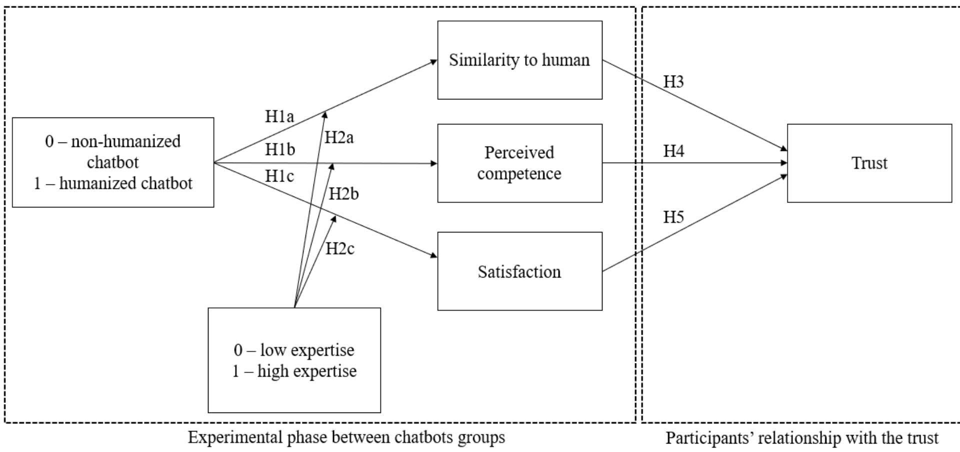

Figure 1 - Proposed theoretical model.

H1a: The user of the humanized chatbot attributes more similarity to human than the user of the non-humanized chatbot.
H1b: The perceived competence of the user is higher in the humanized chatbot than in the non-humanized chatbot.
H1c: Users of the humanized chatbot have greater satisfaction with interaction than users of the non-humanized chatbot.
H2a: Users who rate chatbots correctly interpreted messages attribute more similarity to humans.
H2b: Users who rate chatbot correctly interpreted messages rate a higher perceived competency.
H2c: Users who rate chatbot correctly interpreted messages are more satisfied.
H3: The greater the similarity to human attributed by the user, the greater the trust in the chatbot.
H4: Users who have perceived greater competence attribute greater trust in the chatbot.
H5: Users who are more satisfied with the interaction trust the chatbot more.

Method

Experimental method

The method used in the research is the experimental method. Thus, to test the proposed model, a detailed experiment was conducted. In the experimental causal research, the objective is to understand the effects of independent variables on the dependent variable. In the model presented, it is possible to observe the presence of three dependent variables: similarity to human (Van den Broeck et al., 2019), perceived competence (Schneider & Stern, 2010) and satisfaction (Munawar, 2020a, 2020b), expertise (Nordheim et al., 2019) as a variable of moderation and a covariate: trust

(Skjuve et al., 2021). The research carried out with the experimental method can provide the necessary information to falsify the existing propositions and hypotheses, exceeding the limit where qualitative research is located.

Chatbot construction

Overall, there are three ways to make a chatbot more like a human: human figures, identification (name), and the imitation of the human form of language (Go & Sundar, 2019). Thus, the differences between the chatbot applied in the control and experimental groups are arranged in Table 1.

Feature	**Non-humanized chatbot**	**Humanized chatbot**
Name	Unnamed presents itself as the "virtual assistant of the page."	Presents with the name "Clarice" (random name), the virtual assistant of the page
Profile picture	Without any human figure, with the symbol of Yellow September	With a humanized human avatar
Use of expressions	Ends sentences with an end point	Ends the sentences with expressions such as: "got it?", "you know?" reticence and exclamation point.
Response time	Responds immediately	Type for 3 or 4 seconds before responding (programming available on chatfuel)

Table 1 - Features of the non-humanized vs. humanized chatbot.

Most of the experiments read used a male chatbot versus a female chatbot. The female usually stood out in the positive dependent variables, such as trust, satisfaction, and humanization (Toader et al., 2019). This study also uses these variables, so a female chatbot was chosen to characterize the chatbot as humanized.

Chatbots were built with the online Chatfuel tool. In chatfuel there are two choices of possible conversations: a with buttons, in which there are a maximum of 3 subject options, and Artificial Intelligence, in which the participant can ask a question or comment and, with the use of artificial intelligence, will be answered. Both forms were used in the construction of the chatbot. These two options are on the left side of the chatfuel main screen, within the "Automation" group, with the "Blocks" option referring to the construction of a conversation with buttons and the "Set Up AI" option for Artificial Intelligence.

In the conversation through bots, blocks of text are added, and under these blocks, up to three bots can be inserted. Each button has a link that directs you to a new tile, depending on the user's choice. In creating each block, you can also add "typing", which simulates the typing of the robot, as occurs in any conversation with a human user. In this function, you can edit the amount of time the chatbot will enter before sending the message described in the block, ranging from 1 to 20 seconds.

The journey of including artificial intelligence is a little different. Starting from the same blocks that were explained earlier, in the function "Set UP AI" are placed all the possibilities of questions or phrases that the user can say, and that user will receive the text message of that block without the need to press any buttons, as shown in Figure 2.

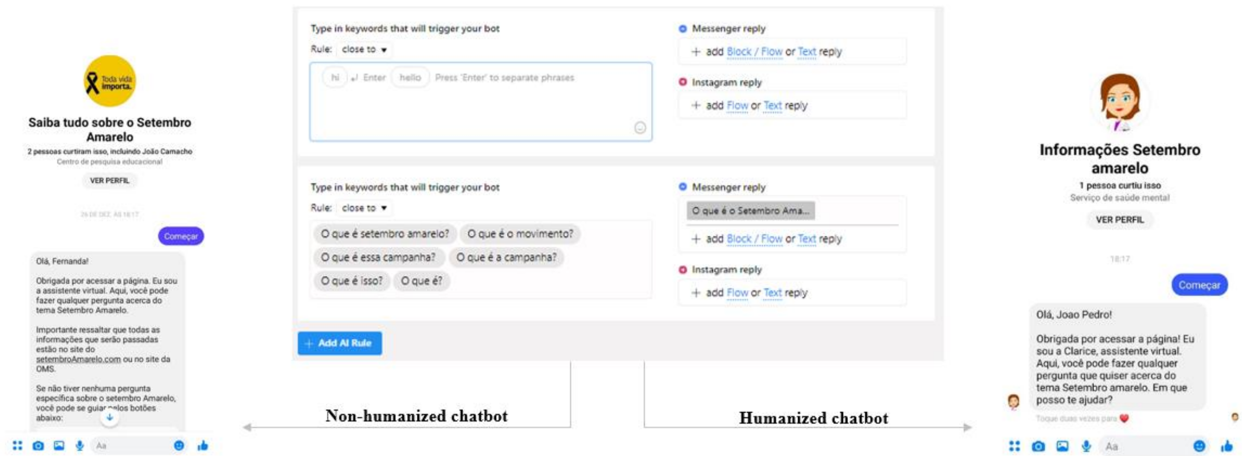

Figure 2 - Imputation of Artificial Intelligence in chatfuel and Chatbot presentation message

Journey of the participant of the experiment and data collection

Before the beginning of the application of the research, a project of this work was submitted to the ethics committee and approved for then following the data collection.

This information will be scored in the introduction of the questionnaire, ensuring participants free to give up participation in the research at any time, ensuring the confidentiality of the data, and informing their rights and which bodies to resort to if they feel uncomfortable at some point in the experiment.

The benefit of participation in the research is to understand the essential variables in the construction of a chatbot, besides receiving various information about the Yellow September.

For the experiment, two groups will be separated: one will interact with the generic chatbot (control group), and the other will interact with the humanized chatbot, with a female personality, name, and profile avatar (experimental group).

The sample of people is classified as non-probabilistic. The selection of people was for convenience, according to the contacts that the author of this work already has on Facebook. The interaction will occur as follows - participants (only over 18 years old) were contacted by Facebook messenger and invited to participate in the survey with a brief explanation of the work, without explaining that two different groups interacted with different chatbots. The strategy used to organize which chatbot the participants interacted with was to start all the collections of the humanized chatbot. When reaching the mark of 300 respondents, the data collection of the participants who interacted with the non-humanized chatbot began. After that, the following steps were:

- The participants who agreed to participate in the survey will receive a link directing to the chat of the created page ("Yellow September Information" for the human chatbot and "Learn all about the Yellow September" for the non-humanized chatbot).
- By clicking on the link, the participant was forwarded to the chat and started interacting with the chatbot.
- In the chat, a button wrote "Start" will appear. When you click, the presentation chatbot message will be sent automatically, as shown in Figure 2.
- After 2 minutes of the first interaction (clicking "Start"), a link was sent to the questionnaire for the participant to answer the survey. This message schedule after a specific time is a possibility in chatfuel. The schedule was 1 minute after the welcome message was delivered. The questionnaire was built on the QuestionPro platform online.

Sample Selection

The total sample collected was 558 individuals who were submitted to the Mahalanobis distance to remove the outliers and remove 47 questionnaires from the sample. In the post hoc test, a sample of 511 individuals was used. The sample size for the pre-test should have been at least three and a maximum of 15 participants (Hair et al., 2018). For this study, the pre-test was performed with 15 individuals to verify if there was an understanding of the stages of the research instrument.

Some missing's were found in the data collection database since not all participants answered all questions in the questionnaire. So, to replace these empty values, the expected maximization missing replacement method was used, which uses existing data to estimate the best response of the individual. This method can only be used if the missing data are completely random, using the Little MCAR test, with a significance greater than 0.05 (Enders, 2003). The test was performed in the database, the randomness of the missing's (p=0.075) was proven, and the substitution method of empty values was performed, making the 511 samples valid with all complete responses.

Data Analysis and Discussion

Demographic characterization

The total number of valid samples was 511, with most participants composed of women (61.4%), as described in Table 2. The predominant age group was young people between 21 and 30 years of age, representing 67.1% of the sample, as described in Table 2.

Gender	**n**	**Percentage (%)**
Female	314	61.4
Male	197	38.6
Total	511	100.0

Table 2 - Demographic profile of the sample (gender).

Age group (years)	**n**	**Percentage (%)**
Up to 20	52	10.2
From 21 to 30	343	67.1
From 31 to 40	42	8.2
From 41 to 50	40	7.8
Over 51	34	6.7
Total	511	100.0

Table 2 - Demographic profile of the sample (age group).

When crossing the gender and age group variables, it is possible to analyze that the female group is the majority in all ethnic groups, being in the range of up to 20 years where the difference between groups is greater, composed of 65.4% of women. The percentage between genders is close in the age group of 31 to 40 years, with men representing 45.2% of the sample.

The analysis of the age-by-age crossing shows that 66.9% of the female group belongs to the age group of 21 to 30 years, and this age group is the majority among men (67.5%). The part of the sample aged 51 years, or more was the least represented among both women (6.7%) and men (6.6%).

When analyzing gender in relation the variables used in this study for the experiment, it is observed that in all cases the participants "female" presented difference of higher means. In this sense, the female group perceived a greater similarity of the chatbot with a human than the male group ($t_{(509)}$=1.984; p=0.048; $\bar{x}_{fem} = 3.373; dp_{fem} = 1.009;\ \bar{x}_{male} = 3.188; dp_{male} = 1.058$).

In the same way, the female group attributed greater perceived competence in both chatbot groups ($t_{(509)}$=3.096; p=0.002; $\bar{x}_{fem} = 4.729; dp_{fem} = 0.4370;\ \bar{x}_{male} = 4.592; dp_{male} = 0{,}5530$). In

the satisfaction variable, the female group also presented higher means, and the male group was more dissatisfied with the interaction with the chatbot ($t_{(509)}$=2.659; p=0.008; $\bar{x}_{fem} = 4.573; dp_{fem} = 0.5698$; $\bar{x}_{male} = 4.427; dp_{male} = 0.6587$).
In the female group, differences in means were verified in relation to the male group also in the variables of expertise and trust. The male group observed lower chatbot expertise than the female group ($t_{(509)}$=3.368; p=0.001; $\bar{x}_{fem} = 4.754; s_{fem} = 0.4189$; $\bar{x}_{male} = 4.618; s_{male} = 0.4862$). The same occurs by analyzing the means of the trust variable, and the female group is the one that assigns greater trust to the chatbot ($t_{(509)}$=3.460; p=0.001; $\bar{x}_{fem} = 4.687; s_{fem} = 0.4918$; $\bar{x}_{male} = 4.521; s_{male} = 0.5766$). The results of the research that will be presented later were not attributed to the differences in means between the groups of men and women, were not significant allowing the use of the full sample ($t_{(509)}$=0.246; p=0.805).

Exploratory Factor Analysis
Exploratory factor analysis was used in the data analysis of this research. In factor analysis, the initial focus is on the common factor of the items that make up the selected variables. Each of the selected scales underwent exploratory factor analysis. The first analysis of the scales of similarity to human, perceived competence, satisfaction, expertise, and trust occurred through the common factor, present in Appendix in detail.
For this analysis, the Kaiser-Meyer-Olkin test (KMO) and the Bartlett's test of Sphericity were used. In the KMO test, it is ensured that there is a significant correlation between the items of each variable to justify factor analysis (Lorenzo-Seva & Ferrando, 2006). The test is calculated from the division between the squares of the total correlations by the square of the partial correlations, after the removal of the linear effect of the other items. The sample adequacy measure (KMO) may not be less than 0.600 to be considered adequate and must be above 0.700.
The Bartlett test verifies the null hypothesis that the correlation matrix is a matrix where there is no relationship between the variables studied. The higher the bartlett's scouting test result, the greater the chances that the correlation matrix is not an identity matrix, leading to the rejection of the null hypothesis. This test also evaluates the overall significance of all correlations in a data matrix, and the value of bartlett's scouting test with significance level of p<0.05 indicates that the matrix is factorable (Tabachnick & Fidell, 2007).
The KMO values showed satisfactory results for all scales. In the Bartlett's scouting test, the result was significant for all scales, with p<0.001. After verifying these values, the factor load was observed, and some variables were excluded in Satisfaction (SA2) and Expertise (EX2).
The commonality was also observed in the variables of each scale, most of the variance is explained by the extra factors. After the exclusion of variables due to low communality factors, the values were adjusted for each of the observed scales, with adequate values to explain the total variance of the sample and reliability, also confirmed with Cronbach's Alpha (Table 3).

Table 3 - Results of the Tests of KMO, Bartlett and Cronbach's Alpha

Construct	Number of Items	KMO Test	Bartlett Test	% Of variance	alfa de Cronbach (α)
SH	4	0.781	p<0.001	64.072	0.807
PC	4	0.767	p<0.001	57.179	0.745
SA	3	0.703	p<0.001	72.428	0.802
TR	3	0.693	p<0.001	66.992	0.746
EX	3	0.655	p<0.001	65.932	0.725

The variables were grouped by the mean arithmetic based on the measurement of the following constructs and respective items of the scales: Similarity to Human ($\bar{x}_{SH}$= SH1, SH2, SH3, SH4), Perceived Competence ($\bar{x}_{PC}$= PC1, PC2, PC3, PC4), Satisfaction ($\bar{x}_{SA}$= SA1, SA3, SA4), Expertise ($\bar{x}_{EX}$= EX1, EX3, EX4) and Trust ($\bar{x}_{TR}$= TR1, TR2, TR3).

Experiment Analysis

Hotelling's T^2 test showed that there is an effect of the type of chatbot (0 - non-humanized and 1-humanized) on similarity to human (SH), perceived competence (PC) and satisfaction (SA) according to the Pillai's Trace=0.025; $F_{(3, 506)}$=4.294; p=0.005 as a function of variance-covariance matrices not being homogeneous (p≤0.001). Subsequent univariate ANOVAs showed that there is an effect of the chatbot type on similarity to human [$F_{(2, 508)}$=45.340; p<0.001; $\eta^2 = 0.151$]; there is also an effect of the type of chatbot on perceived competence [$F_{(2, 508)}$=111.180; p<0.001; $\eta^2 = 0.304$]; finally, there is an effect of the type of chatbot on satisfaction [$F_{(2, 508)}$=122.885; p<0.001; $\eta^2 = 0.326$].

When analyzing the effect of the type of chatbot on the similarity to human, it was verified that the type "1- humanized" ($\bar{x}_{hum} = 3.401$; $s_{hum} = 1.004$) had a higher average than the "0-non-humanized" ($\bar{x}_{n\_hum} = 3.168$; $s_{n\_hum} = 1.055$) observed in Figure 3, which confirms to H1a that the user of the humanized chatbot attributes more similarity to human than user of the non-humanized chatbot. This is due to the fact that all differences in the characteristics of the humanized and non-humanized chatbot increased the user's perception of how much that conversational agent looks like a human being.

One of the differences pointed out between the two chatbots was the presentation. In the non-humanized chatbot, the profile picture was generic, only with the image of the yellow loop, representing the Yellow September campaign, and in the welcome message the chatbot presented itself as a "virtual assistant". While in the humanized chatbot, the profile picture was of a woman-like avatar, and this chatbot presented itself as "Clarice". In previous studies, it is pointed out that designating a genus for the chatbot increases the perception of social presence.

Studies conducted in previous chatbots focused on mental health found that users tended to describe as friends the conversational agent, when they understood the chatbot as empathic, warm or affectionate (Prakash & Das, 2020). With the differences in the way of communicating the two chatbots, in which the humanized demonstrates more commotion with the theme Yellow September, this relationship of empathy could be established, increasing the user's perception of the similarity to human.

The presence of a human avatar also represents different perceptions of users in both groups. There are studies that have concluded that the chatbot with human photo , called "full-bodied chatbot" are perceived by the user as more empathetic and supportive than the equivalent chatbots without an associated face (Gennaro et al., 2020), which is exactly the difference between the two chatbots in the present experiment.

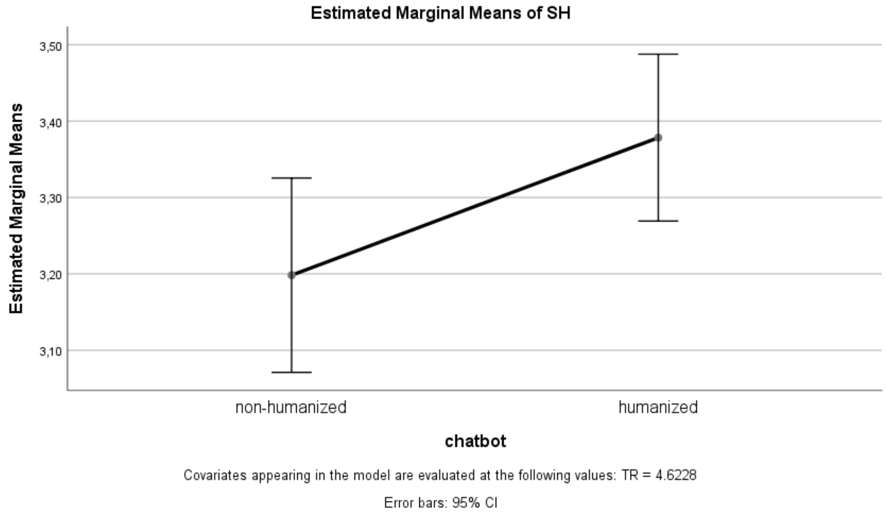

Figure 3 - Estimated marginal means of similarity to human

Similarly, when analyzing the effect of the type of chatbot on perceived competence, it was found that the type “1- humanized” (had an average higher than the “0- not humanized” ($\bar{x}_{hum} = 4.741$; $s_{hum} = 0.426$)$\bar{x}_{n\_hum} = 4.588$; $s_{n\_hum} = 0.552$) , as observed in Figure 4, which confirms the H1b that the competence perceived by the user is higher in the humanized chatbot than in the non-humanized chatbot. In this case, the language difference between chatbots is the biggest point that caused this difference in user perception in competence.

The high perceived social competence of users who interacted with the humanized chatbot refers to the ability to communicate effectively and the management of interpersonal relationships, obtaining positive results. This competence can be considered a communicative competence, allowing an effective presentation and transmitting the message in a persuasive manner (Valkenburg & Peter, 2008). The importance of communication is reflected by the differences in the text of chatbots’ messages.

The form of communication also influences the way people engage in online interactions (Baym et al., 2004) and a perceived high social competence relates more efficiently to online communication (Park et al., 2021). Analyzing competence in a multidimensional way, both chatbots have the same conceptual competence (same purpose) but operational competence (how to achieve this purpose) was the difference between the two groups (Canobi et al., 2003; Schneider & Stern, 2010).

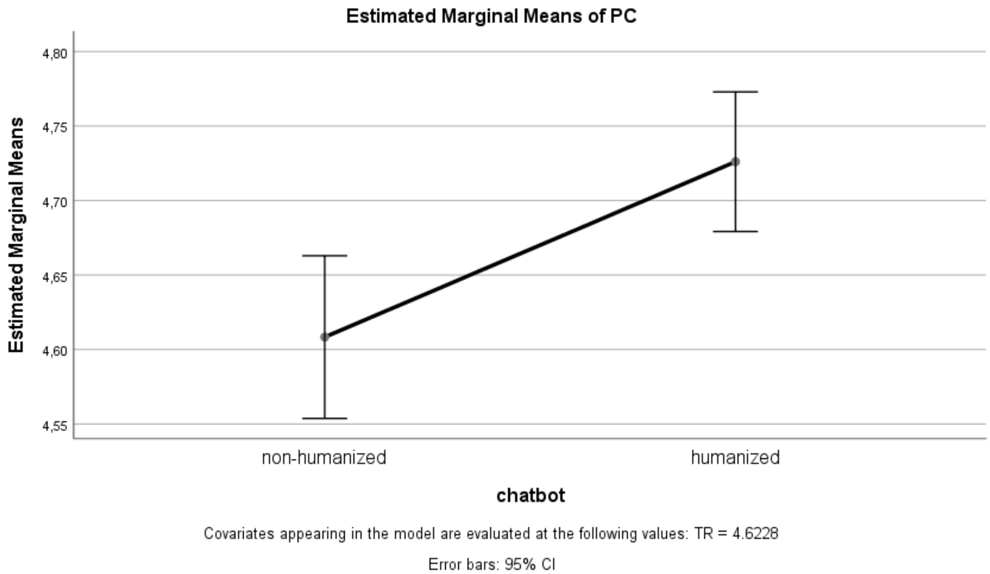

Figure 4 - Estimated marginal means of perceived competence

When analyzing the effect of the type of chatbot on satisfaction, it was found that the type "1- humanized" ($\bar{x}_{hum} = 4.581$; $s_{hum} = 0.551$) had a higher average than the "0- not humanized" ($\bar{x}_{n\_hum} = 4.430$; $s_{n\_hum} = 0.672$) as observed in Figure 5, which confirms to H1c that the user of the humanized chatbot has a greater satisfaction with the interaction with humanized chatbot than with the non-humanized chatbot.

Some differences in expressions were used in chatbots when addressing sensitive issues. For example, in one of the answers that pointed out the number of annual deaths by suicide, the phrase begins with the use of the expression "unfortunately" and ends with an expression of popular sadness "☹". There is evidence that people have a more positive impression of a chatbot that expresses emotions than of a neutral chatbot (Ho et al., 2018). In addition, the presence of these demonstrations of emotions generates a relationship of empathy, and emotional bonds tend to develop in more satisfied clients (Qoyum et al., 2020).

The presence of a personified name as in the case of the humanized chatbot "Clarice" has a relationship with the increased levels of satisfaction as interactions intensify. As more details about the chatbot are included, the user gets more detailed knowledge and the awareness about "Clarice" is included. This awareness has a direct relationship with the high levels of satisfaction (Khan et al., 2021; Munawar, 2020a, 2020b).

In addition to the inclusion of the name, the presence of the avatar in the humanized chatbot also influenced the group that interacted with this chatbot. Previous studies have linked the inclusion of an avatar in a retail site with the increased sense of social presence, which elevated the view that customers have about the brand, higher levels of satisfaction and purchase intention (Holzwarth et al., 2006).

The user's perception of the chatbot enhances satisfaction about it (Munawar et al., 2017). Therefore, if the quality of interaction with the humanized chatbot is superior to the perception that the user had about the chatbot, the satisfaction is also higher (Hussian, 2016).

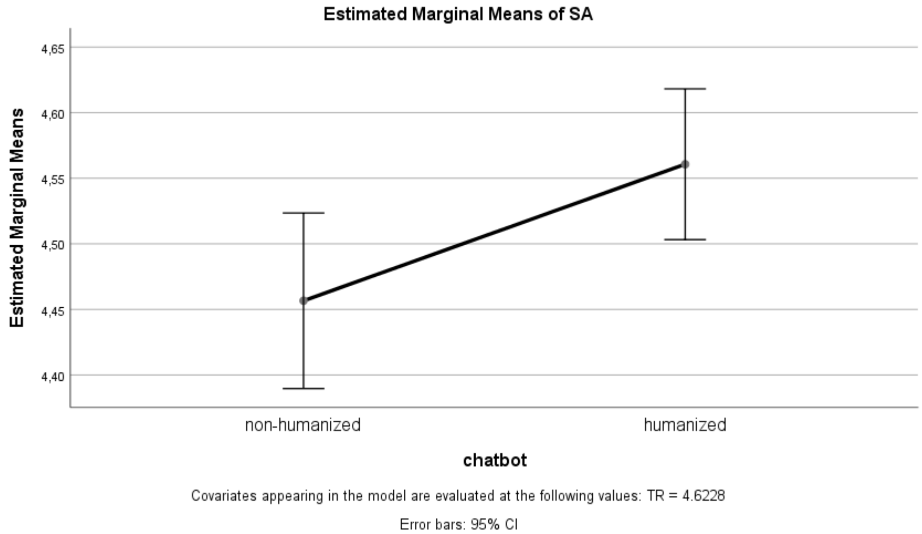

Figure 5 - Estimated marginal averages of satisfaction

Analysis of Moderations

Moderation analyses were performed using a macro for SPSS software v25 (Hayes, 2017). Each moderation was analyzed individually, these analyses are step 1 (moderation of expertise in similarity to human), step 2 (moderation of expertise in perceived competence) and step 3 (moderation of satisfaction expertise).

In hypothesis 2a, a factorial design 2 (humanized chatbot vs. unhumanized chatbot) x 2 (high expertise vs. low expertise) was used. When analyzing moderation, the expertise did not moderate the relationship between chatbot groups (β=0.011; p=0.9548). This result rejected this hypothesis, since there is no relationship between expertise and the similarity to human, perceived by the user.

Similarly, hypothesis 2b used a factorial design 2 (humanized chatbot vs. unhumanized chatbot) x 2 (high expertise vs. low expertise). When analyzing moderation, in Figure 6, the expertise moderated the relationship between chatbot groups and perceived competence, so that the higher the expertise, the greater the negative effect of the non-humanized chatbot group on perceived competence (β=-0.233; p=0.0026). This finding confirms this hypothesis, since the graph indicates that high expertise positively influences the competence perceived by the user.

Finally, hypothesis 2c also used a factorial design 2 (humanized chatbot vs. unhumanized chatbot) x 2 (high expertise vs. low expertise). When analyzing moderation, in Figure 7, the expertise moderated the relationship between chatbot groups and satisfaction, so that the higher the expertise, the greater the negative effect of the non-humanized chatbot group on user satisfaction (β=-0.288; p=0.0016), confirming this hypothesis, where high expertise has a positive influence on satisfaction.

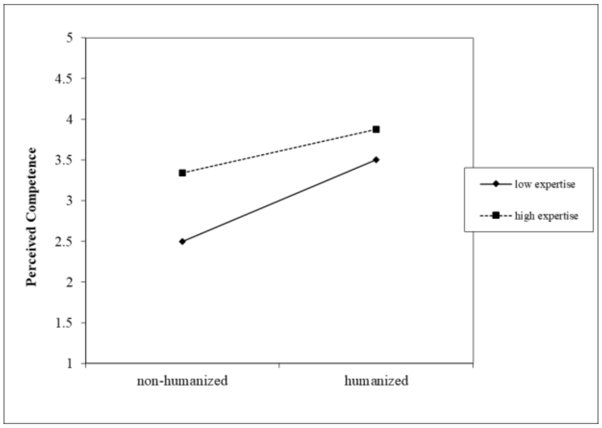

Figure 6 - Graph of moderation of expertise in the relationship of chatbot and perceived competence

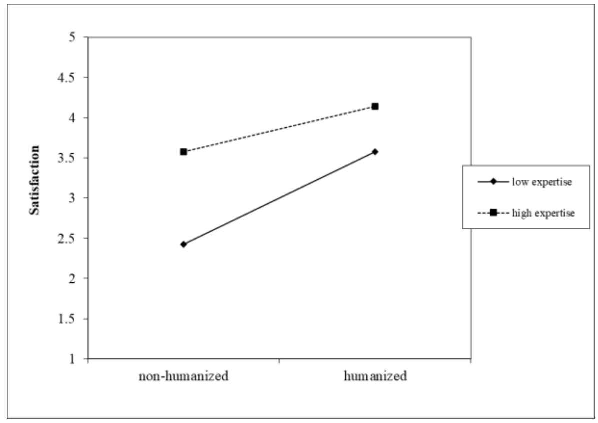

Figure 7 - Graph of moderation of expertise in the relationship of chatbot and satisfaction

Analysis of Covariance and Regression

In this study, the variable of trust covariance was used in the Hotelling's t-squared statistic (T^2) tests to identify the effect of the humanized and non-humanized chatbot with the independent variables like human, perceived competence, and satisfaction. In this sense, it is possible to understand this statistical procedure is equivalent to a regressive analysis. Therefore, when performing the regression test of the direct relationships between the independent and dependent variables, we obtained as a result $F_{(3, 507)}$=108.686; p<0.001; Durbin Watson test=2.032 to verify temporal autocorrelation; and R^2=0.391 (39.1%) which we can observe that linear regression showed that the variables similar to human, competence and satisfaction, provide for trust. The equation of the line of this data is:$\mathrm{TR} = 1.656 + 0.071\ SH + 0.3\ \mathrm{PC} + 0.295\ SA$.

H3 was accepted (β=0.138; t=3.571; p<0.001; VIF=1.237) confirming that the greater the similarity to the human attributed by the user, the greater the trust in the chatbot. The Theory of Social Information Processing (Taddei & Contena, 2013) relates the so-called social cues to the level of trust established between the user and the chatbot. These social cues relate to the language used during the conversation, the level of interactivity and the ability to express emotions, and these characteristics are attributed to a chatbot that looks like a human.

When analyzing H4, it was verified that it was accepted (β=0.276; t=6.117; p<0.001; VIF=1.693) confirming that users who have perceived greater competence, assign greater trust in the chatbot. There are some studies that relate the use of an erroneous anthropomorphic avatar in a chatbot, related to a perceived low competency, with the decrease in user trust and satisfaction with the service (Honig & Oron-Gilad, 2018). In addition, there is strong evidence that the perception of social presence and perceived competence in a chatbot play a crucial role in the development of trust (Toader et al., 2019).

Finally, H5 was accepted (β=0.338; t=7.422; p<0.001; VIF=1.723) confirming that users who are more satisfied with the interaction, rely more on chatbot. Anthropomorphism has a strong effect on both satisfaction and trust, and both variables are positively related to levels of purchase intent (Hsiao & Chen, 2021) and play a key role in building relationship marketing (Garbarino & Johnson, 1999). A previous study in the banking sector identified that trust levels were significantly affected by satisfaction levels (Eren, 2021).

Conclusion

Implications of research

In this work, differences were identified between the groups that interacted with the non-humanized and humanized chatbot in the factors related to the chatbot and these factors influence the trust perceived by the user. Thus, the objective of the work was achieved.

In terms of similarity to human, perceived competence and satisfaction, users who interacted with the humanized chatbot realized more these characteristics when compared to the group of users who interacted with the non-humanized chatbot. And it was found that higher levels of these three variables result in higher levels of user trust in this service.

Thus, this research helps to understand what characteristics that chatbot needs to have to achieve more trust, which is one of the biggest challenges that this technology presents (Skjuve et al., 2021). These characteristics were the presence of a humanized avatar and the presence of the presentation of a name, seeking anthropomorphism (Go & Sundar, 2019), and a way of communicating closer to the human form, seeking a natural language.

All these characteristics were present in the humanized chatbot and, therefore, users attributed greater similarity to human than when compared to a chatbot that presented itself only as a "virtual assistant", had a generic profile picture (the yellow September loop) and with less fluid responses, with blocks of text without humanized expressions. This greater similarity to human results in an empathic relationship (Gennaro et al., 2020) that is essential in the approach of the theme "Yellow September".

In addition, it was attributed, mainly by the way of communicating more natural of the humanized chatbot, higher levels of perceived competence (Valkenburg & Peter, 2008). The competence relates to the user's understanding of how much that chatbot fulfilled its, in this case the chatbot's proposal was to bring quality information about the theme "Yellow September" and closer communication with that of the human brought greater understanding of this information passed by the chatbot.

Another advantage of the humanized chatbot was the highest levels of satisfaction with the interaction. As discussed in the literature review, satisfaction is directly connected to the perception of product quality or, in this case, service (Munawar, 2020b). The perception of quality (Chaouch, 2016; Sufian, 2007) in the humanized chatbot was higher than when compared to the quality of the non-humanized chatbot, since the goal of the two chatbots was the same, to inform about the Yellow September campaign, but the way to achieve this goal was different and thus the perception of quality as well.

In addition, it was found that the variable expertise acted as a moderate in the relationships between chatbot groups with perceived competence and with satisfaction. Thus, the low expertise, that is, the lack of clarity of the answers and the incorrect interpretation of the user's commands (Nordheim et al., 2019), further accentuates the differences in perceived competence and the levels of satisfaction between the two groups.

The variables of similarity to humans, perceived competence, and satisfaction impacted the user's trust in the chatbot and the establishment of fundamental trust when the theme treated is sensitive and still considered taboo. This trust is essential for quality information to arrive at those who have not yet accessed it, contributing to greater awareness of the population.

Practical implications

This study provides reliable and quality information about the Yellow September campaign for individuals. It helps individuals better understand their mental health issues and encourages them to seek help if necessary or understand when someone in the circle of close people is at risk. In addition, interacting with a chatbot about sensitive topics helps the learning process to establish familiarity and trust with this communication channel.

In the context of society, it is important to disseminate the information to reduce the number of suicides, identify risk factors, and assist in seeking help in advance. Recently, it has gone viral to teenagers a game called “blue whale”, in which suicide is encouraged. Access to information on the subject can prevent games like this from becoming major tragedies, as young people are the most at-risk group. The so-called death postvention occurs when someone takes their own life and affects the people in their circle. It is important to create safe spaces for care for these people and caution when addressing the subject.

It is important the presence of trained professionals so that past information focuses on teaching the population about the risks and what to do to avoid them, and not disseminating information about means of suicide can have the opposite effect, being the trigger for people at risk. The government is essential in this context and can use technologies such as chatbots to raise awareness of important issues. The government also has a mission to facilitate the population’s access to mental health professionals.

This study brings contribution to companies that provide chatbot services to other companies, assisting in the choice of key features in the construction of chatbots. The adoption of informative chatbots has several advantages within companies, helping both in suicide prevention, as well as in the well-being and quality of life of employees, improvement in the organizational climate, higher levels of motivation and helping in the prevention of psychic suffering, helping not only those who already have mental health problems, but also contributing so that those who are healthy do not get ill.

The use of chatbots related to mental health in companies can be a support mechanism for remote work. It can be used as a thermometer for the team’s mental health without exposing the employee to direct interaction with other employees, thus avoiding the hesitation to seek help for fear of prejudice and myths about mental health. Fast resolution and complete availability of chatbots can help with greater user satisfaction, while noisy experiences and poor service generate dissatisfied customers. Therefore, automation through chatbots can bring information that feeds back and improve stake-able company visibility strategies.

Limitations and suggestions for future research

During the development of the research, some limitations were found. The first refers to external validity since the sample mostly analyzed is composed of residents of São Paulo. Besides, users are part of a personal circle since the sample was for convenience. Another feature of the sample is that all users of chatbots needed to have a Facebook account, excluding people without internet access and people who did not have an account on the social network. This limitation is the chatfuel platform; that main communication tool is Facebook Messenger. Using the Facebook feature also brought the limitation of user exposure since the platform account leads to access to the personal information of participants, having to have a greater caution on account of the Brazilian General Data Protection Law. However, mapping the users’ profiles and accessing their personal preferences and demographic data is advantageous. Facebook is the social network with the largest number of users in Brazil.

In addition, in future research, the development of prototypes with a more complex Artificial Intelligence can be better explored, leaving the language even more natural and mapping which behaviors of the user can be considered risky behaviors already performing an intervention. Thus, it would be possible to increase the number of participants and engagement in the survey, giving users the freedom to express their feelings and receive personalized and assertive responses.

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Appendix - Description of the research instrument

Construct	Item	Statement	Cross-loadings / Communalities	Average	Sta dev
Similarity to Human (SH)	SH1	In my opinion, the experience with the chatbot was like any service made by a human.	0.820 / 0.672	3.59	1
	SH2	I noticed several features in the chatbot that are human.	0.827 / 0.684	3.79	1
	SH3	At some point I was in doubt whether it was a chatbot or a human during the interaction.	0.792 / 0.627	2.49	1
	SH4	There are no differences between the speech education of the chatbot and a human attendant.	0.761 / 0.580	3.34	1
Perceived Competence (PC)	CP1	The chatbot fulfills what it proposes.	0.764 / 0.584	4.68	0
	CP2	During the interaction, I had no problems with the chatbot.	0.769 / 0.592	4.80	0
	CP3	The chatbot was able to easily understand my questions and answers.	0.734 / 0.538	4.59	0
	CP4	In my opinion, the chatbot has demonstrated a complete mastery of the subject matter.	0.757 / 0.574	4.64	0
Satisfaction (SA)	SA1	I felt satisfied at the end of the conversation with the chatbot.	0.835 / 0.697	4.52	0
	SA2	The chatbot interaction did not live up to my expectations.	*	*	
	SA3	I was pleased with all the answers given by chatbot.	0.880 / 0.774	4.61	0
	SA4	I would use this chatbot if I needed any knowledge about the subject "Yellow September".	0.838 / 0.702	4.42	0
Trust (TR)	CO1	I completely relied on all the answers given by chatbot.	0.820 / 0.673	4.73	0
	CO2	I trust the chatbot is safe.	0.812 / 0.660	4.54	0
	CO3	The information provided by this chatbot was completely reliable.	0.823 / 0.677	4.60	0
Expertise (EX)	EX1	I had no problems with the chatbot's knowledge of the subject matter.	0.745 / 0.555	4.62	0
	EX2	The chatbot was able to correctly interpret all my messages.	*	*	
	EX3	The chatbot answered my questions correctly.	0.825 / 0.681	4.71	0
	EX4	The chatbot's answers were concrete, clear, and easy to understand.	0.861 / 0.742	4.77	0