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Humanization builds trust: the effect of human-like chatbots on the willingness to disclose personal information online.

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Let’s not let humanity get lost in automation.

- The robot Sophia

Index

INTRODUCTION

Intelligence and emotion is what distinguishes humans from machines. The evolution of artificial intelligence, that is able to understand not only the cognitive but also the emotional aspects of human thinking and communication, frightens and fascinates at the same time. The inclusion of emotions in smart systems powered by machine learning and deep learning seems to make artificial intelligence and human intelligence more and more similar: this evidence has given rise to many questions and debates about what it really means to be human (Bossen, 2020). On the one hand, making technology more human-like risks creating negative consequences in terms of anxiety, discomfort, social disorders or replacement of some human activities (Schanke, 2020). On the other hand, interacting with a technology characterized by anthropomorphic features can be beneficial for people, companies and consumers.

The aim of this thesis is to study the effects of humanization in chatbots – virtual assistants equipped with artificial intelligence able to simulate human behaviour – and to investigate whether equipping this technology with human-like traits can have positive effects on consumer's trust and willingness to disclose personal information online.

The first chapter is dedicated to explaining the motivations behind this research by giving background information on what is called "the new currency" in business: trust. The first paragraph starts with an excursus on the history of trust and what has been considered trustworthy over time, in particular dwelling on the current period of the Covid-19 pandemic. Then it analyses the increasingly influential role of technology in daily life and in relationships with brands: it presents trust as a crucial factor in the willingness to accept and use a new technology. Hence, it examines the relationship between technology and human touch to explore human-machine relationships and the importance of creating a more human-centered artificial intelligence. The second paragraph is an introduction to chatbots and an insight into the benefits and uses in different industries. Specifically, different levels of anthropomorphism of a virtual assistant are explained with examples of past and current chatbots on the market. The third paragraph, indeed, is a case study on the Italian company Enel Energia and its chatbot named Elena: it explains the creation process, the chatbot's values and its level of humanization.

The second chapter provides a literature review on the concepts of trust, willingness to disclose personal information online and humanization in marketing, the three variables covered by this thesis. First, it starts with an overview of consumer trust and the distinctive elements of online trust with a focus on commitment-trust theory. Second, it explores the reasons for consumers' reluctance to release personal data to companies by looking at previous studies on perceived risks and the role of trust in reducing the resulting anxiety. Third, it examines existing literature on human touch in marketing and past research on the effects of different anthropomorphic cues in chatbots.

The third chapter focuses on the empirical research with findings and conclusions. The study aimed at analyzing the effect of humanization on the willingness to disclose personal information online and how this relationship is mediated by trust. The chapter reports the method by explaining the stimuli, the survey design, the measurement scales and the research sample; then it exposes results obtained through statistical tests and concluding remarks. Finally, the thesis ends with theoretical contributions as well as managerial implications and limitations of the study that serve as cues for future research.

CHAPTER 1

HUMANIZED CHATBOTS FOR TRUST

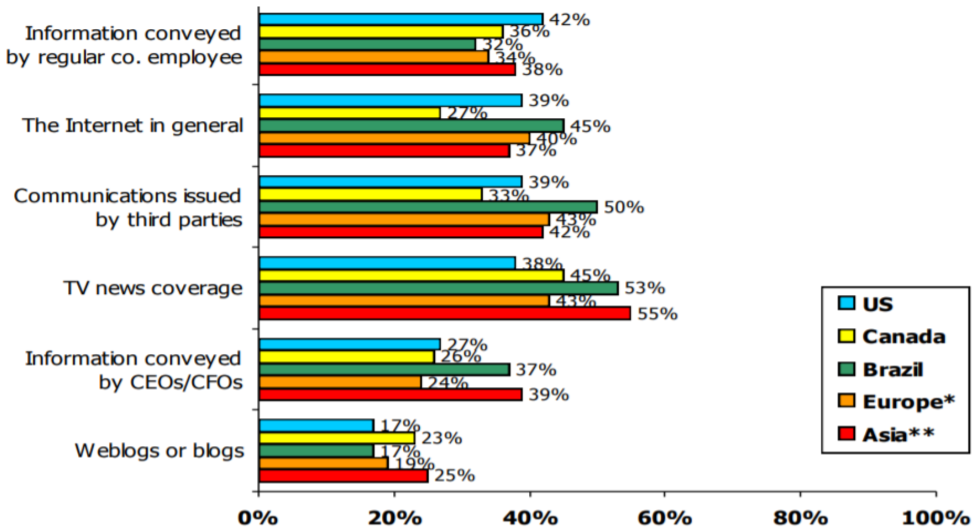
1.1. Digital trust is the currency. Humanization is the key

In 2015 Tom Goodwin, senior vice president of strategy and innovation at Havas Media, stated that trust is the most important asset in the new digital world (Goodwin, 2015). Referring to the new business models, he said Uber, the world's largest taxi company, owns no vehicles; Facebook, the world's most popular media owner, creates no content; Alibaba, the most valuable retailer, has no inventory; Airbnb, the world's largest accommodation provider, owns no real estate (Goodwin, 2015). In the sharing economy, what matters is no longer the ownership but the relationship and companies that create the most value are not those owning assets susceptible to economic evaluation, but those built on trust. Consumers are empowered and engaged in the digital world, and they are becoming more and more demanding: they ask for greater control over their data, secure transactions and trusted relationships with brands (B.L. Dey et al., 2020). Businesses should be able to connect with consumers who expect a trustworthy and transparent experience, who are willing to buy from brands in line with their values and receive the communication they desire. Communication plays a central role because digital platforms allow users to process feedback in real-time and companies to understand consumer behaviours and give them the best experience possible (Unni, 2020). To establish a trustworthy relationship, the presence of a trustee and a trustor is required but, in online communications, the two parties do not share the same space and time (Wang et al., 2005), and sometimes they are not even both human beings because one of them can be represented by a robot. Nowadays building and maintaining trust is even more important for businesses because the customer is sceptical, empowered and gives himself permission to ask questions and complain to the brand (Mitchell, 2018).

1.1.1. What we trust: the trustworthy over time

Trust is a key factor in a relationship: indeed, trust began to be considered a relevant construct precisely with the birth of relationship marketing. While transactional marketing considers the consumer a passive user, relationship marketing takes into account the user's active participation and recognizes that the goal is not achieved at the moment of the customer's transaction – attraction – but the objective must be to build and maintain a long-term relationship – retention (Harker et al., 2006). Many authors started talking about relationships in the early 1990s, but the first to use the term "relational" referring to marketing was Leonard Berry, professor and former president of the American Marketing Association, in the second half of the century: he defined relationship marketing as "attracting, maintaining and – in multi-service organisations - enhancing customer relationships" (Berry, 2002, p. 61). Since Berry, other studies have given new and updated definitions, all agreeing on the central idea of marketing as a continuous interaction between buyers and sellers, nurtured by repeated and instantaneously generated exchanges. Interest in relationship marketing emerged due to the increasing recognition of its benefits and due to technological advancements (Berry, 1995). This paradigm has led to the proliferation of loyalty marketing, encouraging many companies to provide loyalty programs: this strategy, however, does not build relationships (Harker et al., 2006). Loyalty, which takes the form of cards or points collection programs, is effective in retaining customers but does not create true engagement: it makes the consumer easily switch from one brand to another depending on which one offers more rewards (Harker et al., 2006). Almost twenty years after his first paper, Berry offered a new perspective by stressing the role of trust at the heart of relationship marketing and highlighting that what creates a relationship is a risk-reducing benefit that makes it valuable to the customer. He also explicitly stated that low-trust organizations are excluded from relationship marketing (Berry, 2002). Since 2000, trust in government and institutions began to decrease in both United States and Europe, until it declined in 2004 when people started to suspect or reject authorities. In 2005, NGOs and businesses were considered the most trustworthy and, for the first time, the Internet became communication source for reliable information, causing a decline in the previous top-ranked medium, TV (Edelman, 2006).

Fig. 1.1 *- Credibility of information sources*

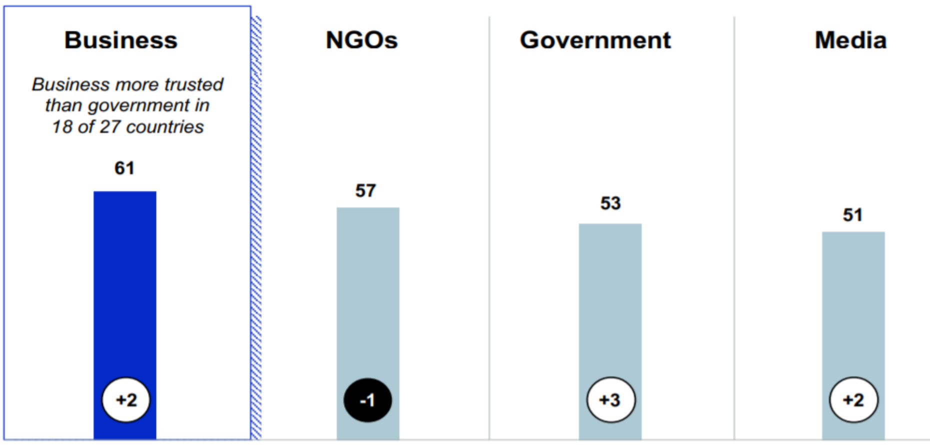


Source: Edelman Annual Trust Barometer, Jan 06

In the same year, a trend started four years earlier was confirmed, that is the tendency to trust "a person like yourself" more than the CEO of a company or PR people. This change records the transition to a new communication approach that moves from a top-down to a peer-to-peer engagement through a variety of different channels and it marks the end of the message control in favour of credibility created through dialogue (Edelman, 2006). The global financial crisis of 2008 resulted in a sharp drop in trust: the economic gap generated inequalities, which led people to have less confidence in institutions and government as well as causing a collapse in trust in business due to the perception of its responsibility in global issues (Uslaner, 2010). In the following years, trust in every industry declined, but technology remained the most trusted at a global level: indeed, being trustworthy and communicating honestly became as important factors as value for money (Edelman, 2009). This trend remained constant and the institutional bodies showed that they were unable to meet people's expectations, which is why in 2011 other dynamics responsible for building trust emerged, including the listening to customer needs, the ethical behaviour and the centrality of the person over the profit (Edelman, 2012). From the following year, trust in business and media saw a slight increase until the largest gap in history between business and government was recorded in 2013: companies were credited with the ability to drive change through technological innovations but also by focusing on engagement and integrity as areas to invest in to build trust. With the sharing economy and new technologies, in 2014 innovation was seen as an imperative in the market and trust in new media grew up so much that digital media established themselves as the first information source and 72% of millennials agreed that online search engines were the most credible source.

These evolutions opened the door to a new kind of trust, which is not taken for granted by role or title but must be gained and companies are expected to keep up with changes to engage their employees and consumers. *"In today's world, trust must be earned"* said Richard Edelman, President and CEO of the firm in 2015 (Edelman, 2016, Executive Summary). Thus a loss of belief in the system was recorded and even traditional media, and also its advertising, lost faith in favour of online media and the credibility of peers. Only in 2018 there was a turnabout due to the urgent need for a change because people were demanding new companies' standards of behaviour and solutions to problems like discrimination, the threat of automation or fake news. The employer and the CEO were recognized by 75% as the most trusted entities - as they are closer to people and more controllable than institutions - and as partners in fighting for work and society rights as well as a source of information on topics such as technology and economy (Edelman, 2019). Again, 2019 was a year of mistrust generated by a concern for the future and by the fact that competence and ethics, the two most requested dimensions of trust, were not perceived as being present in any entity or company (Edelman, 2020). Another decisive event, the global pandemic, has marked the history of trust.

Fig. 1.2 *- Percent trust from 2019 to 2020*



Source: Edelman Annual Trust Barometer, Jan 2021

Not only all the media have gradually lost credibility, but people have also begun to suspect leaders and institutions of lies and disinformation, while recognizing in business the only guardian of quality information and responsible of guiding change and acting promptly (Edelman, 2021).

1.1.2. All we need is trust: the Covid-19 pandemic

The Covid-19 disease initially represented a health crisis, but soon revealed its economic, political, psychological, social and even technological implications. How this emergency has been and is being managed is impacting people's credibility and confidence in institutions, media and brands, making trust as critical as it has never been before. Expectations towards the government have risen up and citizens are asking companies to act and adapt with flexibility and timeliness in introducing new measures for employees and consumers (Edelman, 2020). In this outbreak, scepticism grows but it can be faced by making citizens informed and with transparency; however, this requires communication that helps the audience to receive and process information, to understand uncertainties and to interpret scientific data (Balog-Way et al, 2020). In a period of economic and social uncertainty and instability, brands are no longer asked only to sell quality products, but to take a stand on social issues and find solutions using the resources at their disposal because showing emotional intelligence and demonstrating empathy with their stakeholders and customers prevail over advertising, price and product levers in building trust. A correlation was found between the economic performance of a brand and the trust it receives from consumers (Deloitte, 2020). During the pandemic, people are facing a trust dilemma by starting to have doubts about the information conveyed by the media and the official communications of the institutions were accompanied by information on social media, thus creating fake news or misleading news that generated confusion and increased mistrust (Schröck et al., 2021). According to the latest results from the Edelman’s trust global report, 70% of respondents say trust is more important today than in the past and the PwC Global survey confirms that brand trust is a key driver for purchasing decisions in uncertainty (Edelman, 2020; PwC, 2020). Thus, embracing transparency and focusing on customer relationships make people more aware and involved in consumption because it increases the perception that a brand is communicating authentically (Loomly, 2020).

The importance of these features for a brand has emerged even before the pandemic, but what makes them so essential now? The Covid-19 crisis has accelerated digital adoption in all countries and sectors, even those that were not ready yet, by creating a necessary and sudden jump in digital technologies and by asking institutions and brands to give an adequate answer to people. Success depends on this, as consumer confidence in the digital world influences purchase decisions and people value trust over convenience (Okta, 2021). Furthermore, being a trustworthy organization fosters technology deployments and innovation, accelerates digital transformation initiatives and makes it possible to face challenges, even the most turbulent ones such as the current pandemic, without losing customers, but rather acting as a reference point (Hill, 2020). The digitalization curve has peaked in the last year due to growing urgencies: 67% of companies have accelerated their digital transformation and 63% have increased their digital budget as a result of COVID-19. Organization leaders recognize that digital is a prerequisite to be competitive and understand the need to improve the firm's capability, even in the post-Covid age, to digitally connect with customers and to create new ways of communicating through long-term solutions that go beyond the short-term challenge (KPMG, 2020). But all technologies depend on trust because what makes them useful are the positive expectations of users who are confident that they will have benefits and therefore adopt and use them: in fact, the digitization of companies must go hand in hand with the digitization of users (Kroeger, 2020).

For example, artificial intelligence often suffers from problems of distrust towards the functioning of the algorithm, but also towards the purposes for which this technology is currently used (Kroeger, 2020). So fairness and transparency are essential to gain trust, but they only describe the *what* - that is what technologies like AI do - and tell it to people. Capgemini's Trusted AI Framework claims that this is not enough: companies should communicate also the *how* and the *why* (Capgemini, 2020). It is necessary to explain how technology can be the solution to a problem, how giving the consent to data processing can serve for a better product/service, how artificial intelligence can speed up a process and improve the user experience. Above all, it is necessary to explain why technology is important, that is its purpose. People don't believe in a tool for its functionality (the *what*) or for the way it works (the *how*), but for the reason it is used and if it is the best option in that context. It is not possible for someone to trust a technology when he does not understand the goals behind its application: the pandemic has forced people to adapt to digital solutions, often without users realizing the *why* behind it, thus without grasping the reason and being motivated (Capgemini, 2020). Having no alternative but to use the digital, individuals are asked to make a leap of faith to use new and unfamiliar technologies, such as telecommuting or teleconferencing programs (Yamani, 2020). For the transition from faith – that is a firm belief without proof – to trust – that is a belief that results from empirical evidence, observation or experience of facts, circumstances and relationships – a brand should prove to be able to guarantee honesty and demonstrate the ability to meet expectations by supporting the consumer in the evolution towards the digital (KPMG, 2020). Therefore integrity, honesty and authenticity are the three pillars on which business has to leverage, especially in this period. In particular, according to Kantar's COVID-19 Barometer, people do not want companies to promote themselves, but expect them to explain what they are doing to tackle the crisis and to show it in an authentic way, because the more communication is perceived as authentic, the more the brand is trusted (Nützel, 2020).

1.1.3. In technology we trust

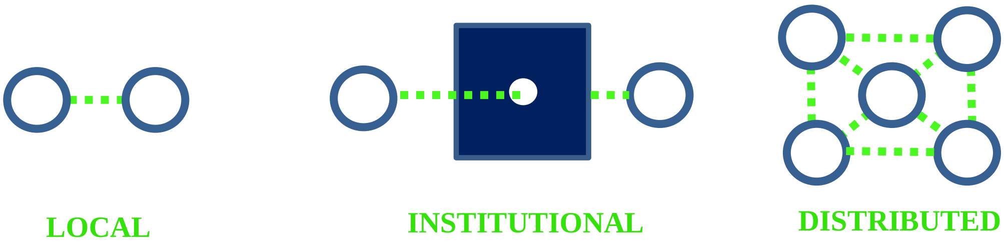
As it is the driving force of the digital age, technology turns out to be the most trusted industry, despite a general decline in trust recorded in 2020 (Edelman, 2021). Indeed, with the crisis of leadership, people do not believe in authorities or companies, but in their ability to use and control the powerful technologies that allow them to deliver a lasting and preferred experience to the consumer. According to Salesforce research, in 2018 60% of customers believed companies did not act with their best interests in mind and 92% of customers were more likely to trust companies that give them control over the information they share. Nowadays, more and more companies are adopting AI, cloud, IoT and mobile in their strategy and this trend is destined to rise, so that the worldwide spending in artificial intelligence is expected to reach $97.9 billion in 2023, and huge investments will also cover the IoT and the Blockchain (IDC, 2019). These investments are encouraged and supported by consumers, especially Millennials and Generation Z, but they are also accompanied by fear and concern that personal information will be compromised by technologies such as AI and Interned of Things.

Innovation has always alarmed people and technological innovation creates enthusiasm on the one hand and disbelief for something that could jeopardize human capabilities and his role in society on the other hand. Therefore, it is clear that when innovations such as AI or IoT take over, a deeper understanding of their value must be encouraged, so that consumer trust would be grounded on this awareness (Salesforce, 2018). In fact, if concern prevents trust, the disappointment of expectations is the main cause of trust erosion for companies and if a brand promises something it cannot deliver, this inconsistency creates frustration: when trust is broken by people or technology, it is difficult to earn it back, considering also that digital amplifies dissatisfaction and potentially influences other consumers. It is not only important to be reliable at the beginning of the purchase funnel, a phase in which even a leap of faith would be enough to attract the customer, but also to remain reliable throughout the whole customer journey because the user is ready to test the brand at any time. That is why trust must be an assurance, the result of a process of multiple interactions, proves and offers along the way (Schulte, 2019). The speed of technological change and the volume of information accessible via smart devices make people adopt new tools even before they know them well, so before evaluating their goodness, and this creates mistrust because people cannot keep up with complexity (Hyde & Sheppard, 2019). The fact that human beings tend to refuse and do not trust what they do not understand explains why, for example, artificial intelligence is seen as a black box: it can also be fascinating but it is often perceived as being unclear and not transparent. The business has to make technology interpretable because transparency does not equal more trust; it requires not only showing how things work but explaining it to the interpretative lens of the users (Rao & Cameron, 2018).

Thus, to produce benefits for companies and consumers, technology needs trust, but it is also true that trust can be strengthened and enhanced by technology: companies need to invest in transformation efforts that, enabled by the digital, can build long-term digital trust (Albinson et al., 2019). If the barometer shows an overall decline of trust in institutions, does that mean that trust has disappeared? It means that digital is attracting people's trust because it seems to be the new “technological institution”. The digital world keeps track of experiences and creates reputational capital. “*Reputation is the measurement of how much a community trusts you*” and “*Trust is a confident relationship to the unknown*,” said the trust researcher Rachel

Botsman in her TED Talk in 2016. To move from the land of certainty to the land of uncertainty, which can be represented by a person or an unknown tool, trust is needed as a mediator and a driving force (Botsman, 2016). According to Botsman, three steps lead a person to trust something or someone enough to jump from the certain to the uncertain and bridge this gap: the first level is about trusting the idea that what is encountered can bring benefits and may be worth it; the second level is about trusting the platform which makes this step possible; the third level is about trusting the other part of the relationship. For example, people use eBay because they trusted the idea of buying and selling second-hand items online, then they considered the platform that allowed this business to be trustworthy, that is what allowed users to trust those who sell or buy an item. Today's new kind of trust is the third chapter of its evolution over time: local, institutional and distributed. When the members of a community knew each other and shared the same space and time, trust was accountability-based and occurred through one-to-one exchanges. In the mid-nineteenth century, people began to move and transactions took place even at a distance, so the first intermediaries such as banks and corporations were born: by necessity, trust was placed in guarantor authorities, it became institutional and commission-based. This allowed people to have someone to rely on, but gradually a centralized and often opaque system was created. The digital age needs the transition to a distributed trust that goes back to being accountability- and reputation-based (Marshall, 2018).

Fig. 1.3 *- Trust evolution*



Source: Rachel Botsman, June 2016

It is no longer a top-down process but a decentralized and distributed system across networks, marketplaces and platforms; the intermediary is no longer an institution, but a technological platform. And if the platform uses the element of artificial intelligence, then this change is accelerated: it is what the blockchain has done. Although 2008 is the official year of its birth, the technology behind bitcoin has remained obscured by the most popular digital coins for a long time; nowadays talking about blockchain and bitcoin has been much more mainstream, but its knowledge is not widespread. Technically, the blockchain is *"a ledger distributed and managed by a network of computers, each of which has a copy of it"* (Comandini, 2020, p. 61). It allows every transaction to be publicly recorded by removing the need for a third party to allow the exchange and, among the three steps of trust, it removes the need to trust the other party directly but locks up trust in the platform: people have confidence in a digital record installed on the blockchain (Comandini, 2020). Digital trust was found to be positively related to user acceptance because the user is only required to rely on the technology that guarantees the actions of other users; it serves as a heuristic towards blockchain, as individuals are more likely to address risk and privacy concerns with minimal time and cognitive effort (Shin, 2019). Studies on the Technology Acceptance Model (TAM) have identified trust to be a determinant of intention to use because it influences the intention to accept a new technology thanks to its positive effect on perceived ease of use and perceived usefulness (Harryanto et al., 2018). As Simon Sinek explained in his TED Talk in 2011, trust comes from common values and beliefs, hence the fact that individuals want to be surrounded by those who "believe in what they believe". If trust is there, the likelihood of experiencing something new increases, because of the conviction that someone or something will take care of the consequences and the possible failures (Sinek, 2011).

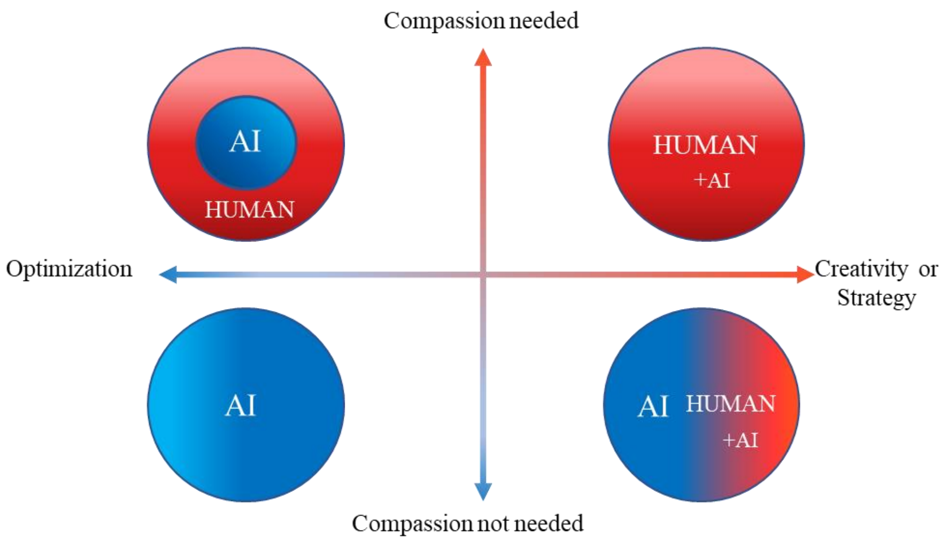
1.1.4. Human and artificial intelligence

Technology is revolutionizing the way people communicate. This is what has always happened in history when the press made it possible to inform large masses of the population, mp3 allowed music to be portable, social networks made it possible to keep contact with anyone. AI and machine learning are receiving increasing attention thanks to the numerous fields of application and they are among the emerging technologies destined to change the world in the next future (WEF, 2019). However, as with all innovations, worries over the AI impact on privacy, jobs and daily life have emerged: a survey conducted by Brookings in 2018 showed that 34% of respondents said AI would make their lives easier but 32% were concerned and believed that it would represent a threat to humanity (West, 2018). These data highlight the fact that artificial intelligence must not be treated just as a technical problem, but as a social and philosophical one to take into account how society copes with AI and what can be done to make people believe in the possibility of creating a human-AI symbiosis (Jeltes, 2020).

It emerges from a Salesforce research that 84% of respondents believe it is essential to be treated as a person rather than a number and that those belonging to Generation Z say they want engaging, human and personalized experiences (Salesforce, 2018). Managing and leveraging a large amount of data, offering a fast and impeccable service is not enough if the individual feels treated only as a consumer of the company's target; everyone wants to be a valuable customer - a *gold* customer - and wants to feel an emotional connection with the brand. Even if they ask for the efficiency of a machine, what people want is to be listened to, to be appreciated and taken into consideration. A global Facebook-commissioned survey found that 77% of shoppers say they would like to have the opportunity to contact a brand directly to ask questions or provide feedback because, with the increase of digital technologies, users expect to be able to communicate quickly and have transparency and availability back (Facebook IQ, 2021). To satisfy these customers, a return to the human touch is needed: brands using AI-based tools must ensure that they are accompanied by human interaction, they must make technology more human to meet people's needs and understand the decisions that the machine is unable to make (Hall, 2019).

Unlike the first two waves of AI, the direction where technology is going tends to be more human-centered. The first phase of Internet AI (the 1950s-1970s) consisted of recommendation engines collecting data from clicks, likes, comments to learn and anticipate personal preferences. In the second phase of Business AI (the 1980s-1990s) statistical models of pattern recognition or speech recognition were introduced but the most relevant innovation was the ability to create correlations, such as predicting a driver's probability of having a car accident. The third wave (2006-2018) has been an important leap: Perception AI merged the digital world with the physical environment thanks to solutions from sensors to smart devices, from speech interfaces like Alexa and Siri to computer-vision applications of face recognition (Lee, 2018). Nowadays we talk about the fourth wave, the one represented by the Autonomous AI, which is able to operate autonomously thanks to the ability to hear and respond to the outside world: the main applications are humanoid robots or self-driving cars but also other industries such as medicine are involved (DynAgility, 2019). Therefore it is inevitable to consider an approach that takes into account ethics, comprehensibility and interpretability of AI. It is no longer a human-machine interaction but a human-machine integration because the two parties are collaborative partners and combine human flexibility and machine accuracy and consistency (Pekarčíková et al., 2020). Kai-Fu Lee, one of the world's most experts on artificial intelligence, clarifies that AI takes people away from routine jobs, it helps and stimulates creatives, it is an analytical tool at the service of humans for tasks and jobs that require warmth and human capabilities, and it is a partner in jobs of compassion and creativity (TED, 2018).

Fig. 1.4 *- The four waves of AI*



Source: Kai-Fu Lee, Aug 2018

More automation does not mean fewer human abilities. In its integration with the human aspect, AI should be designed by considering humanistic qualities such as emotions, respect, humour, politeness. Often misunderstandings can occur in human-machine interactions because people do not explain well what they mean or fail to say something: these are problems that a human partner could understand and interpret, but which constitutes a limit for AI due to the absence of a context and a cultural background. So, even more, a technical and training improvement must be accompanied by improvements to make people understand what is happening, guide them through the interaction and create a bond between humanity and automation (Selçuk, 2020). The central question is how much and what to anthropomorphize to create a positive impact and avoid the uncanny valley effect[1], which could lead to human rejection of the robot. Cultural or individual differences can influence the robot's appearance and language preferences, as well as determine different people's reactions to the stimuli they receive (Syrdal et al., 2007): diverse degrees of humanization must be considered depending on the context, industry, target and tasks. In general, anthropomorphism can create an impression of human-likeness and positively facilitates human-machine interaction: the first practical benefit is familiarity, which allows the user to predict the machine's behaviour and mitigate frustration when interacting with an AI rather than with another human (Złotowski et al., 2015). Therefore, human-like design is important both for the anthropomorphization of robots and for the human tendency to anthropomorphize non-human objects. When thinking about a non-human entity in human ways, an individual makes it capable of moral attention and consideration, makes it accountable for its actions and worthy of gratification or punishment, he considers it less threatening and is more inclined to approach it. That is why robots designed to interact with humans are humanoid using human expressions, gestures, language, voices and eliciting complex emotional reactions such as empathy (Schwab, 2019). It has been found that the more the robots are perceived as empathic, the easier the relational process is and the easier it is to create an emotional connection. However, if in human relationships empathy means identifying the other's emotions, in human-machine relationships it is not required to recognize the user's emotional state. This implies making an assessment of the personal and individual user experience and, when the virtual agent thinks the user is potentially experiencing an emotion, another emotion can be triggered back. For example, if at some point in the conversation it is predicted that the individual can have a reaction of anger, the agent will prepare itself to react with the appropriate empathic emotion. Usually, when a request is met or a joke is made, the user is likely to give positive feedback; instead, when a misunderstanding occurs or expectations are not met, it is likely that the user gives negative feedback of anger, frustration, annoyance (Ochs et al., 2008). In general, empathy is more effective in negative contexts, where it is more vital for a bot to provide emotional support. It is important to bear in mind, however, that an incorrect and inconsistent empathic reaction has a worse effect than a non-reaction: if the agent does not assess the user's emotional status, it will lose credibility and this inaccuracy will have a detrimental impact on trust (Cramer et al., 2010).

The key to building trusted AI is, thus, leveraging emotional intelligence by training robots to understand and anticipate how people feel, which is a skill that technology can learn through multiple interactions and

[1] The uncanny valley is a feeling of discomfort that the user experiences when a robot has a high degree of humanness that the user perceives it as disturbing and upsetting (Mori, 1970).

through the amount of collected data (Kaliouby, 2019). However, robots do not need to be perfect human copy to instil trust, but they need to create a relational bond and be social actors able to incorporate as much as possible some human values, such as ethical behaviour and respect for privacy. Indeed, it is relevant to consider that, if the virtual agent had human-like characteristics and if the human-machine relationship evolved as a social relationship, it would not be necessary to create trust. Trust would be there by default, as it occurs in human-human relationships that deserve it (Coeckelbergh, 2012).

1.2. Chatbots: advantages, objectives and uses

Conversational marketing can help businesses to be more human. It builds relationships by making the interaction with a brand more personal and engages customers in real-time dialogues to foster direct, instant and customer-centric communication. Indeed, mobile messaging is a growing trend: the smartphone is the first channel used by companies to communicate and the OTTs (such as Google, Facebook, Amazon) collected 80% of mobile advertising in 2020. Chatbots, an abbreviation of chatter robot, which literally means talking robot, ride this trend because they are able to manage interactions within instant messaging apps by establishing a conversational flow with the user (Osservatori Digital Innovation, 2021). The conversation starts with engagement: users can engage with the brand when and where they want, on the website or the social network pages, and receive a quick response to their needs. The second stage consists of understanding the lead, that is to qualify the engaged user to understand if he is a high-value customer, a returning visitor or a user who needs urgent assistance, to catalogue him and decide the actions to be taken. At the third stage, the bot recommends the user the next steps of the funnel to let him continue the conversation within the chat if it is able to satisfy the request or to direct him to a human operator (Tiinus, 2021, Jan). Thanks to the ability to be useful in different industries and for different use cases, nowadays chatbots are receiving increasing attention from both business and users.

A Salesforce research shows that, in 2019, 69% of consumers prefer to use chatbots because they deliver quick answers to simple questions and the response time people expect from a chatbot is actually the same as that from a human agent (Sweezey, 2019). In particular, it emerges that 85% of customers on Facebook believe they should receive a response within 1 hour, but the average response time of companies is 1 day and 3 hours, which is more than 5 times as much (Amaresan, 2021). People have become more demanding and, if they choose to dedicate their time to a brand, they expect it to look after them. Dialogue, which etymologically means "exchange between intelligences", allows companies to feed the relationship, so it is essential to make sure that the mediator takes care of this exchange, especially if it is a robot. Therefore, first of all, it is important to avoid making mistakes such as falsehood and using instant marketing with the sole objective of selling, inserting a call to action in every turning point of the conversation, betraying trust or exploiting the personal data. When used at its best, the chatbot can bring numerous benefits to a brand. It offers the opportunity to sell products and services, enabling the user to purchase through a simple click and an electronic payment: the chat may contain the link to the website or e-commerce, a feature that makes the bot an instant buying tool. In the customer support function, it ensures high responsiveness to messages, without cutting down the space for creativity, but indeed including emojis, videos, images, audio files that enrich the answer; 24/7/365 availability leaves the human agent time to dedicate to more complex activities. It allows the brand to know its audience in real-time, to learn preferences and to offer a personalized experience thanks to the information that the user has previously shared (Zambito, 2019). Personalization is the main feature of the chatbot because it does not only mean adapting the conversation to the individual needs, but it refers also to the ability to decide the appearance, the content, the format, the tone of voice of a chatbot according to its use and objective.

Among the various industries that artificial intelligence is changing, healthcare is leveraging chatbots to transform patient care and improve care delivery. For patients, the greater benefit – the easier access to the right doctor – is combined with the less time spent communicating with the offices and in non-useful treatments; for hospitals and doctors, virtual assistants reduce the workload and lead to a decrease in the waiting and consultation times, avoid unnecessary treatments and connect patients with the right healthcare provider with expected cost savings of $3.6 billion globally by 2022 (Topflight, 2020). In this field more than in others, artificial intelligence solutions cannot lack human touch to provide assistance that improves the outcome of patients who choose or accept to rely on technology. Quincy, the chatbot solution of QuiqSOFT[2] Technologies, enables real-time communication between patients and care team members by encouraging users to share their health information to ease processes like finding a doctor or scheduling an appointment. The platform, which is available to different health providers, creates chatbots with the role of caregivers able to provide empathic aid from the moment of engagement to the end of the medical treatment and to give assistance even in chronic diseases by creating a relationship with the patient (Karl, 2020).

Artificial intelligence, however, not only serves for greater efficiency and productivity but also plays an important role in the softer side of care, that is, the emotional support. Today, many social robots and empathy-based chatbots are used to combat the isolation of the elderly: they are daily companions who remind the older to take their medicines, eat or go to the doctor, and respond instantly to their needs (Fadhil, 2018). Finance is also embracing artificial intelligence to help with expense tracking, tax deductions and online transactions or to suggest personalized savings tips to gain customer's trust due to the perception of better money management. However, there is still a long way to go, in this sector as in others. Forrester research from 2020 shows that chatbots can only handle customers satisfactorily when they need to provide answers to simple questions and there is still some scepticism about using this technology for financial services: 48% of Italians would use a chatbot for their financial management, which is a significant but not

[2] Web Designing, Mobile Application Development, Software & Web Development company (www.qliqsoft.com).

substantial percentage; 34% of Americans, on the other hand, trust a chatbot only when the activities are trivial and they would not entrust more complex tasks to a virtual assistant (Abba', 2020). However, the use of chatbots for conversational marketing solutions has more than doubled from 2019 to 2020 (Drift, 2020) but trust always proves to be the core of interaction because people want to feel that contact with brands is authentic, meaningful and responsive. Indeed, the 2018 chatbot report revealed that the biggest obstacle for customers using chatbots is that many prefer to deal with a real assistant: this is why 43% of interviewed employers said that they are increasingly tending to base their chatbot strategies on the human experience by trying to handle requests with kindness, politeness and emotional connection, and to handle conversations in a way that is closest to what humans would do (Wooler, 2019).

1.2.1 A face, a voice, a personality

Given the human tendency to respond to computers and bots the same as to other people, adding anthropomorphic features to chatbot design is not only crucial but unavoidable to create a better understanding between machines and humans. Anthropomorphism is concretely translated into various forms, from appearance to language (Brahnam, 2009). Firstly, if people's reactions to virtual agents are similar to human ones, this humanness should also be reflected in the visual design through cues that could make the interaction more natural. It is easier for individuals to get familiar with the chatbot and trust it to resolve their issues when it appears to be more human-like because it has been studied that a visual leads to perceptions of greater credibility, likeability, empathy and general positive attitude towards the system than having no visual representation. However, the human appearance should be accompanied by a chatbot designed to be empathic and able to deal with affection; otherwise, it would result in inconsistency that leads to a negative user experience (Nguyen et al., 2009). If anthropomorphic characteristics of the visual appearance do not match with the general humanization of the bot, the participant will have overestimated the capabilities of the virtual agent based on appearance but will not be satisfied with the performance. For this reason, if the avatar is anthropomorphic, the conversation cannot be robotic because the expectations raised could not be met and would cause frustration (Donkelaar, 2018). An adequate appearance is that consistent with the personality of the robot, which in turn must be in line with the personality of the company and its brand identity. If the goal of a brand is to improve company performance by offering information quickly and notifying the user, the chatbot personality will reflect this objective in its icon.

For example, the American Express bot sends messages about purchases, offers recommendations and gives the possibility to add a card within the conversation: these are all features that translate into an icon represented by the company logo (Parisi, 2017). To generate the experience of co-presence in a shared virtual environment, an avatar with a visual cue representing a real person is needed. The goal of Nadia, the virtual chatbot created by Soul Machines[3], is to help people with disabilities and connect with users on a more subtle emotional level to learn through experience by reading people's emotions and facial expressions. It has been designed to make a more human service available and to deal with complex subjects: for this reason, it emulates humans even visually to the point that its resemblance to a real person is sometimes inconceivable (Maack, 2017). Between these two endpoints, there is a continuum in which many other chatbots that use more robot-like or more human-like icons are placed. The Italian phone company Vodafone, for example, has decided to use a little red robot that automates simple and repetitive work such as downloading invoices or discovering new offers, it combines with live chat and handles 94% of customer interactions by solving more than 70% of customer queries (Industria Italiana, 2018). Ira, the Indian chatbot that answers questions about HIV/AIDS, aims to provide information to motivate the population affected by this disease to act responsibly: for this powerful and delicate mission, an avatar with a more human and friendly appearance than a robot or a simple logo was needed because the intention was to avoid discrimination and embarrassment in talking about this topic (The Jubi of Everything, 2019).

Fig. 1.5 - *Conditions of chatbot appearance*

American Express | Toby by Vodafone | Ira by Yes4me | Nadia by SoulMachines

The avatar is not the only way to give chatbots a personality, even the voice - the tone, the gender, the words used, the pauses, the interlayers - can be a distinctive element. Voice is the simplest way to communicate, convey personal emotions and receive quick feedback with zero wait period: being the fastest, most intuitive form of communication, its use will increase and the speech recognition market is expected to grow at an annualized rate of 17.2% to reach $26.8 billion by 2025 (Tejani, 2020). Voice-enabled technologies provide advantages in terms of immediacy and real-time customer interaction, enhance multitasking by letting people operate hands-free and take a further step towards personalizing the brand identity (Engati Team, 2019). If the text-activated chatbot allows the user to answer with short written phrases or buttons and the brand to enrich the chat with videos, emoji or gifs, the voice-activated chatbot brings speed and proximity because it is a more intense vehicle of emotional cues. For chatbots, however, the voice is more complex than the text as each user expresses himself in his own dialect, silences can be easily interpreted as misunderstood sentences, people use expressions and turns of words that they would not use when writing. Indeed, voicebots

[3] Soul Machines is the world leader in humanizing AI to create highly digital people with a patented digital brain that contextualizes and adapts in real time to situations similar to human interactions (https://www.soulmachines.com).

require speech recognition and speed synthesis capabilities because they use pre-recorded answers to address different queries within a few seconds in a natural language (Gallemard, 2020). The most advanced chatbots are a hybrid solution of voice and text to provide a smoother, human-like experience that is expected to completely replace human-based CRM in some industries (Reportlinker, 2020).

Whether the chosen voice is more robotic or more human, natural and friendly, it imbues a personality into the chatbot, consequently humanizing its relationship with users and contributing to creating a competitive differentiator. Therefore, a face and a voice are the visual and vocal external representation of the chatbot's personality traits, which show the user if the brand wants to be more ironic, cheeky and funny or more institutional, precise and serious; if the conversation is warm and human-like or if it is cold and robot-like (Marr, 2019). It is important not to underestimate the process of creating the AI personality because the chatbot becomes a brand ambassador that should reflect the qualities and values of the company. Indeed, the impressions that the user forms during the experience with the virtual assistant will consequently affect the represented brand (Cassini, 2017).

1.2.2 Chatbot self-disclosure

A well-defined personality can make a chatbot so similar to a human that it sometimes becomes difficult for the user to recognize it because text or voice can sound so natural that it is not so obvious that the person the user is writing or speaking to is an artificial intelligence. There are conflicting opinions on this issue and some brands have decided to have their chatbots say that they are virtual assistants, while others have chosen not to reveal their identity. The pros and cons of both alternatives are clear. On the one hand, the reasons for using this technology to present softwares as real people are economic and aimed at reaching better performance, so companies have an incentive to deceive. Some research shows that chatbots that don't reveal their nature outperform inexperienced sellers but when they turn out to be artificial and their sales performance drops down (Engler, 2020). On the other hand, problems related to privacy and ethics arise as the consumer has the right to know if it is an automatic system that is influencing his choices, especially if it regards financial advice or sales promotions.

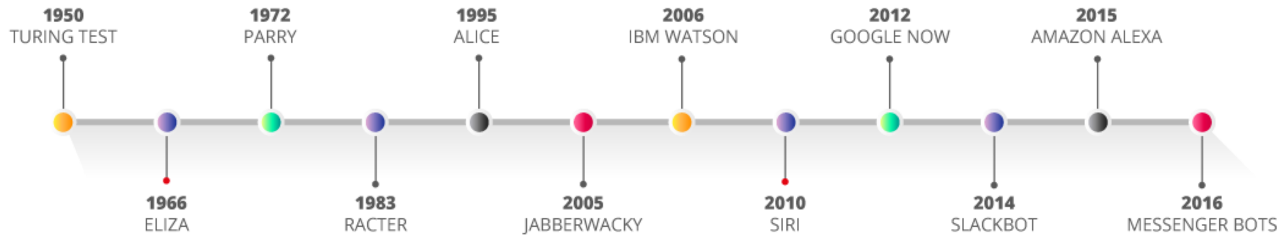
Thus, firms experience the chatbot disclosure dilemma, that is a trade-off between transparency and efficiency, which leads them to wonder what to sacrifice between the two. In addition, this issue can also be seen from the point of view of the trade-off between chatbot performance and chatbot expectations: it is essential to ensure that the virtual assistant is able to satisfy the customer's requests and that the lack of disclosure will not have negative effects on the perception of the virtual experience (Mozafari et al., 2020). Chatbot disclosure, which means that the virtual assistant reveals its identity, can make clients aware that they are not dealing with a human: when the chatbot announces its automated nature at the start of the interaction, the consumer sets reasonable expectations, which are different from what it would be if interacting with a human. Consumers do not want to experience a feeling of deception during the process, which happens when the flexibility and empathy they expect from a human being do not occur and they realize that their interlocutor is a chatbot only at a later time (Gutierrez, 2019). The reason why most chatbots on the market launch the conversation with a first sentence like *"Hi I'm x, the virtual assistant of company y. How can I help you?"* is transparency. The company chooses not to hide anything from the user but to show that it is behaving honestly and it has no intention of causing harm by making him believe something that it is not and that the choice of continuing to converse with an AI is up to him. Being transparent also means clarifying how the data that the user reveals will be treated and what objectives they will serve because, if he chooses to speak to a VA, the individual must know that his personal information will be handled safely and not abused (Reddy, 2017).

1.2.3 From ELIZA to Google Duplex

In 2018 Google revealed its new innovative system based on artificial intelligence: Google Duplex, a voice assistant that allows users to interact with another person, even if virtual, in a spontaneous conversation that appears to be completely realistic (Rita, 2018). The history of virtual assistants, however, begins in 1966 when the first chatbot, ELIZA, was developed by MIT Professor Joseph Weizenbaum. Contrary to Google's current goals, the creator of the first chatbot aimed at demonstrating that communication between man and machine was superficial because it was based on a simple exchange of automatic replies by pairing questions to a list of possible scripted responses (Pepicq, 2019). The program, that had to play the role of a therapist doctor, was very basic, it was not endowed with real intelligence and, above all, it was completely lacking in feelings and emotions. Despite his intention, Weizenbaum had to change his mind because people started conversing with the bot and had the illusion of talking to a human being and even confided their innermost thoughts in it (Pepicq, 2019). Although unable to contextualize events, ELIZA could mimic human language and engage the interlocutor thanks to an identifying conversational style that gave the impression that the machine understood more than it was capable of. What was surprising is that the first person to interact with the chatbot showed a sense of intimacy and an emotional attachment that persisted even when the creator revealed the operating mechanism behind it (still unknown to most) and its inability to understand many queries.

This first experiment highlighted that a human being was not needed for everything and a simulation of a human conversation could generate feelings and affection; furthermore, it brought out the human tendency to trust and create an emotional bond with an artificial intelligence (Schwartz, 2019).

Fig. 1.6 *- Chatbot evolution*



Source: edureka!, 2020

Since that time, chatbots have evolved, diversified and proved to be both useful and pleasant for customers even though they were not able to offer many benefits and a great user experience. The first version was a rule-based chatbot answering to simple FAQs only by following precise rules that it was trained on: the idea of AI was still a long way off and a team of scientists and technicians was needed to develop and teach new tasks to the virtual assistant, which resulted in high costs. The 1990s saw the implementation of artificial intelligence in two innovative entities, Dr Sbaitso (1992) and Alice (1995) that became known for a robotic voice and for having improved pattern recognition, respectively. In the following years, chatbots became more intelligent and machine learning allowed them to extract insights from a large amount of data, to talk humorously and to compete with humans, as IBM's Watson did on a TV show by beating former champions (Mehlinger, 2019). In 2011, another important step was recorded when Siri, Alexa and Google Home were released and made virtual agents available to everyone, bringing AI into smartphones and homes. More than chatbots, these are smart speakers or multitasking voice assistants integrated into daily lives that are not limited to solving problems but become interlocutors in a two-way conversation (Redazione Celi, 2020). Facebook did not take long to keep up and in 2016 it opened its Messenger platform to host chatbots so that users could interact with the already 50 million companies on a social network they were comfortable with. This innovation has not only identified a new type of customer service to deal with urgent needs and issues through a multiple ranges of functions and contents - texts, images, buttons - but it has also revolutionized the business by building a new sales and recommendation channel (Yeung, 2016).

From ELIZA to Messenger bots the level of humanization has been increasing to redefine the way of communicating with the web and with companies, a revolution that Google has taken over again with its Google Duplex launched in 2018. It is the evolution of Google digital assistant for conducting natural conversations to carry out real-world tasks over the phone and completing simple tasks, such as scheduling appointments or making reservations. The novelty does not consist in the variety of functions or language, but in the natural and fluent way in which the chatbot manages to talk and carry out an interaction mostly without errors or misunderstandings: Duplex understands the nuances of a conversation, interrupted sentences, misspelt words, complex expressions and fast speech without even letting the user know that it is processing the information. It sounds so spontaneous that the first tests carried out on a small sample showed that many did not realize they were interacting with Google and this prompted them to use the same language they would have used with other humans (Leviathan & Matias, 2018). The human-sounding voice is far from the robotic voice of previous virtual agents and it is even complete with pauses, inflections or interlayers like "uhm" or "mmm", expressions that it is also able to understand if spoken by the user and match them with human vocal patterns or adjust the rhythm of the conversation (Madrigal, 2018). Duplex was a technical achievement with improvements in machine learning and natural language processing, but also a system that has taken years of listening to human voices and gathering large amounts of data that trained the machine and will continue to be useful for future releases. Indeed, the voice assistant is still evolving and needs to receive constant updates. Currently, it only focuses on small domains such as making appointments at restaurants or hairdressers, it requires human involvement - about 15% of all Duplex calls require a person to step in - and struggles to deal with the unexpected: for example, it happens when a restaurant does not take reservations for the number of people Google asked for (Chen & Metz, 2019). To improve it, it is necessary to equip the bot with a memory, which means it will be able to store conversations it has conducted and remember them to respond accordingly to questions that belong to the same context: only in this way a conversational bot can provide customers with a fast and seamless experience. The main barrier lies in the contextualization because the technology is still not good at understanding the context and needs a lot of data to improve, but the future will see increasing automation of simple processes with slowly reducing the need for human intervention. In just three years, many steps forward have already been made: today Google Duplex is available in 49 US states and, compared to 2019 when 25% of calls were handled by human operators, from October 2020 99% of calls are fully automated (Vincent, 2021). Google’s current goal is not to remain confined to some areas but to slowly enter people's life and make it easier in several scenarios (Zaman, 2021).

1.3. Virtual assistants for the energy industry: the case of Enel Energia

Automation, artificial intelligence and chatbots are receiving increasing attention in the utility sector, where these technologies are used innovatively and provide significant benefits. Companies operating in the field of water, electricity and gas collect, process and store huge volumes of data that allow them to know a about people's behaviour, preferences and consumption regarding essential daily services. Machine learning allows utilities to manage datasets to identify problems and solve them quickly, predictive analytics anticipate behaviours, such as the propensity to change service provider or the churn rate, chatbots provide instant assistance and collect insights from customers (Uljanovs, 2020). The energy industry is the largest user of AI today and the use of chatbots are part of a bigger digitalization process that is changing the control of energy, optimizing resources, promoting more sustainable consumption and transforming communication with consumers (Booth et al., 2020). Users, who are increasingly aware of their consumptions, ask for control and expect online access in those sectors that have traditionally been the least engaging but in need of trust to generate loyalty and retain their customers. Virtual assistants for energy companies make it possible to have a more direct and long term relationship with citizens and customize supplies according to individual needs while, at the same time, reducing management and call centre costs (Jenny, 2018). There are several benefits a chatbot can bring to an energy provider: the first is 24x7 availability since AI is mostly used to optimize customer care. The ease of access to information and the ability to self-service is a great cost saver in this sector and automation can give this level of autonomy to which consumers are accustomed to (Consult Energy, 2019). The second advantage is call reduction: energy companies implementing chatbots in their strategy speed up e-mail or telephone processes that require time to devote to repetitive tasks such as reading meters or reporting breakdowns or water and electricity shortages. On the one hand, the transfer of management from human to technology allows the customer care team to deal with more complex processes that are not feasible for the virtual agent or require some kind of human contact. On the other hand, the bot responds to the most common queries with constant availability: it can be trained with the most frequent FAQs addressed to the company, for example about consumption, supply plans, bills to pay, and reduce the call turnout (Perdigão, 2021). Another benefit concerns consistency and integration with other touchpoints for a multichannel approach: the quality of the service does not vary depending on the operator serving the customer or on the time and the day people call because the assistance will always be the same no matter the case. Besides, the bot integrated with the business systems can keep track of the users it has already served through customer numbers or home addresses they are likely to refer to when asking for support again. This eliminates the risk of talking to an always different human operator and the frustration resulting from the customer's need to repeat personal data to be identified every time he calls the call centre (Herianto, 2020). Finally, it is not a paradox that the use of technology can create a more human approach because it results in being more customer-centric. Also and above all in this industry, where a growing number of companies are adopting AI, it is important to invest in the chatbot personality, because digital agents act as consultants to advise customers or assistants to help them during emergencies. The energy sector, like other utilities, needs human touch to communicate and conversation to bring customers closer to the business by making them feel connected, informed, safe (Harper, 2020).

1.3.1 Company presentation and digital innovation

Founded in 1962 as an Italian public body, Enel is a private company operating in over 30 countries and continues to expand into new markets. A pioneer in the world of sustainability and renewable energy, today it faces the challenges of clean energy and digital development with innovations such as infrastructure digitalization and smart technologies[4]. The liberalization process of the electricity market that began in Italy in 1999 allowed Enel to expand its borders, but today the supply of electricity to domestic customers can

[4] Smart technologies include devices allowing companies and households to use energy more efficiently, reducing the need to build more power stations and thus reducing pollution (https://www.theguardian.com).

take place both in the protected market and the free market. Its vision can be summed up in the keyword "openness", which means being open to the outside world, to technology and within the company among people; the mission is represented by the concept of "Open Power" which means opening access to energy to more people, guiding the use of new technologies, developing new services - such as electrical connectivity - and joining partners who share the same mission.

Among the values guiding the Enel group, trust and innovation are the basis for progress and oriented towards transparency because openness also means being clear and honest: sharing takes place in the spirit of “open data” to make company data accessible to all stakeholders. Innovation opens the company to new possibilities and technological innovation opens up to digitization, which is linked to data and information (Enel Group, 2021). In the last two years Enel has produced 90% of the existing data that are considered the fourth factor of production and digitalization. Hence artificial intelligence is based on the use of clean, ordered and stored data that *electrify* technology and make the way energy is produced and distributed more *intelligent*. Since 2016, Enel has founded its digital strategy on the pillars of assets, people, customers and defined its use of AI as *"augmented intelligence that allows you to extract the maximum possible value from data"* explains Giuseppe Amoroso, Head of Enel's Digital Strategy and Governance (Enel, 2019). Even the pandemic has not changed the focus but allowed the company to reconfigure its way of functioning in a very short time: indeed, for the quarterly plan 2020-2022, Enel confirmed the amount of 5 billion euros of the 2017-2019 strategic plan invested in digital. It has chosen to go beyond the As-Is approach, that is to work only on existing assets, but to digitize the distribution network and the relationship with its customers (Luiss Business School, 2020).

1.3.2 Relationship with customers

With a view to transparency, which takes the form of clarity, readability and completeness of information, Enel has adopted an omnichannel approach to interact with its customers. Regarding physical communication channels on the territory, 900 Enel points in Italy and a wide-coverage sales network create teams of consultants and salespeople to know and listen to customers. For direct and immediate contact, the company has a call centre active every day from 7 am to 10 pm which provides both general information regarding energy supplies and specific assistance to individual needs. To meet the need for autonomy that many consumers require and to which they are increasingly accustomed, Enel has designed a portal to monitor consumption, services and bills (Enel Energia, 2021). By accessing his private area, the user can carry out operations such as paying the invoices, activating the web bill or changing the billing address within a single platform. The launch of this Customer Area, which took place in October 2019, was the result of a study of the dynamics of relationships with people and of the change in digital needs with the aim of improving the user experience and adapting it to expectations. Among the options to receive assistance, in addition to the call centre number, the customer area offers a live chat that puts the user in contact with an operator to speak via web and have immediate support in a real-time conversation. For faster use and a simpler digital interface, the app allows customers to control their consumption and perform the same operations even from their smartphone, which is the most intimate and most used device also for utility services. One of the main advantages is the customization of notifications, thanks to which each customer receives updates on when to do the self-reading and on the latest offers. Another benefit is the loyalty program ENELPREMIA WOW which gives the opportunity to participate in competitions and prize activities, as well as receive discount coupons to spend at selected third-party partners, an initiative in line with the mission of opening up to partnerships also in marketing (Enel Energia, 2019). If an Enel customer wants to get in touch with the company, he also has other ways to do it: the brand is present on the major social media channels, where it opens the way to interaction and comparison. Social channels are not directly aimed at customer assistance but can indicate the most suitable ways to be assisted based on requests. Facebook and Twitter, in particular, want to create social engagement and active support: hourly continuity is central, given that 80% of people primarily use social media to ask for information from a brand. Hence the commitment to be available from 9 am to 9 pm for personalized service and a smooth experience (Enel Energia, 2021).

1.3.3 Elena, the virtual assistant

A new way of communicating with Enel Energia is the chatbot, Elena, which represents a step forward in the relationship with customers: the availability of the bot has no time limits and gives further autonomy with quick and easy answers that optimize the handling time of requests. Live for one year and a half in support of social and telephone channels and available on Facebook Messenger, WhatsApp, Telegram, on the website and at the toll-free number, the virtual assistant is equipped with artificial intelligence that makes the virtual user experience smooth and usable. Always supported by a human operator in case of need, it is currently able to independently manage various processes including activating the web bill, inserting self-reading or checking the status of payments (Enel Energia, 2021). It is the result of an in-depth qualitative and quantitative research project: the qualitative approach aimed at verifying that the positioning was in line with the company and with indications for the development of the chatbot identity; the quantitative approach, instead, had the purpose to understand the customer willingness to use the chatbot and to test the best suited avatar to represent it. Interviews and focus groups with consumers have given insights into shaping the traits and functions of the conversational agent; then, a questionnaire was used to test the qualitatively generated hypotheses on a larger scale.

The results revealed different strengths and weaknesses depending on the vocal or written channel and on the type of social network in which the bot is integrated. In its first version, Elena proved to be quick and fast in the transition to the operator, but often not very conclusive concerning some queries due to a poor initial decoding capacity. On the one hand, Telegram, the first channel to be launched, turned out to be the best performing but, above all, because the typical customer is more advanced than that of other social networks. There was a good response and interaction capacity thanks to the well-functioning buttons, but poor awareness of the channel. On the other hand, Facebook received good results in terms of comprehension, but was accused of being generic in the answers; it was also little considered for assistance because it is usually expected to host a live chat. In general, Elena respects Enel Energia's positioning of support and precision because it is easily accessible and close to the customer, it is very specific, although it still needs to be trained in some scenarios. The welcome and informality also emerge: although these features are not characterizing positioning values of the brand, they are still necessary for a conversational exchange. The identity of the virtual assistant is made up of a distinctive appearance, language and name. Indeed, part of the market research focused on the most suitable avatar for Enel's chatbot, asking respondents their preference between a robot, a male character and three types of female characters. The answers of the survey, submitted to both customers and some employees of the company, favoured the animated female human and, in particular, all age groups preferred a woman avatar dressed in pink with short brown hair.

Fig. 1.7 *- Chatbot Elena*

Source: Enel, 2021

This character shows an affinity with Enel's values: it appears to be professional, reliable, but also friendly. It is polite and speaks to the customer in a precise but empathetic way. The choice of the name Elena was also the result of a long study because Elena is an Italian personal name, quite well known and easy to pronounce, and it recalls the Enel brand name. Having defined its specific identity, the chatbot personality is constantly evolving as well as its learning ability, the scenarios it can handle, the words it can recognize and the questions it can answer. The goal is to offer an increasingly fluid and effective customer experience, aiming at a greater call deflection – which is the ability to manage requests in complete autonomy – and a greater understanding of human language to create a relationship of trust between man and technology. This research thesis fits into this scenario and aims to achieve relevant insights that can also be useful to Elena's experimentation and improvement team.

CHAPTER 2

THEORETICAL BACKGROUND AND CONCEPTUAL FRAMEWORK

2.1 Consumer Trust

Studied from many and different perspectives - in psychology, philosophy, politics, economics - trust is a complex and manifold multi-sided construct. Being such a complex concept, there are many definitions of trust. From a marketing point of view, it is defined as *"a willingness to rely on an exchange partner in whom one has confidence"* (Moorman et al., 1992, p.315) and it has assumed an essential role in establishing and maintaining a long-term relationship between a seller and a customer. Therefore, consumer trust is the confidence in a product, person or company, it is the consumer's expectation that the seller is trustworthy (Sirdeshmuk et al., 2002) and will be able to keep his promises. Trust plays such an important role and has been studied extensively as it influences consumers' attitudes and brand-related behaviours including perceptions, purchase, loyalty, commitment, and referrals (Elliott et al., 2007). Brand related behaviours, such as purchasing, praising and defending the brand, involves risk and brand trust can reduce it.

Luhmann argues that familiarity is a precondition of trust because trusting is only possible in a familiar world: however, it is required especially in situations of high perceived risk and uncertainty (Luhmann 1979). Thus, trust encourages risk-taking by trustors because the trustee is considered trustworthy and the likelihood that his actions will be beneficial instead of opportunistic is high enough to engage in a relationship (Das et al., 2004). Considering risk and trust as intrinsically related, the latter can alleviate the fear that the trustee will act to his advantage and this faith will impact consumer mindset metrics, such as brand consideration, purchase intention, behavioural and attitudinal loyalty (RAJAVI et al., 2019).

2.1.1 Trust elements and antecedents

To use it as a lever for success, trust should be broken down into different parts and each element should be identified and examined. Young and Albaum define trust as *"an evolving state including both cognitive and affective elements"* (Young et al., 2003, p.255): it emerges from the perceptions of competence and positive motivation in the relationship partner to be trusted. Precisely, trust is found to be made by a cognitive and an affective dimension, and multiple factors facilitate or hinder trust at specific times in the interpersonal relationship (Webber, 2008). Cognitive trust is the trusting behaviour motivated by "good rational reasons" why the object of trust deserves trust (LEWIS et al., 1985) and it is defined as the consumer's willingness to count on a service provider competence and reliability (Moorman et al., 1992). Competence-based trust means expecting that a brand has all the technical skills and experience needed to fulfil obligations (Lui et al., 2004), that is, those features that allow it to achieve a good performance. A firm or brand is perceived as competent if the consumer thinks it can carry out tasks and activities that are relevant to its role (Dowell et al., 2015). Reliability is the idea that a brand will perform as promised or declared (Kim et al., 2018) and that is compliant with expectations. In addition to these two, a third element has been identified as a component of cognitive trust: integrity, which is based upon honesty (Lee, et al., 2008), refers to a partner keeping their word or promises and being adherent to a set of principles such as credible communications, a sense of justice and congruent actions (Mayer et al., 1995). So, cognitive trust arises from the knowledge that allows predictions of future events: consequently, it is more and more needed when there is a state of incomplete knowledge and it is not possible to verify with certainty how the partner (brand) will behave (Doney et al., 1997). Cognitive trust by itself does not make a brand a trusted partner, because affective trust is also required. Affective or emotional trust is the confidence placed in a brand based on feelings generated by care and concern demonstrated (Johnson-George et al., 1982). McAllister argues that it is based upon interpersonal reciprocity and developed through interactions and frequency of contact over time: people investing in these relationships believe sentiments are genuine and reciprocated (McAllister, 1995). Some researches have identified two components of affective trust: relational, which is based on the norm of reciprocity and linked to faith, and intuitive, which refers to a personal judgment based on ideas and feelings about another's character and behaviour (Dowell et al., 2015). Other studies have identified honesty and benevolence among the elements of emotional trust, which explain how a party's perceived trustworthiness is also based on feelings and emotions (Becerra et al., 2013). Honesty is the confidence that the brand will be sincere or the feeling of security generated by the relationship (Johnson et al., 2005), while benevolence refers to the extent to which one party believes that the other has good intentions and will look after his interests even without formally asking (Lee et al., 2008). It follows that cognitive trust is based on reasoning, while affective trust in emotional relationships. Both components play a fundamental role and trust implies the coexistence of the two; however, one prevails over the other depending on the type, duration and phase of the relationship. For example, it has been proved the importance of relational and emotional trust in the early stage of a relationship, when there is a lack of experience, so trust is placed with no evidence-based reason based on ability, but rather based on the hope, faith or expectation (Dowell et al., 2015).

In addition to identifying its elements, much research has focused on what trust is determined by. Service provider expertise and product performance are antecedents of cognitive but not affective trust, while sales effectiveness, similarity of business values and frequency of interaction are antecedents of liking, which develops affective trust (Nicholson et al., 2001). Other findings show cultural similarity, consisting of a shared language and a shared vision, as a trust predictor, underlining that sharing cultural values is crucial in the formation of cognitive and affective trust (Levin et al. 2003). A model of trust in the online environment reveals that internal factors including perceived ease of use, perceived usefulness and reputation have significant effects on online trust (Ha, 2004). In addition, other characteristics like communication, personalization and human service have been marked as predictors of trust (Alam et al., 2010), pointing out the active role of online providers in creating and maintaining consumer trust as well as the importance of personalized experience and human service in web communications.

2.1.2 Online trust

Trust plays a key role in online transactions and communications, mostly due to the lack of direct contact with the trustee. McCole explicitly states that online purchasing necessitates online customer trust (McCole, 2002), while Egger argues that a minimum level of trust needs to exist when the customer submits his or her personal data in undertaking financial transactions (Egger, 2006). It has been proved, indeed, that building online trust means influencing online consumer behaviours and obtaining benefits in terms of purchase intention (Gefen, 2002), online customer experience, loyalty and the firm's competitive advantage (Alam, 2010). As with offline trust, online trust also implies the presence of two parties, a trustor and a trustee: on the one side the consumer and on the other side the website or, more specifically, the brand behind that website (Wang et al., 2005). The main difference from offline communication is the higher complexity and greater risks associated with the online environment, where uncertainty and anonymity make consumers more vulnerable. Several studies have focused on website characteristics as antecedents of online trust by proposing a mediator role of trust in online behaviours. An empirical study has elaborated the effect of key web factors – including navigation design, visual design and enabled communication and social presence – on trust in online brands (Ganguly et al., 2009). Generating a higher perception of navigation design increases the website's pleasantness and helps consumers save time and overcome perceived performance and financial risk (Harridge-March, 2006). For example, if the information the user is looking for is difficult to find or the text is too long and lacks images, consumers will be less likely to return to the website due to a poor user experience (Petrie, et al., 2009). Visual design is also determinant because aesthetic beauty positively affects trust: colours, graphics and photographs create the *look and feel* of a website and act on the consumer's perception (Cyr et al., 2008). Enabled communication, like the option to speak with a salesperson, generates consumer's trust by allowing solving problems and ambiguities (Mukherjee, 2003). Finally, the interaction is central to trust-building and to improve customer attitude towards the brand. Social presence, the online user' sense of awareness of the presence of the partner (Gunawardena et al., 1997), has been tested to result in higher trust in the online store (Ganguly et al., 2009).

These findings outline the key role of the human touch in web communications and the effects that sociability and warmth have on users who interact on the Internet. In examining the role of trust in online environments, existing literature has focused on research into the effects of online brand trust on purchase intention and how decisive it is in purchasing decisions. Becerra and Badrinarayanan suggest that, when deciding to purchase a brand, consumers are more influenced by cognitive trust factors, such as perceived ability and performance, rather than affective trust factors and they are more likely to provide positive referrals (Becerra et al., 2013). It has been studied that two sub-dimensions of online trust, integrity and ability, influence online purchase intention (Hwang et al., 2012) and promote more involvement. Integrity is the consistency of an acting entity's words and action, the belief that a trusted party adheres to accepted rules of conduct, such as keeping promises (Palanski et al., 2011). Ability is the belief that the trusted party wants to act for the good of the consumer while pursuing profit. Thus, to increase the integrity dimension of online trust, subjective aspects, such as providing feedback mechanisms and reducing uncertainty by rules of conduct, should be emphasized (Hwang et al., 2012). To increase the ability dimension, it is necessary to communicate the honesty and sincerity of a brand to make the consumer more inclined to trust it due to proven authenticity (Sung et al., 2010). The objective of increasing online purchase intention is more complex precisely because consumers perceive online interactions as being riskier than offline ones, which provide the physical experience of seeing, hearing and touching products as well as the people you communicate with (Heijden et al., 2003). The main concerns are security and risk of loss, together with the idea of limits associated with the digital environment when it comes to data security (Delafrooz et al., 2011). Indeed, when in a context of uncertainty but also greater complexity, users look for shortcuts to ease difficult decision processes. Brand trust is a cognitive shortcut for purchase decisions ((Luhmann, 1979) because it convinces that the chosen brand will be able to meet expectations regarding its future behaviour and allows the consumer to skip the analysis and evaluation steps whenever he is faced with situations of doubt and insecurity.

Existing research has also focused on the effect of brand trust on brand referral intentions: trust has been found to influence consumer's intention to recommend a brand online and provide positive statements about it (Shaari et al., 2016). Given that online trust augments positive judgments on a brand, consumers are more likely to promote a brand and give positive feedback when they trust the brand to live up to expectations (Rigby et al., 2003). Trust's variables, including competence and integrity, reduce the uncertainty of extending the consumer-brand relationship duration (Suh et al., 2003) and users who develop online trust are more likely to spread positive word-of-mouth referrals (Kim et al., 2013). Research on online purchase models shows that electronic word-of-mouth, defined as the exchange of product or service evaluations among people who meet, talk and text each other in the virtual world (King et al., 2014), is mediated by online trust which, in turns, has a direct influence on customers' behavioural attitude towards the online purchase intention that can reinforce the customer behavioural intention (Di Virgilio et al., 2017). It is remarkable that, especially in cases of anonymity in online environments, brand trust has the power to influence two components of brand evangelism: brand purchase and positive brand referrals. Therefore, it is likely that brand trust could produce not only brand adoption but also brand advocacy behaviours by fostering consumer-brand relationships. Consumers' willingness to promote a brand and immerse themselves in online interactions has been tested to be a notable consequence of trust: if brands are trusted, consumers are more likely to engage in risky and difficult behaviours in support of the brand, such as purchase and positive brand advocacy (Becerra et al., 2013).

These researches highlight that, although trust is a subjective matter related to and affected by individual differences and situational factors (Crafter et al., 2013), brands can invest resources and concrete efforts to build and maintain a general climate of trust on the Internet because customers will feel more comfortable in interacting and transacting as well as disclosing sensitive information online.

2.1.3 Commitment-Trust theory

Trust implies by definition the willingness to rely (Moorman et al., 1993), which is a component of behavioural intention that pushes those who trust an exchange partner to act and take the risk. Consequently, trust is complete and a brand can be considered trustworthy if one is willing to rely on that brand and desires to commit himself to the relationship (Hrebiniak, 1974). Commitment can be defined as a psychological attachment and bond between the individual and the brand (Burmann et al., 2005): only reliable parties will be chosen as they are deemed beneficial and profitable in the long term because commitment entails vulnerability and exposure (Morgan et al., 1994). It follows that trust is a key determinant of commitment and mistrust decreases it by making people less likely to get involved. Focusing on the relational aspect of trust, Morgan and Hunt establish the commitment-trust theory, a model with trust and commitment appearing in pairs as mediating variables. Those elements have been found to mediate the relationship between antecedents and outcomes that contribute to successful relationship marketing. Shared values stand out as a precursor of both variables: when sharing same values and culture as the brand partner, consumers are more committed to the relationship because they are more likely to trust the other part (Morgan et al., 1994). Indeed, if both parties have the same symbolic system and visions, their interests can be compatible and they tend to believe they will benefit both and will trust each other thanks to the consistency of their values (Sitkin et al., 1993). Another predictor is communication, which has been demonstrated to positively affect cognitive and emotional trust (Farrelly et al., 2003). By contributing to solving disputes and aligning expectations, the sharing of meaningful and timely information fosters trustworthy relationships and reduces information asymmetries (Anderson, et al., 1990). Defined as the self-interest seeking with guile (Williamson et al., 1975), opportunistic behaviours have a negative correlation with trust, which means that the more one of the parties behaves opportunistically, thinking only of its interests and benefits, the more trust in the relationship decreases (Mukherjee et al., 2007). Self-interest maximization results in a reduced relationship commitment because consumers perceive they can no longer trust the brand they were engaging with.

Among the outcomes of the commitment-trust model, acquiescence turns out to be influenced by trust through commitment: indeed, being stability a desirable performance outcome, individuals are less likely to terminate the relationship when they are committed to and trust the brand, therefore they accept and agree with its requests and policies (Morgan et al., 1994). Commitment and trust directly affect cooperation, the situation in which partners work together to achieve common goals (Anderson et al., 1990), and promote high involvement. Being committed to a relationship means being willing to cooperate: this also implies consumers trust in the other party, because it allows them to manage risk and uncertainty associated with the interaction, especially if it is a new one (Jones et al., 1998). What trust has an impact on is also uncertainty, a situation in which one cannot make specific provisions, neither about the environment nor about consequences of a chosen alternative (McMullen et al., 2006). In particular, making the consumer trust the brand reduces his decision-making uncertainty as the trusting partner will be more confident that the trusted party will take actions he can rely on (Achrol et al., 1988).

Subsequent studies have revisited the commitment-trust theory by focusing on the cognitive components of trust and the mediating role of commitment (Dowell, et al., 2015). At the early stage of a relationship, the affective elements of trust - relational and intuitive - matter more; instead, cognitive elements - competency, integrity and goodwill - are important predictors also at a mature phase. To test if a brand is trustworthy, at first the consumer wants to see if it is honest and able to keep its promises (Dowell et al., 2013), later if it fulfils the role within the interactions and has the knowledge needed to complete the tasks (McAllister, 1995). These findings suggest that, to develop the first form of trust, firms should create a link with people to communicate that they can carry out the actions they have declared transparently. At a later stage, to develop the second form of trust, firms should demonstrate capacities and expertise, because competency is found to be the most relevant predictor of relationship performance (Dowell et al., 2015). As a mediator, commitment has a positive association with all the cognitive components of trust: it is shown to have a critical role in long term relationships and, as commitment rises, conflict decreases and satisfaction increases (Jap et al., 2000).

2.2 Personal information disclosure

Data allows companies to have accurate and usable insights to personalize content and design new products and services. On their side, consumers should be willing to release their personal data and make firms able to use them. In the online environment, acquiring consumer information is easier and more suitable because the way and the possibilities of extracting it is faster and more direct (Zimmer et al., 2010). Moreover, the punctual collection of consumer actions, habits and interests is the hot core around which a customer-centric communication process is structured and a relationship marketing orientation is embraced. Thus, to create a two-way interaction, marketers have to understand the importance of turning to the database as a source for creating a dialogue and identifying customer needs that can be served in the long run (Schoenbachler et al., 2002).

However, this process is not always immediate. It happens that, on the one hand, collecting data to build buying patterns and customer profiles is a win-win situation for brands as well as consumers because it allows them to receive personalized and ad hoc offers; on the other hand, consumers are often uncomfortable when they decide to share information on the Internet (Zimmer et al., 2010). When they act in online exchanges, which are characterized by being more uncertain and impersonal, people perceive greater risk than in a traditional exchanges and the urgency to avoid loss becomes stronger than the possibility of pursuing gain (Rieck, 1999). The main concerns for consumers are privacy issues, information misuse or lack of confidence in the brand’s ability to solve problems: these risk beliefs create a perception of vulnerability and have negative effects on disclosure behaviours (Xu et al., 2021). Research has revealed that what can alleviate this perception of risk is trust: it not only increases the intention to release information but improves the overall relationship quality. That is why consumers should have confidence in the brand before disclosing their personal and sensitive data (Milne et al., 1999).

2.2.1 Perceived risk and disclosure consequences

Evidence shows perceived risk as the main factor limiting the intention to release information online, and trust as what can reduce it. In the marketing literature, risk is often defined as a consumer's belief about the potential uncertain negative outcomes from the online transaction (Kim et al., 2008) or as the uncertainty resulting from the potential for a negative outcome (Havlena et al., 1991). Some theorists point out that both trust and risk deal with probability and risk is incorporated into trust, so situations involving trust are a subclass of those involving risk (Stern et al., 2015). In addition, perceived risk is often regarded as the probability of unfavourable outcomes or the probability under conditions of uncertainty (Yates et al., 1992). Therefore, it may be concluded that the consumer experiences it when he is not able to and cannot foresee the consequences of an action. Das and Teng specify that risk is a complex construct that can be discerned into two types: relational and performance risk (Das et al., 1996). Performance risk is the probability that alliance objectives are not satisfied despite satisfactory cooperation among partner firms and the likelihood of not achieving the goals in a relationship given good intentions and efforts (Sengün et al., 2007). It depends on the characteristics of the environment so that it is also defined as an environmental risk, or on the (perceived) capabilities and skills of the partner. Relational risk concerns the probability of not having satisfactory cooperation because of the potential for opportunistic behaviour and the likelihood of having a partner who is not fully committed to the relationship and who does not act as expected (Das et al., 1996). Also called behavioural risk, it is based on the partner's conscious intentions because it is the uncertainty arising from the fact that the partner does not voluntarily behave as wanted. It follows that performance risk is linked to competence trust, while relational risk is linked to goodwill trust (Das et al., 2004). We can say that, even if the trustee is deemed to have all the required skills and abilities, the risk associated with the relationship does not completely disappear. Indeed, trust that influences performance risk does not change relational risk linked to the intention and willingness of the trustee, which does not decrease. To reduce this risk, brands must leverage on the goodwill trust, which is the belief that the trustee will act in the interest of the trustor and will carry out whatever is requested and expected in good faith (Bradach et al., 1989).

Given these statements, opportunistic behaviour harms this type of trust, which is inversely proportional to relational risk. When the trustee and the trustor make an exchange in an online context, trust becomes even more important: in fact, it is a question of relational risk in digital communications, in which the factors that allowed to have certainties related to closeness and personal contacts disappear (Schultz et al., 2007). In this case, the higher the initial perception of risk, the higher the trust needed to facilitate the communication.

According to Pavlou, perceived risks on the Internet consists of two dimensions: the impersonal nature of the online environment and the uncertainty of using a global open infrastructure (Pavlou, 2003). The first refers to the distance between the two parties to which the online forces by definition, a feature that causes less control over the actions of the other and increases the risk of conduct at the expense of the trustor. The second refers to the uncertainty that might lead to privacy threats and misuse of personal data released online (Hui et al., 2007). Based on the findings of the exposed research, it appears that a close correlation flows from trust to perceived risk, with the former reducing or eliminating the latter and helping to influence the individual behavioural intention to provide personal information. Accordingly, consumers will disclose when perceived risk is offset by trust and when perceived benefits outweigh perceived losses (Foa et al., 1974).

When making decisions about whether, what and how much to disclose, individuals consider the consequences of giving disclosure according to the loss-benefit ratio (White, 2004). The construct of perceived disclosure consequences (PDCs) introduced by White focuses on social disclosure risk considerations by referring to privacy concerns and embarrassment. In particular, what worries users about privacy is the loss of control over telephone, e-mail and other personal data that may include demographic or lifestyle characteristics and purchase habit information (Phelps et al., 2000). Most consumers are concerned about the ways companies use personal information about them and the perceived “downside risks” associated with disclosure (Westin, 2003). They would like to monitor the way their data is collected, gathered, stored and used by marketers – the so-called “dissemination control” – as well as the kind and the volume of advertising they receive – the so-called “environmental control” (Phelps et al., 2000). Few studies have investigated the type of personal information provided and found that consumers are more likely to release some types of data than others: they are less reluctant to give demographic and lifestyle information than financial, purchase-related and personal identifier information. The findings suggest that the reason for this reluctance is the fact that individuals are protective of this second category because they are perceived as likely to lead to more marketing offers and to cause harm as a result of unsolicited intrusion or unjustified appropriation (Nowak et al., 1992).

How can brands minimize these effects and work on disclosure avoidance? One of the most effective verified solutions is relationship building, which is associated with established satisfaction and trust (Derlega et al., 1993). Indeed, individuals are more likely to reveal about themselves to those with whom they have a deep relationship, compared to those with whom they have occasional exchanges. Some of the factors underlying the positive effect of relational depth on disclosure are familiarity, commitment and trust as features of close relationships (Fournier, 1998). Finally, previous literature that has analysed risk in online environments has highlighted the inevitability of taking risks in these contexts, given the lack of knowledge of the two parties who have no direct contact (Delgado-Ballester et al., 2008). Furthermore, since the risk is associated with the possibility of suffering harm or loss (Yates, 1992) – which is expressed as the result of hazard and exposure (Chicken et al., 1998) – evidence shows that the willingness to disclose personal information online can be fostered by decreasing the perceived risk of personal information on the Internet.

2.2.2 Trust and self-disclosure

The direct and positive relationship between trust and self-disclosure has been confirmed by several studies. Frye and Dornisch found that participants with higher levels of trust tended to report high levels of comfort with disclosure and this comfort was not sensitive to the intimacy of the topic (Frye et al., 2010). Because of this comfort, individuals are confident that their data will not be used without their permission or against them, so trusting users do not care no matter what information they release, which can also be very sensitive. Conversely, non-trusting individuals are concerned about the way their disclosures would be used, especially if related to intimate and embarrassing topics (Buss, et al., 1957). As the literature presented in the previous paragraphs has revealed, uncertainty and vulnerability are requirements for trust because there would be no need for it if the trustor has complete control and knowledge over the actions and intentions of the trustee (Moorman et al., 1993). Moreover, it is also clear how feeling uncertain and vulnerable leads individuals to avoid disclosure, precisely because the requirements to do so are missing. These elements in common also prove the link between the two variables concerned. The use of trust in disclosing situations – for example when the user is asked to leave his personal e-mail in an online form – might shorten the decision making problem by reducing effortful cognitive evaluations about the trustee (Scholz et al., 1998). In terms of trust-building strategies, since they take place without face-to-face interactions and without seeing or trying the product, online communications rely on trust as a major driver of relationship marketing. Building an online relationship takes time and effort to develop a long-term bond between the seller and the buyer: continuous communication is a fundamental part of this process because it allows building a climate of trust step by step (Ganesan et al., 1997).

On the one hand, the purpose of many companies is to acquire as much data as possible to use them for profiling and better targeting; on the other hand, it has been studied that treating an individual only as a user to be profiled risks creating avoidance to release requested data. Indeed, if they only feel short-term engaged in transactions, consumers are more reluctant to disclose compared to if they feel they have a long-term relationship with the brand (Schoenbachler et al., 2002). This aspect explains the difference between trust and loyalty in getting users to release personal information. Defined by Oliver as a *deeply held commitment to rebuy a preferred product/service consistently in the future, thereby causing repetitive same-brand or same brand-set purchasing* (Oliver, 1999), loyalty is a complex construct but it is often synthesized as repeat purchase patterns. To induce this kind of behaviour, many brands have started investing in loyalty programs, which are designed to reward repurchasers with extra products or supplementary goods and services (Dowling, et al., 1997). Thus, these tools are meant to lock the customer in by offering an accumulating benefit and increase the switching cost of the buyer over time: this implies that users often remain loyal to a brand because it benefits them, but the real level of engagement is low. CRM and loyalty programs allow businesses to know customers with customized profiles thanks to advanced database modelling because companies can own first-party data from customers about their purchase patterns, behaviours, history and preferences (Gomez et al., 2006). Surely it is an easy way to acquire information; however, these tactics have been found to potentially lead to repeat purchases but not real relationships. It is necessary to distinguish between an exchange built on repeated purchases and one built on trust: the former improves customer redemption and satisfaction, the latter creates a relationship (Schoenbachler et al., 2002). Once they trust the organization, consumers are more likely to disclose information, because they know it will be used for a better service. Literature on privacy protection online has suggested that rewards may increase consumer's repurchase intentions, but individuals may consider giving their permission to collect and share personal information (PI) because of the expected reward from the loyalty program (Park et al., 2012).

Research focusing on US online shoppers has moved forward by studying the difference between the effect of loyalty versus commitment: commitment was found to have significant effects on sharing with advertisers and data brokers, while loyalty programs did not (Jai et al., 2013). These results show again that it is the involvement and the bond with the brand – the definition of commitment, which is linked to trust – that lead the consumer towards a disclosure behaviour rather than the expectation of a reward. Another line of research has analysed factors predicting the attitude toward disclosing personal data online. Anxiety, which arises from uncertainty and potential risk associated with expected consequences and negative outcomes of disclosure, has been identified as an antecedent of the willingness to share personal data (Robinson, 2018). It is interesting to look at anxiety as a negative emotional reaction to a situation or a stimulus (Gilbert et al., 2003) and compare it with its opposite, comfort, which is what creates the consumer's confidence in disclosure (Frye et al., 2010). Thus, individuals who perceive online transactions and communications as offering positive and convenient opportunities report less disclosure-related anxiety. Therefore, higher anxiety in disclosing personal data online and negative attitudes toward disclosure is associated with each other (Robinson, 2018).

2.3 Human touch in marketing

In addition to traditional levers, a fifth cannot be excluded from the 4P model of the marketing mix: People, which is the human component that represents an essential element for today's marketing world. Considering how digitization has changed the way to reach, understand and contact people, marketing has undergone many transformations and consumers have become more empowered in their interactions with brands (Hollebeek et al., 2014). On the consumer side, empowered individuals want to feel a sense of control: they do not blindly trust brand promises but seek information and no longer want to be treated as passive consumers, but as human beings who can actively make choices (Zimmerman et al., 1998). On the business side, companies need to consider transparent and authentic communication, taking into account new integrated technological developments (Fletcher et al., 2020). Artificial intelligence is gaining a lot of attention thanks to its increasing potential: it is reinventing existing products, creating new and more personalized experiences, interacting with customers, improving the understanding of the market and suggesting actions to be taken (Arsenijevic et al., 2019). These tools allow the optimization and automation of many processes with many benefits in terms of profit, but with the risk of losing the needed human touch to interact with the newly empowered consumer.

Instead, to talk to people, you have to think like people: especially in the online world, where the absence of face-to-face interactions decreases the degree of consumer trust, the human touch is what produces emotional reactions that generate engagement and make an experience memorable (Solnet et al., 2019). Because of the high uncertainty and anonymity of the contact, web communications need to be framed as connections to build confidence, intimacy and trust (Wang et al., 2005). Nowadays, the Internet and social media ensure that companies have access to an amount of data that was previously unimaginable and allow analysis and measurement to obtain useful information. Data means potential insights; automation means efficiency and speeding up of processes; technology means innovation. However, the human touch is what prompts the business to use methods of communication that create true intimacy (Solnet et al., 2019).

2.3.1 Social presence and anthropomorphism in online interactions

When it comes to online contexts, the absence of social proximity and face-to-face interactions make communications more impersonal, anonymous and automated (Hassanein et al., 2007). Thus, the shift from offline to online results in the lack of warmth and sociability due to a decreased presence of human and social elements which characterize offline experiences (Gefen et al., 2003). Social presence bridges this perceived distance in time and space and projects some level of closeness between participants (Cui et al., 2013). It has also been seen to depend on media information richness, according to which rich media enable people to interpret and achieve an agreement about unanalysable, difficult, and complex issues, while lean media are appropriate for communicating about routine activities (Suh, 1999). Social presence has been studied in depth up to the formulation of a theory which frames it as a quality inherent in a communication medium and the extent to which a medium allows users to experience others as being present (Fulk et al., 1987). The social presence theory defines social presence as a medium's capability to express the human sense through a mediated interface (Short et al., 1976): several pieces of research have studied how this effect can be achieved in different ways depending on the channel, the brand, the type and the number of social cues included. According to some studies, social presence concerns warmth and a psychological connection with the user, which means that consumers are able to perceive the mediated interaction as personal and the source of communication as sensitive and sociable (Yoo et al., 2001).

Other studies claim that social presence can help a medium to bring the virtual interaction closer to the face-to-face communication that qualifies offline shopping (Cyr et al., 2007) and this has a desirable consequence in online contexts. Indeed, since the two parties communicate or make a transaction in a different time and space, the lack of human warmth constitutes a barrier to trusting the other at least for some consumers: social elements give the sense that the brand is “right there” as a physical person and allow to overcome consumer barriers (Riegelsberger, 2002). In this way, computer-mediated communication not only creates a feeling of closeness but also shows the brand's willingness to empathize with the consumer (Osei-Frimpong et al., 2018). Biocca and Harms contribute to the definition and measurement of social presence by identifying three levels of presence: perceptual, subjective and intersubjective levels (Biocca et al., 2002). The first level refers to the co-presence of the embodied other, which is the awareness that mediated bodies like pictures, computer characters or robots are virtually co-present, even though they can quickly appear and disappear: this dimension explains how even parasocial interactions generate a social response in people's perception. The second level, the psycho-behavioural accessibility, is the perceived accessibility of the emotional, understanding and behavioural states of the other, which is the origin of the feeling of mediated social presence and reduced uncertainty in relationships (Planalp et al., 1985). At the third level, the mutual social presence, users think of the relationship as being mutual. Thus, it is perceived as an asymmetrical interaction in which the individual expects to receive a response to a stimulus and, at the same time, the interactants share a sense of social presence among each other.

In line with this literature, two dimensions have been associated with the concept of social presence: the notion of “intimacy” and the notion of “immediacy” (Short, et al., 1976). Intimacy is the result of functions like eye contact, smiling or proximity, while immediacy is the psychological distance between the communicator and the recipient: the second can be divided into technological immediacy – which is obtained through the transmission of a large amount of information in the shortest time – and social immediacy – which is conveyed through verbal and non-verbal cues (Walther, 1992). In computer-mediated communication, different features can be implemented to make users perceive intimacy and immediacy: emoticons, photographs or video clips are some of the elements to provide social presence perception and supply the missing non-verbal cues such as facial expressions, posture, tone of voice, silences in conversation (Basso et al., 2001). Judged as an evolving variable, social presence has been studied to be made up of three macro dimensions: social context, online communication and interactivity affect it in some way. For example, if privacy is missing in the communication context or if the task to be performed is complex, individuals are less likely to perceive a high degree of social presence (Tu, 2000). Therefore, being trained in using a medium is also crucial because it reduces communication anxiety and increases confidence. Expertise and familiarity have been found to have a positive relationship with social presence (Perse et al., 1992). Finally, interactivity is a substantial contributing dimension: there are plenty of definitions of this variable, but the most adequate in this case is the one that frames it as *the extent to which the communicator and the audience respond to or are willing to facilitate each other’s communication needs* (Ha, et al., 1998). According to this specific point of view, the aspect of mutual desire and mutual need is highlighted to facilitate interaction and allow dialogue in two-way communication. Interactive content generates the expectation of immediacy and reciprocity which, if not received, can have negative consequences on human-computer relationships and decrease the salience of the exchange (Tu, 2000). The key concept from which theories and studies on social presence develop can be seen in the idea that humans respond socially to technologies (Nass et al., 1995), which is also the starting point of CASA studies. This research investigates the “Computer are social actors” paradigm as an accurate picture of human-computer interactions by demonstrating that social patterns and dynamics guiding human-human connections can be equally applied well to human-computer interactions because they also are social and interpersonal (Nass et al., 1994). Politeness norms, gender stereotypes, personality responses, pleasantries and flattery effects have been identified as some examples of social cues that are able to stimulate the sense and imagination of interacting with other human beings (Fogg et al., 1997). The choice of language can increase the perceived psychological closeness and warmth of a web interface since natural and informal conversations evoke reactions of desirability and liking similar to those produced by humans (Nass et al., 1993). Furthermore, it is not pleasantness, but also usability and enjoyment that benefit from incremental levels of social presence because when the connection is warm and lived by the interactants as a sensory experience, then it is also perceived as being more useful and more enjoyable to engage in (Hassanein et al., 2007). In the case of a website, some respondents to research on e-service environments stated that they felt the context is more like a party chat room than a cold and distant website that just wanted to sell a product or a service (Cyr et al., 2007). It is important to underline that social presence is not a static variable, but a dynamic one: it can develop in levels, which is why some studies name several degrees of social presence (Tu, 2000; Perse et al., 1999). Therefore, it is evident that not only different media have different levels of perceived presence, but also that the same medium can increase or decrease its degree depending on the social cues it includes or removes. It follows that social presence can be trained and “inculturating” the source of communication increases opportunities for participation as well as encouraging the creation of a pleasant and fruitful relationship with the user (Tu, 2002).

One of the most important social cues has been indicated to be politeness, which is the social norm of using good manners and education that individuals use in expressing themselves when confronted with another individual (Lerman, 2006). By definition, expressing one's own politeness implies that the other part is able to understand and appreciate it, therefore the receiver is normally a human being with feelings and emotions. However, research has shown that people are polite to computers too and media that are close enough to humans – such as virtual assistants, for example – are more likely to encourage social responses and receive a human treatment (Reeves et al., 1996). The use of politeness expressions also serves to convey a sense of similarity and empathy, especially to identify complaints and deal with concerned or unsatisfied customers (Lerman, 2006).

This introduces the concept of anthropomorphism, which can be defined as the attribution of humanlike traits and the perception of these characteristics – such as physical appearance, emotional states or mental states and motivations – in either real or imagined nonhuman agents (Epley et al., 2008). Many users tend to anthropomorphize computers by treating them as social actors and research shows that they are also keener to be honest with a computer than with another person when it comes to delicate and sensitive topics. These results are even more interesting if we consider that the experiment was conducted on computers not equipped with artificial intelligence, so with few human-like characteristics capable of making them perceive as anthropomorphic (Reeves et al., 1996). Subsequent studies have dug into the link between the degree of anthropomorphism and social responses, pointing out a linear positive relationship between the two variables: the more computer representations are perceived as similar to human beings, the more people elicit social behaviour and apply social rules to their computer-mediated interactions (Nass et al., 2000). In addition to the evidence of an improvement in social judgments and perception of similarity, the hypothesis that high levels of anthropomorphism exert a great social influence and cause the medium to be perceived as more competent and trustworthy has also been confirmed (Gong et al., 2008). Therefore, precisely because users address social responses to computers and anthropomorphize them, it is important to design media with social and anthropomorphic traits: indeed, the violation of a social norm or a robotic behaviour can cause the medium to be seen not only as incompetent but also as offensive (Reeves et al., 1996). The absence of these attributes triggers the perception of "being teased" and the idea that the brand using the medium does not put enough effort in communicating and approaching the user (Osei-Frimpong et al., 2018): distrust and frustration could easily be the result.

To create effective results, it is useful to take into account the determinants of anthropomorphism, the reasons why people feel the need to impart human personality traits to technology. The three-determinant model – called SEEK model by Epley – explains when, how and why people are more likely to assign a personality to computerized agents: the key factors are sociality, effectance and elicited agent knowledge (Epley et al., 2007). Among the cognitive factors, the latter is the most predictive: it involves the knowledge about human beings in general, which could be used as a base when dealing with non-human agents. The subsequent application of this knowledge is likely to influence the tendency to anthropomorphize. Then, effectance describes the motivation to interact with nonhuman agents and it reduces the associated uncertainty by increasing confidence in predictions of agents' future actions. Finally, sociality in anthropomorphism refers to the desire to establish social interactions by enabling a human-like connection with non-human agents, a need that increases especially when other humans are not present. This three-element model illustrates the reasons for users to assign personalities to technological tools: evidence in line with the extensive literature gives proof of the importance of human touch in online interactions.

2.3.2 Virtual re-embedding for trust

One of the main characteristics of online environments and one of the most evident to its users is the separation of time and space, which is called virtual dis-embedding. In his book "The consequences of modernity", Giddens refers to it as a lifting of social relations from physical contexts of interaction and their restructuring through indefinite time-space intervals (Giddens, 1990). The consequence of this disjunction is the absence of social cues and the decrease in consumer trust due to the lack of social presence. Although this time-space dissociation can be viewed as an annihilation of the traditional dimensions of communication, it is able to create a sense of simultaneity and to promote a sense of co-presence, given the co-existence of people in a virtual space. This is the so-called Internet time, a condition that can coordinate highly dispersed activities in a new form of participation, which can be identified as the McLuhan village (Slater, 2002). Thus, on the one hand, dis-embedding is linked to empowerment: not being confined to one place and time, the consumer can connect with anyone and potentially be anyone. On the other hand, though, the greater complexity and variability make dis-embedded interactions riskier due to the space-time distance and to the effect of technology (Riegelsberger et al., 2003).

To overcome these potential negative repercussions, the practice of re-embedding allows a brand to reintroduce face-to-face interactions into distant interactions and, in this way, build trust. If the goal is to increase online trust in a virtual environment, then we refer to virtual re-embedding, which consists of incorporating social cues – photographs, videos, text, voice – in online design. There are two approaches to the phenomenon, transparency and anthropomorphism, but the second one is the most thoroughly explored: it indicates the use of human-like representations as cues to be included in the web interface to function as a signifier of usability and trust (Steinbrück et al., 2002). The insertion of a photograph (a consumer or an employee) is a simple positively evaluated technique to make a site perceived as more reliable. More interactive cues, such as a chat or a call back opportunity, amplify media richness and provide real-time responses that increase attention and engagement. Therefore, the virtual re-embedding strategy is not to count among the trustbusters, which are factors that could be a risk to consumer trust if the brand does not take care of them. For example, usability, response time and technological features may damage the brand and make it less trustworthy. In contrast, re-embedding is a trust builder because it counteracts the risk of losing trust and, instead, helps to increase it. In addition to this approach, cues of social presence and the brand reputation emerge as the most relevant among these second elements (Riegelsberger et al., 2003).

2.3.3 Artificial Intelligence and conversational marketing

Talking about artificial intelligence means opening a chapter of enormous potential and possibilities, and above all, it means talking about the future. The areas that take advantage of it range from healthcare to human resources, from robotics to e-commerce, and there are several AI application solutions implemented in the marketing field (Khokhar et al., 2019). Due to this variety and multiplicity of areas, there are many ways in which artificial intelligence could be defined: here a broad definition of Poole and Mackworth who define AI as *"the field that studies the synthesis and analysis of computational agents that act intelligently"* (Poole, et al., 2010). The interesting part of this sentence is the use of the word "intelligent" referring to technology: a machine is intelligent when it is able to formulate a thought (Wirth, 2018). This brings us back to the mid-twentieth century question "Can machines think?" posed by the mathematician Alan Turing and its test to verify the degree of intelligence of a machine based on its ability to be indistinguishable from a human being (Turing, 1950). Turing asked whether machine's algorithms are capable of producing a convincing display of cognitive behaviour by emphasizing the possibility of software being trained to reproduce human skills (Fazi, 2019). With technological evolution, developments in artificial intelligence create software capable of learning, building predictive models and imitating human intelligence in the execution of tasks such as speech and image recognition, decision making and recommendations (Khokhar, et al., 2019). It is clear that this is the case where most of all a computer aspires to resemble a human being and so human-computer interactions are similar to human-human interactions. The software gets close to the human brain thanks to machine learning and natural language processing technologies, which make it possible to advance the intellectual capacity of AI.

Machine learning allows knowledge acquisition starting from available processed data, to generalize results and draw conclusions thanks to the performed analyses (Hair, et al., 2021). It requires a large amount of data, the Big Data, and a huge processing power that makes it the best approach to the development of human-level AI (Lee et al., 2018). Natural language processing (NLP) is a range of computational techniques for analyzing and representing naturally oral or written texts to achieve human-like language understanding (Liddy, 2001). It includes functions of recognizing and producing normal human conversational behaviours and facilitates computer-mediated communication because natural language represents a natural interface when interacting with a machine (Hirschberg et al., 2015).

Listening, personalization and dialogue are the keys to a long-term relationship with customers and these needs find application in conversational AI, the technology that recognizes speech or text inputs and enables the user to talk to it (Miner et al., 2019). Humans use conversation to build trust through a gradual mutual exchange of knowledge and thus the achievement of intimacy and confidence: this reciprocity can reduce the perceived uncertainty and the suspicion towards the other (Bickmore et al., 2005). Kevin Lund refers to the conversation as the king of content marketing, specifying that, if the content is the *what*, the conversation is the *how:* it humanizes the brand, it adds a personal touch and offers personalized solutions to suit their needs (Lund, 2018). By using a person-centred approach, conversational AI can increase users' perception of technology, which is the degree to which a user feels technology is human-like versus machine-like. This perception depends on three dimensions: social presence – the concept that I have previously addressed – social affordances, and affordances for sociality (Lankton et al., 2015). Social presence is what makes technology seem more human-like and the ability to convey social cues, such as the smiling voice of conversational AI (Torre et al., 2020). Social affordances are the possibilities for action a technology offers to a user via its social nature: for example, a website with human images and facial features that can display human emotion and enable the conversation action potential is possible thanks to the Natural Language Processing technology (Torre et al., 2020). Affordances for sociality are the possibilities for action a technology offers to a user by enabling him to interact with others: some examples are synchronous chats to call friends and meta-voicing, which gives users the opportunity to engage in online conversations by reacting to others' content or activities such as re-tweets (Majchrzak et al., 2013). Thus, the greater the perceived humanness of technology, the greater the exhibition of human-like behaviours and the ability to engage in conversation and debate (Natsoulas, 2004).

Why is conversation so important to marketing? Starting from the analysis of human conversation, two main purposes can be identified: the transactional purpose (task-based) and the social purpose (interaction-based). In the first case, a practical goal is pursued, which may consist of solving a problem, answering a question, completing an operation; in the second case, the goal is to build a relationship, maintain and cultivate it (Eggins et al., 2005). It is evident that in practice the two purposes often occur jointly and overlap. Focusing on the second, it is important to specify that the desire to get in touch with the other is inherent in the human being and the willingness to socialize leads him to try to get to know people: talking and having a conversation is the biggest part of knowing people. Therefore, establishing a dialogue with a brand means wanting to deepen its knowledge and better understand what are the basic values that guide its actions. However, the research findings show that agent-based conversations have been described as being more functional, so the identified purpose is transactional rather than social: it happens because establishing an emotional connection with a machine and emulating a human interaction has been judged to be complicated (Clark et al., 2019). Nevertheless, users have more confidence in an agent when the way of expression is natural and small talk is used. It means language is free, a light conversation is carried out and opinions are shared, which occurs when people are relaxed and comfortable (Bickmore et al., 2005). The goal of this kind of chatting is mainly to build a relationship and trust between the parties as well as to establish a style of interaction – social, linguistic, and psychological conventions – that can make the conversation as natural as face-to-face dialogues with another people (Bickmore et al., 1999). Based on this evidence, it can be stated that conversational marketing applies to multiple aims: it is effective for performance objectives to increase leads and sales, but also to improve the overall browsing experience and listen to customers and prospects.

2.3.4 Chatbot humanization

Conversational AI is making great strides by proposing new developments to improve the customer's user experience. In many industries, it is even changing business processes by proposing an approach that makes the most of humans and machines: for example, chatbots have taken over many call centre operations, which are traditionally the most time-consuming and labour-intensive activities, but also the most routine-based (Campbell, 2020). They make these actions faster, simpler, more automated and leave human operators with more complex tasks that require their intervention.

What are these chatbots? A chatbot is a system that uses artificial intelligence to establish an automated and structured dialogue with users. It is a software program that mimics human conversation to converse with people via text or voice (Shawar et al., 2007). Depending on its multiple uses, a chatbot can come in different forms and, according to Phillips, three classifications of virtual assistants can be distinguished: Menu/Bottom-based chatbots, Keyword Recognition-Based Chatbots and Contextual Chatbots (Phillips, 2018). The first type is the most basic one consisting of a logic-based structure presented in the form of buttons that users can click to select the option answering their query. This function allows quick reply to help users recognize which of the alternatives his request corresponds to and facilitates the online journey by proposing pre-set questions. However, it is simplistic when it happens that the buttons are not enough to enclose all the possible queries of the user who, not finding what he is looking for, can be frustrated or disappointed (Phillips, 2018). If, on the other hand, users have the opportunity to give their inputs by writing their own words, then the right type of virtual agent is the Keyword Recognition-Based chatbot: it is able to recognize and process words to match them with the answers it can provide. The advantage is freedom of typing and the recognition of a wider spectrum of questions; the disadvantage is that, if the text is too complex, the chatbot fails to identify the keywords and cannot respond adequately. Here comes the third type, a chatbot that learns about customer behaviours thanks to AI and analyses the meaning of the set of words to return a contextual response thanks to the NLP: it is advanced enough to offer a range of functionalities associated with engagement and interactivity (Thompson, 2018).

On the business side, even in its basic version, the chatbot offers benefits to companies in terms of engagement, 24/7 availability and cost efficiency, allowing a personalized digital experience and offering as much two-way communication as possible (Artemova, 2018). On the consumer side, however, the chatbot as a non-human digital assistant is not claimed to be the preferred choice since facts also suggest that, when talking to an AV, people explicitly request the intervention of a human operator. Some empirical results show that consumers prefer a conversation with a real human being over a traditional chatbot and this rationale holds for both the satisfaction as for the comfort of the conversational partner's perceived humanness (Hendriks, 2019). To be able to match the needs of companies and consumers, the importance of humanized chatbots emerges: indeed, anthropomorphism plays a central role in chatbot perception because it makes people feel more connected and more engaged, it generates interactions and influences consumers' decision-making behaviours (Aggarwal et al., 2012). People's anthropomorphic attitude is linked to the tendency to like and trust computers that seem to understand users' requests because the more the conversation appears to be adherent to the rules of social conduct, the more consumers judge the chatbot as reliable in terms of technical competence and consistency (Mercieca, 2019). Therefore, making a chatbot more human-like encourages greater emotional comprehension that can increase the perception of being heard and understood.

The first step towards humanization is building a chatbot personality. Indeed, when starting a conversation with a declared virtual assistant, consumers consider a chatbot as having a distinctive personality and factors such as politeness, response time and conversational ability affect their perceptions (Saarem, 2016). Polite and kind agents offer a more positive interaction experience compared to machine-like and impolite ones even though customers are aware that they are conversing with a virtual agent (Inbar, et al., 2015). Friendliness of virtual agents, in fact, evokes sensitive human contact due to the perception of receiving extra attention during the service encounter: using an informal and courteous language can increase the feeling of social presence and anthropomorphism that, in turn, contribute to establishing a chatbot personality (Verhagen et al., 2014). All relationships are influenced by the judgments of others and personality has a huge impact on users' willingness to interact with someone. This crucial variable in designing a VA is the combination of behaviours, motivations, characteristics, qualities that forms a character: Smestad identifies some key components on which a chatbot personality should be based. First, the virtual agent must be aligned with the macro goals, the values, the mission that the brand pursues through an appropriate tone of voice. The words, the pace, the silences, the vocabulary must be consistent with what the brand represents and coherent across all the touchpoints managed by the bot, from the telephone to the digital channel (Smestad, 2018). Customizing the tone of the conversation according to the client's mood and the way of expressing could enrich the experience and be a precondition for making the client feel comfortable (Valtolina, 2018). Second, qualitative and quantitative research can help identify the needs of the brand's target audience to understand trends, desires and expectations: today, for example, privacy and protection of personal information are priorities for digital users, so demonstrating data security meets this need by reassuring customers (Følstad et al., 2018). Finally, the chatbot role must be reflected in the assistant's personality traits and in the way it handles its tasks. If it has to do the job of assisting clients in customer care, its identity will be more reassuring and comforting; while if its role consists of being a shopping assistant or a sales agent, then its identity will be motivating and convincing to guide towards the choice or experience of a product/service (Sands et al., 2021). These elements contribute to the creation of a model of the VA personality that the designers will benefit from and give rise to a chatbot figure in line with the positioning of the brand and the purpose.

Based on these assumptions, the most appropriate traits of appearance and character must be also selected to make it as human as necessary: therefore, the level of humanness must be evaluated. Humanness relates to non-human agents behaviour and focuses on human capabilities and physical characteristics of the conversational partner; instead, anthropomorphism is the attribution of human characteristics to something which is inherently non-human – an animal, an object, a machine (Hendriks, 2019). How and how much humanizing depends on many factors, including the purpose: a research shows that digital assistants who helps in managing appointments should have a more informal and simple language than the formality and professionalism required to shopping assistants (Saarem, 2016).

2.3.4.1 Visual cues

The perception of humanness is also determined by the chatbot appearance because the interaction is more likely to be perceived as natural if a chatbot appears to have human-like traits. Visual cues are the first to create a feeling of social presence because appearance has the power to curb mistrust towards computer-mediated interactions by eliciting social manners that normally happen among humans (Zamora, 2017). The avatar is the main visual influence when approaching the chatbot: using an avatar over no representation of has been found to increase the naturalness of the conversation and create an experience of emotional closeness (Bente et al., 2008). Many kinds of research have investigated this aspect by proposing different stimuli to the sample with the aim of finding the most effective one concerning needs, desires and expectations of the target audience: stereotypes, for example, are a factor to take into account when designing a chatbot avatar. Brahnam and Weaver showed that female VAs often fill the roles of shopping assistants and service providers, while male VAs are often used as doctors and technology experts. This role allocation reflects the expectation of the roles that men or women would usually play in real interactions (Brahnam et al., 2015).

A research on the anthropomorphization level of the avatar showed respondents three conditions of chatbot appearance: a logo, an animated human and a human picture to study the change in trust, satisfaction and purchase intention as the stimulus changes. Results confirm the preference for the human picture and show that, although companies tend to use the organizational logo – usually to affirm brand awareness and recognition – a human picture leads to greater satisfaction and better user experience (Assink, 2019). A chatbot with a human appearance was seen to have positive effects on purchase intention online compared to a chatbot with an animated appearance: this effect was also seen to be mediated by social presence (Schurink, 2018).

2.3.4.2 Linguistic cues

Compared to a conversation with a human interlocutor, the human-chatbot exchange is characterized by shorter and faster messages, which take place in the mode of clicking a button in the menu-based chatbot and in the mode of words written by the user in a keyword recognition-based chatbot. The biggest difference between VA conversations from face-to-face conversations is the lack of vocabulary richness and complexity, which many current chatbots don't allow (Assink, 2019). On his side, the user tends to use the same human language even in a computer-mediated speech, as he needs to have the most natural and smooth experience possible: thus, creating a good natural language will result in a better perception of the interaction (Garcia, 2018). Indeed, if building trust is a long process, it takes a moment to generate mistrust and dissatisfaction. When the conversational agent does not respond properly or misunderstanding occurs, allowing people to write anything increases these risks: the user shows disappointment and gets annoyed by talking to a virtual agent rather than to a person (Saarem, 2016). To avoid these errors, it is necessary to train the software, but it is also useful to include cues that make it perceive less like a machine.

Humour, for example, is a relevant and complex part of social verbal interactions and introducing it into the chatbot language is beneficial in alleviating boredom and boosting engagement, although it requires more advanced training (Smestad, 2018). Humorous expressions are distinguished by recognition techniques that can listen to jokes, try to understand the sentence and respond with humour using emoji or a pattern of indifference, anger or approval responses depending on the type of humour identified. An experimental study on a humorous bot, for example, used smiley emoji if it recognizes a funny phrase (Augello et al., 2011).

2.3.4.3 Vocal cues

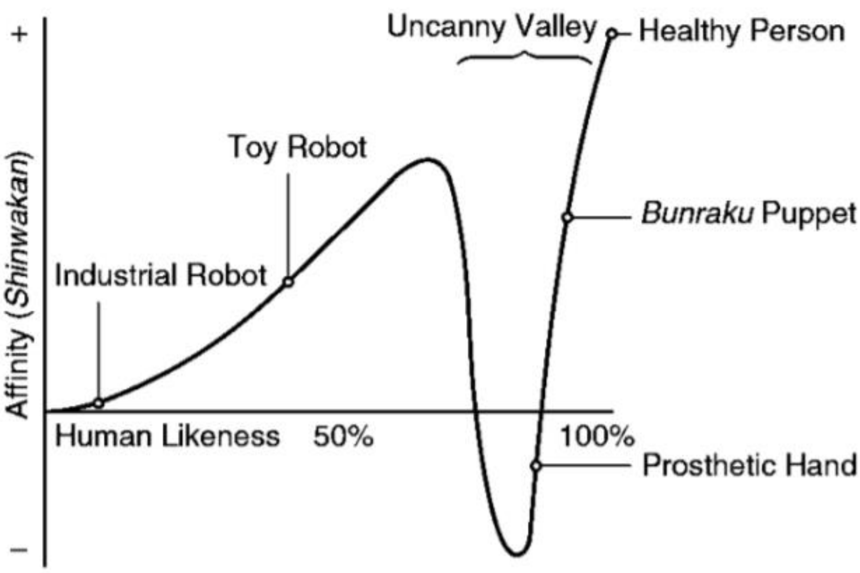
Voice is emerging as a new digital interface for communicating and people increasingly tend to speak more and type less. Apple’s Siri, Microsoft’s Cortana, Amazon’s Alexa and Google Home are the most known voice assistants that run on speaker devices or smartphone and can perform many tasks including answering queries, setting reminders or making lists, calling or sending messages, connecting to other devices to play music (Hoy, 2018). The development of these assistants is the ability to provide personalized advertising in line with the users’ tastes and preferences: here is the growing interest of many brands in the voice experience (Loiacono, 2019). Voice interaction with conversational agents is a relatively new field of research because, even in its application, voice recognition technology is improving its accuracy and providing new developments. Voice-activated chatbots interacting through voice are able to accept a command in an oral or written form and answer by a vocal reply.

Since the language style is essential, the most highlighted capabilities are the tone of voice, the cadence, the pace and gender: research shows that a soft and smooth female voice – as well as a name – is the one that most gives a feeling of being trustworthy (Sotolongo, 2018). Recent findings reveal the persuasiveness of voice-enabled chatbots by stressing the effectiveness of the social role of a friend with an informal language style compared to the formal language of a secretary-type agent. The first one has been found to have higher possibilities to build a positive attitude towards the brand and the product (Rhee et al., 2020).

2.3.5 The uncanny valley effect

On the basis of previous research, it emerges that chatbot humanization has positive effects in terms of satisfaction, pleasantness, purchase intention, engagement. However, it is necessary to take into consideration to what extent humanizing chatbots continues to produce successful results and what is the threshold beyond which the so-called uncanny valley effect occurs. The more a chatbot is perceived as human, the greater the acceptance and the more pleasant the interaction; however, when the robot becomes too human, a sudden change in terms of familiarity and social interaction takes place and the user experiences the conversation as being unpleasant (Skjuve, et al., 2019). The uncanny valley effect was introduced by Mori's theory, which describes it as the feeling of discomfort arising when a robot is human to such a high degree that the user perceives it as disturbing and upsetting (Mori, 1970). At this level, a negative emotional reaction of discomfort occurs, leading to the rejection of the humanoid robot since it becomes complex to classify the robot within a category: it is not perceived as a real human, but it is so humanized that it is no longer seen as a robot. This phenomenon can be also applied to digital assistants (Wagner et al., 2019).

Fig. 2.1 *– Uncanny valley effect*



Source: IEE Spectrum

Politeness and sociability as well as the chatbot's ability to respond with human-like words may provoke negative reactions: the use of too many emojis has also been found to result in user rejection (Thies et al., 2017). Human-like cues, such as a human photo or too many emojis, can trigger an uncanny effect because they could make the bot be perceived as "weird". Similarly, research has shown a more positive reaction towards a text-based chatbot than an avatar chatbot since the latter was seen as an unsuccessful attempt to imitate a human being (Ciechanowskia et al., 2018). This effect highlights the caution in the humanization of virtual agents and the urge to avoid pretending them to appear too human.

2.4 Theoretical model and hypothesis

2.4.1 Literature gap and research question

In light of the current literature review, this research aims to make a contribution to studies on conversational virtual assistants with a focus on the role of trust in human-digital agent interactions. In particular, the ultimate objective is to understand whether humanizing virtual agents affects consumer trust, i.e. if a more humanized chatbot can make the user have confidence in the brand he is interacting within computer-mediated communication. Existing literature has investigated antecedents and components of trust by framing it as a shortcut capable of reducing perceived risk and decreasing scepticism, which is one of the strongest barriers people have when engaging in brand relationships (Wang et al., 2005). A positive effect of brand trust on consumers' willingness to disclose personal information online has been demonstrated: indeed, a high level of trust results in greater comfort with disclosure because users report less anxiety (Robinson, 2018) as well as more confidence that their data will be used to their advantage and for better service (Frye et al., 2010).

Past research has explored how the absence of face-to-face interactions and the decreased presence of human elements characterizing the online environment makes the communication more impersonal and automated, causing a lack of warmth and sociability and resulting in a reduction of consumer trust (Hassanein et al., 2007). The human touch has been identified as a factor that can prompt companies to create true intimacy by generating positive emotional reactions (Solnet et al., 2019) and recent findings have indicated the importance of including social cues to create a feeling of closeness and true connection in web-mediated communications (Osei-Frimpong et al., 2018). Conversational marketing powered by artificial intelligence offers personalized interactions through chatbots, virtual assistants able to create a dialogue with the user and thus to increase the perception of being heard and understood (Lund, 2018; Artemova, 2018). Several authors have highlighted the effectiveness of including human-like visual, linguistic and vocal traits in chatbots to define the exact level of humanness (Hendriks, 2019; Assink, 2019; Smestad, 2018; Sotolongo, 2018) that can boost trust in these agents and in the brand they represent, but in a way that avoids the uncanny valley effect (Ciechanowskia et al., 2018).

Moreover, previous literature has found out that individuals are more likely to reveal information about themselves when they feel they have a relationship with the brand rather than if they only have occasional exchanges: feeling treated only as users to be profiled has been studied to be a reason for avoidance in revealing personal data (Schoenbachler et al., 2002). Therefore, results of studies on chatbots and artificial intelligence have revealed the importance of inserting anthropomorphic traits in these assistants to increase trust; another line of studies has given evidence of the beneficial effects of trust on the propensity to release information in online communications.

However, some gaps in existing research can be identified. First, much literature is localized – it studies these effects in restricted geographic contexts or on a selected sample – or focuses only on analyzing one social cue at a time, such as photos, humorous language or emojis. Second, there are no studies that investigate the direct effect of a humanized chatbot compared to a more robotic one on the users' willingness to provide their e-mail or mobile number within a chat. Third, trust has never been used as a mediating variable explaining the relationship between humanized chatbots and willingness to disclose personal information online. It might be interesting to study the difference in trust effects of two levels of chatbot humanization, from a more robotic type to a more human type. Therefore, this research project aims at bridging these gaps in the literature by answering the following two research questions: *How a humanized chatbot (vs a more robotic chatbot) influences consumers' willingness to disclose personal information online?* and *Does trust mediate this effect?*

2.4.2 Framework and hypothesis

Overall, this thesis seeks to demonstrate a direct effect of a humanized chatbot on the willingness to release personal information in technology-mediated communications. In particular, it is assumed that an anthropomorphized chatbot at such a level as to avoid the occurrence of the uncanny valley effect has positive effects on a user's propensity to give even sensitive data – like a phone number – during a conversation with a virtual agent. The level I am referring to is a virtual assistant featuring an animated avatar and natural language that makes the interaction fluid and smooth compared to one with a more robotic language, standard responses and distant attitude or one with an interactive mode, abundant use of emojis and a human image.

H1: *A humanized chatbot (vs a robotic chatbot) positively influences consumers' willingness to disclose personal information online.*

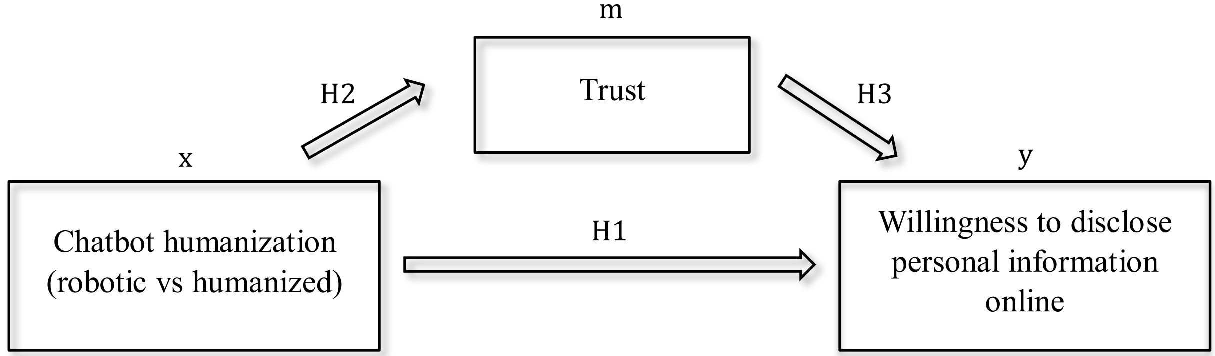
Moreover, I hypothesize that chatbot humanization increases the user's trust in the virtual agent, which represents the voice of the brand in the conversation. I suggest that including elements that improve the language to make it similar to human chats can reduce the scepticism towards the robot and the perception of risk that leads to distrust. Thus, trust is the mediating variable which explains the relationship between the independent and the dependent variable.

H2: *A humanized chatbot positively influences trust.*

Finally, I hypothesize that trust leads the consumer to have greater comfort with disclosure and increased confidence in releasing personal and sensitive information.

H3: *Trust positively influences consumers' willingness to disclose personal information online.*

***Fig. 2.2** – Conceptual model*



Source: Author's elaboration, 2021

CHAPTER 3

EMPIRICAL RESEARCH: STUDY, RESULTS AND CONTRIBUTION

3.1 Method

The theorized conceptual framework was used to test what was stated in the hypotheses: it consisted of a within-subject factorial design with an independent variable manipulated on two levels (x = humanized chatbot vs robotic chatbot), a measured mediator (m = trust) and a measured dependent variable (y = willingness to disclose personal information online) (*Figure 2.2*). The theoretical model proposed a *main effect* between the independent variable (x) and the dependent variable (y) and a *mediating effect* of the mediator (m) which explains the relationship between x and y. Since the following study is a conclusive causal research, the effects of the relationships explained in the hypotheses were tested through an experimental study carried out through an online questionnaire generated with Qualtrics software.

3.1.1 Pre-test

In order to verify the correct manipulation of the independent variable (humanized chatbot vs robotic chatbot) a pre-test was performed to experiment whether respondents actually perceived the two different stimuli as more humanized and more robotic. The short online survey supported by Qualtrics.com. was proposed to a sample of 60 subjects extracted through a non-probabilistic convenience sampling for reasons of accessibility and proximity. The survey consisted of two slightly different scenarios compared to those used in the main study because the intent of this short initial test was only to measure the perceived humanization of a written conversation with a virtual agent. In this pre-test, indeed, two images were compared, while in the main survey the sample had the opportunity to live an experience with a virtual agent specifically created for this research. In particular, the images showed an example of a possible conversation with a chatbot for digital channels that simulated Elena, the virtual assistant of the Italian energy company Enel Energia. In both conditions, only the chatbot humanization varied, with the same communication methods, length, buttons and type of request managed: the first image represented a functional, more artificial and machine-like chatbot; the second image represented a friendly, empathetic and human-like chatbot. On the one hand, a more artificial language, articulate and cold sentences were used; on the other hand, a natural language, simple sentences, emojis and an animated avatar were employed.

The different images were randomly assigned to the survey respondents so that each of the two groups was presented with only one stimulus: 30 participants saw condition 1 (as is chatbot), while other 30 participants saw condition 2 (humanized chatbot). Once the image was shown, they were asked to answer various questions. To evaluate the perception of humanization, a pre-validated scale adapted from Westerman, Cross & Lindmark (2019) consisting of four differential semantic items with a five-point response set was used.

Respondents had to indicate how they perceived the conversation in the image based on the bipolar ends ranging from 1 = Machine-like/Fake/Artificial/Unconscious (Simile a una macchina/Finto/Artificiale/Impreparato) to 5 = Human-like/Natural/Lifelike/Conscious (Simile a un uomo/Verosimile/Realistico/Preparato). In addition, participants were asked to indicate how well four adjectives "likeable, sociable, friendly and personal" (simpatico, socievole, amichevole, empatico) described the conversation they had previously seen on a seven-point Likert scale adapted from Araujo (2018) ranging from "Describes very poorly" (Molto male) (=1) to "Describes very well" (Molto bene) (=7). The answers have been coded so that higher values indicate an adjective that can be associated with the previous dialogue, while lower values indicate an adjective that does not describe the dialogue in the image.

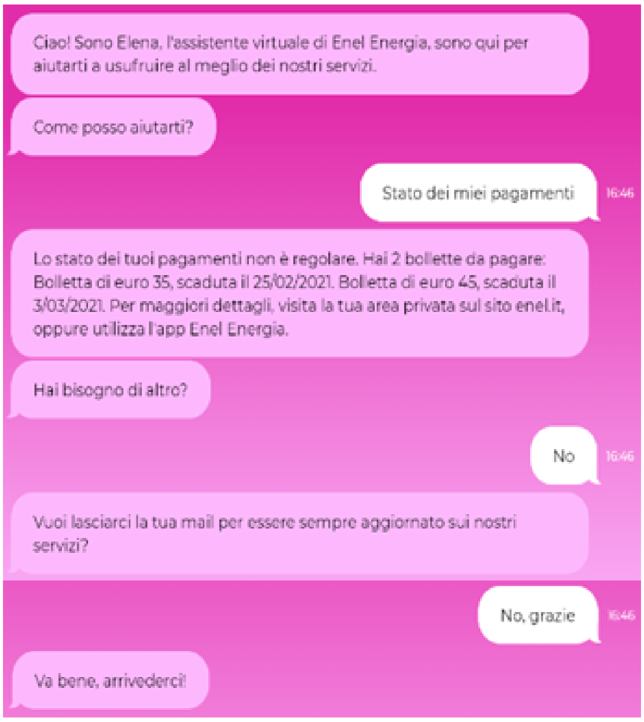
The factor analysis showed the correlation of the items and led to the creation of two factors to measure "humanization" and "anthropomorphism". However, when checking the reliability of the humanization scale, it emerged that the Cronbach Alpha was higher if the item "Unconscious/Conscious" (Impreparato/Preparato) was eliminated; thus, only three items were considered in this scale. Independent sample t-test, conducted to check if there is a difference between the two groups of respondents in terms of humanization, showed that the mean humanization for stimulus1 and stimulus2 do not statistically differ ($M_{stimulus1} = 3.45$; $M_{stimulus2} = 3.55$). For the variable measuring anthropomorphism, the independent sample t-test showed that there was a statistically significant difference between the mean for stimulus1 ($M_{stimulus1} = 5.82$) and the mean for stimulus2 ($M_{stimulus2} = 7.13$). From these analyses (see *Pre-test output* in *Appendix B*), it could be certified that the manipulation performed was satisfactory in relation to perceived anthropomorphism, while the images of the stimulus were not sufficiently different to make respondents perceive the different humanization of the two versions of the virtual assistant.

3.1.2 Scenarios and manipulation of conditions

The main experiment aimed at directly assessing the influence of a humanized versus robotic chatbot on the users' willingness to disclose personal information online as well as the mediating effect of trust. To measure these variables and verify the effects, two different stimuli were constructed. Unlike the pre-test, in the main study the manipulation consisted of two conditions corresponding to two simulations of a virtual agent inspired by the virtual assistant of Enel Energia. The two versions were with Landbot, a codeless conversational interface builder which was used to create button-based chatbots to make the respondent live an experience as close as possible to a real one. This research, indeed, aimed to measure the effects explained in the hypotheses not on a passive sample, who looks at a conversation with a virtual agent that has already taken place, but on a sample that actively carries out the experience first-hand and then expresses opinions about it. Two images depicting the two different versions of the chatbot, representing two examples of a possible conversation with the virtual assistant, are shown below (*Figure 3.1*). In both versions the virtual assistant was designed to respond to exactly the same request, which is the status of payments and bills, to control for the variable "type of request" and prevent it from affecting the user's perception of the bot. Furthermore, in both cases the agent had a clear and well defined personality, it was named Elena and appeared to be professional, polite and reliable; the disclosure dilemma was solved in the same way because both chatbots revealed their identity by making people aware they were not dealing with an operator but they were assisted by a technology. However, there were clear differences between the two types of Elena.

***Fig. 3.1** - Conditions*

AS IS chatbot



HUMANIZED chatbot

Source: Author's elaboration, 2021

The first scenario consisted of a more robotic chatbot with a cold and formal communication, which aimed to resemble the AS IS version of Enel Energia as closely as possible. There was no visual representation with neither a logo nor an avatar and this lack of visual appearance was accompanied by an absence of other visual cues such as emojis or GIFs. The language did not express a personal touch and did not show empathy because it was in line with a goal of improving the performance of the corporate brand by offering information quickly and notifying the user about what he had asked for. The impersonal approach was also evident in the no attempt to get closer to customers, for example not asking for their first name or for confirmation of the correctness of the answer provided. It proceeded immediately with the next question by asking if the respondent needed anything else, assuming that the previous request had been satisfied. Finally, in the last junction of the flow, the customer was asked for his e-mail, but no information was given on the personal data protection policy.

The second scenario consisted of a more humanized chatbot characterized by a warm and informal communication to connect with users on an emotional level while maintaining the primary goal of keeping them informed and getting their questions answered. To increase the perceived level of anthropomorphism, in this case Elena was graphically represented as a female avatar dressed in pink with short brown hair. This humanness was consistent with the use of emojis that had been integrated in the answers to create a friendly relationship with customers. Replies made use of human-like expressions, forms of greeting were acquired by human-human conversations and formal idioms were replaced with warmer equivalent words. In the second junction of the flow, the user was asked for his first name, which was repeated in the following junctions to get familiar with the respondent and let him feel comfortable to chat; in addition, Elena asked for everything to be clear before going on to converse. In this second condition the e-mail request was incorporated with a privacy note stressing that personal data would not be misused or disclosed. This detail was added to reassure those who were thinking about leaving their contact or not and give them a valid reason to trust the virtual agent.

Both conditions were presented to all participants in the experimental study because a within-subject factorial design was adopted. The main reason for this choice lies in the willingness to reduce errors associated with individual differences that could distort the results and impact the experiment's validity. Indeed, individuals bring into the test their own history and, especially in the case of technological skills, their background knowledge of chatbots could influence the responses leading to different perceptions depending on whether a person is more or less expert on the subject. Instead, if participants interact with both levels of the stimulus, they will affect them in the same way. Furthermore, this design required fewer participants to get statistically significant results because the same respondents were exploited twice and provided data for both conditions. These advantages had been valued greater than the benefits of a between-subject factorial design since, in this case, effects of individual differences were more important to control than learning effects that the between-subject design can prevent. It was taken into consideration that participants' speed and expertise could change in the second experience due to the previous treatment, but this risk was valued not to influence the research variables.

3.1.3 Survey design and measures

The main study survey, aiming at measuring the effect of the two scenarios on the same group of respondents, consisted of a personal and socio-demographic section to outline the interviewees' profile, an introductory section to assess some characteristics of the sample, questions on the mediator and questions on the dependent variable. The first section included a presentation of the research providing a brief explanation of the chatbots and explaining that the data collected in the study would remain anonymous. Before showing the first stimulus, respondents were asked to answer socio-demographic questions about age, gender, education, and occupation as well as personal questions about previous knowledge and interaction with a chatbot. In addition, a seven-point Likert scale adapted from Hong, Chan and Thong (2021) ranging from "1" meaning "strongly disagree" (completamente in disaccordo) to "7" meaning "strongly agree" (completamente d'accordo) was employed to measure the general individual's concern about a possible loss of privacy due to the disclosure of information on the web. Then few lines explained that participants would see two stimuli; they were asked to pay attention to both and interact with the virtual assistant by behaving as if it was a real conversation.

Thus, the first scenario was presented, followed by questions on the perception of anthropomorphism and the perception of competence assessed through the use of a seven-point Likert scale adapted from Han (2021) and a seven-point Likert scale adapted from Roy and Naidoo (2021), both ranging from "1" meaning "strongly disagree" to "7" meaning "strongly agree" and consisting of three items each. Two five-point Likert scales adapted from Li and Yeh (2010) and Gulati, Sousa and Lamas (2018) ranging from "1" meaning "strongly disagree" to "5" meaning "strongly agree" were used to measure trust, which is the mediating variable. The two measurement scales, consisting of three items each, were merged since they measured the same construct. Willingness to disclose personal information online was measured through a seven-point Likert scale adapted from Robinson (2018) ranging from "1" meaning "strongly disagree" to "7" meaning "strongly agree". The seven items making up this scale measured anxiety in releasing data on the Internet and concern that sensitive and personal information would be requested by the chatbot. With regard to this construct, an open question was also included to understand, in cases where the respondent would have preferred not to give his e-mail in the conversation, what was the reason for this preference. As it refered only to some cases, this is the only unforced question of the survey.

The second scenario was presented and, before proceeding with the exact same blocks of questions used for the first stimulus, two more questions were asked. The first was a dichotomous question "yes/no" (sì/no) asking the user if he had perceived any difference between the experiences with the two scenarios. The second required respondents to indicate to which of the conversational experiences they had lived, "Experience1/Experience2/Both" (Esperienza1/Esperienza2/Entrambe), they associated the features of empathy, natural and friendly language, use of emojis. The survey ended once the interviewees had answered questions on anthropomorphism, competence, trust and willingness to disclose personal information online also for the second stimulus.

3.1.4 Research sample

The survey for the main study supported by Qualtrics.com. was administered to a sample of 205 Italian participants extracted through a non-probabilistic convenience sampling. Since the research does not require the selection of participants with specific characteristics, the target population was chosen in order to obtain a large and representative sample as well as to ensure generalizable results. The number of responses collected was deemed large enough to conduct the analysis, especially considering that a within-subject design was used and all participants saw both scenarios.

The final sample is a mix of unequally distributed men and women (Male = 39.5%; Female= 60.5%), with the highest concentration in the 20-25 year range (53.7%), in a total range between 18 and 75 years: the under 18 were excluded as they were not considered adult enough to be included in the study, while the over 75 were excluded as they were not considered to have sufficient technological skills to interact with a virtual assistant. Regarding the educational level, it emerged that a large part of the sample is made up of graduates (Master = 29.8%; Bachelor = 39.5%), a fact to be taken into consideration for the interpretation of the results, as virtual assistants are mostly known by this young and educated target. The sample was also described through the two variables of previous knowledge and previous interaction with a virtual assistant: results showed that 87.8% is familiar with virtual assistants, 74.1% has already interacted with a virtual assistant before the experience proposed in the survey.

3.2 Results

3.2.1 Differences in perceived anthropomorphism, perceived competence, trust and willingness to disclose personal information online between the two chatbots

The first element of analysis concerned perceived anthropomorphism, which was investigated through three items proposed in the survey after each of the two scenarios. The reliability analysis showed that all items appeared to be worthy of retention, resulting in a decrease in the Cronbach alpha ($\alpha = 0.91$) if deleted. Therefore, considering the within-subject research design, two factors were created – one for each set of items – called "ANTR1" referring to the first scenario and "ANTR2" referring to the second scenario. The paired-sample t-test was carried out to check whether the means of the two factors were different from each other: it was also used as a manipulation check to verify, in addition to the pretest, that independent variables were actually perceived as different in terms of anthropomorphism. Results showed that the mean of "ANTR1" ($MEAN_{ANTR1} = 4.38$) was statistically different from the mean of "ANTR2" ($MEAN_{ANTR2} = 5.06$), and that the second scenario ("ANTR2") was perceived as more anthropomorphic than the first ("ANTR1"). The same procedure was also employed for three other variables: perceived competence, trust and willingness to disclose personal information online. All the scales reached a good reliability ($\alpha = 0.84$; $\alpha =$

0.79; α = 0.89), therefore no items were excluded and the factors "COMP1" and "COMP2", "FID1" and "FID2", "DAT1" and "DAT2" were created. The paired sample t-tests showed that all the means for the first scenario (as is chatbot) were different from those for the second scenario (humanized chatbot) and that the second chatbot was perceived by respondents as more competent ($MEAN_{COMP1} = 5.06$; $MEAN_{COMP2} = 5.41$), it was more trusted ($MEAN_{FID1} = 3.63$; $MEAN_{FID2} = 3.90$) and had a greater effect on the willingness to disclose personal information online ($MEAN_{DAT1} = 4.02$; $MEAN_{DAT2} = 4.34$) than the first chatbot. These mean differences were statistically significant ($p < 0.05$). A relevant and surprising fact emerged: the chatbot characterized by anthropomorphic traits was able to change the user's perception of competence, although both agents responded to exactly the same requests and had the same level of expertise.

Table 1 *- Mean differences between the two chatbots*

Statistiche campioni accoppiati

		Media	N	Deviazione std.	Media errore standard
Coppia 1	ANTR1	4,3886	205	1,54249	,10773
	ANTR2	5,0650	205	1,43717	,10038
Coppia 2	COMP1	5,0602	205	1,29569	,09050
	COMP2	5,4114	205	1,22046	,08524
Coppia 3	FID1	3,6322	205	,81140	,05667
	FID2	3,9015	205	,78231	,05464
Coppia 4	DAT1	4,0209	205	1,53672	,10733
	DAT2	4,3463	205	1,55325	,10848

Test campioni accoppiati

		Differenze accoppiate					t	gl	Sign. (a due code)
					Intervallo di confidenza della differenza di 95%				
		Media	Deviazione std.	Media errore standard	Inferiore	Superiore			
Coppia 1	ANTR1 - ANTR2	-,67642	1,49797	,10462	-,88270	-,47014	-6,465	204	,000
Coppia 2	COMP1 - COMP2	-,35122	,97026	,06777	-,48483	-,21761	-5,183	204	,000
Coppia 3	FID1 - FID2	-,26927	,64083	,04476	-,35752	-,18102	-6,016	204	,000
Coppia 4	DAT1 - DAT2	-,32544	1,05705	,07383	-,47100	-,17987	-4,408	204	,000

3.2.2 Perceived competence and trust

Given the significant difference in perceived competence and trust between the two chatbots, a correlation analysis was conducted between "COMP1" and "FID1" and between "COMP2" and "FID2" to check whether they were related to each other. The matrices indicated that "COMP1" was positively correlated with "FID1" ($r = 0.744$) and "COMP2" was positively correlated with "FID2" ($r = 0.839$) and both correlations were statistically significant ($p < 0.05$). However, the correlation was stronger in a positive sense for the humanized chatbot, indicating that humanization resulted in a greater connection between the chatbot's perceived competence and trust.

Table 2 *- Correlations between perceived competence and trust*

AS IS

Correlazioni

		COMP1	FID1
COMP1	Correlazione di Pearson	1	,744**
	Sign. (a due code)		,000
	N	205	205
FID1	Correlazione di Pearson	,744**	1
	Sign. (a due code)	,000	
	N	205	205

**. La correlazione è significativa a livello 0,01 (a due code).

HUMANIZED

Correlazioni

		COMP2	FID2
COMP2	Correlazione di Pearson	1	,839**
	Sign. (a due code)		,000
	N	205	205
FID2	Correlazione di Pearson	,839**	1
	Sign. (a due code)	,000	
	N	205	205

**. La correlazione è significativa a livello 0,01 (a due code).

In addition, after verifying the correlation, I tested whether perceived competence had a significant effect on trust through two linear regressions having as independent variables "COMP1" and "COMP2" and as dependent variables "FID1" and "FID2". From the first regression results, it emerged that 55% of the variability of FID1 (y) was explained by COMP1 (x) (R-quadrato = 0.554). The ANOVA table showed that the explanatory power of the model was sufficient ($p < 0.05$) and the VIF value was not greater than 10, so there were no collinearity problems. From the second regression results, it emerged that 70% of the variability of FID2 (x) was explained by COMP2 (y) (R-quadrato = 0.704). Also in this case, the ANOVA table showed that the model fit was good ($p < 0.05$) and there were no collinearity problems. The coefficients table showed that chatbot's perceived competence had a significant positive effect on trust for both chatbots ($b1_{COMP1}$ = 0.46; $b1_{COMP2}$ = 0.53) and that this positive effect was stronger for the humanized chatbot.

Table 3 *- Regression with perceived competence and trust*

AS IS

Coefficienti[a]

Modello		Coefficienti non standardizzati		Coefficienti standardizzati			Statistiche di collinearità	
		B	Errore standard	Beta	t	Sign.	Tolleranza	VIF
1	(Costante)	1,273	,153		8,307	,000		
	COMP1	,466	,029	,744	15,888	,000	1,000	1,000

a. Variabile dipendente: FID1

HUMANIZED

Coefficienti[a]

Modello		Coefficienti non standardizzati		Coefficienti standardizzati			Statistiche di collinearità	
		B	Errore standard	Beta	t	Sign.	Tolleranza	VIF
1	(Costante)	,991	,136		7,300	,000		
	COMP2	,538	,024	,839	21,981	,000	1,000	1,000

a. Variabile dipendente: FID2

3.2.3 Privacy concern and willingness to disclose personal information online

Because there was a significant difference in the willingness to disclose personal information online between the two chatbots, these variables ("DAT1" and "DAT2") have been correlated with privacy concern to check whether there was a link between the two. After assessing the reliability of the scale, the factor privacy concern (PRI) was created: in this case, the variable referred to items proposed in the survey before the respondent saw the two stimuli, so it was not necessary to create two factors for the two chatbots. The correlations matrices displayed that "PRI" was negatively correlated with "DAT1" (r = - 0.283) and with "DAT2" (r = - 0.192) and both correlations were statistically significant ($p < 0.05$). When comparing the two correlations, it resulted that the correlation was stronger in a negative sense for the as is chatbot: it indicated that, as privacy concern increases, the willingness to disclose personal information online decreases and humanization weakens the negative link between the two variables.

Table 4 - *Correlations between privacy concern and willingness to disclose personal information online*

AS IS

Correlazioni

		PRI	DAT1
PRI	Correlazione di Pearson	1	-,283**
	Sign. (a due code)		,000
	N	205	205
DAT1	Correlazione di Pearson	-,283**	1
	Sign. (a due code)	,000	
	N	205	205

**. La correlazione è significativa a livello 0,01 (a due code).

HUMANIZED

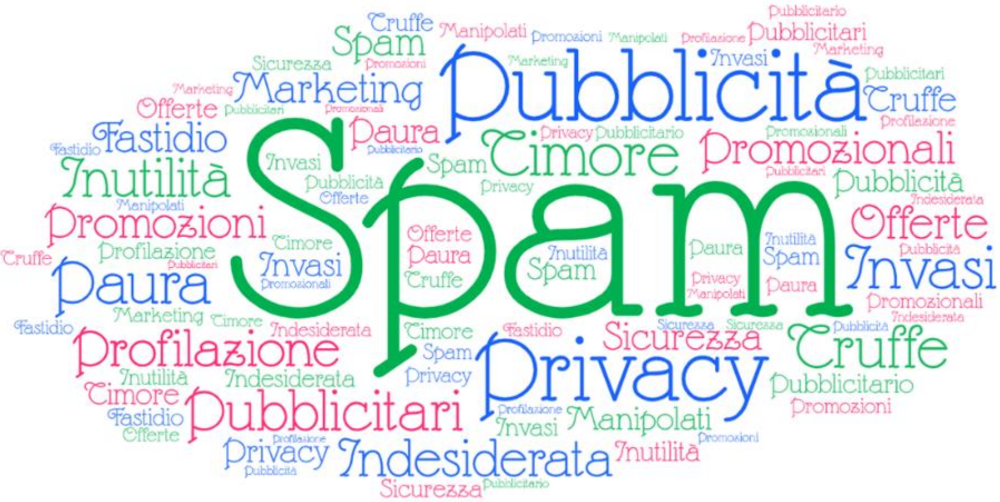
Correlazioni

		PRI	DAT2
PRI	Correlazione di Pearson	1	-,192**
	Sign. (a due code)		,006
	N	205	205
DAT2	Correlazione di Pearson	-,192**	1
	Sign. (a due code)	,006	
	N	205	205

**. La correlazione è significativa a livello 0,01 (a due code).

Although the correlation was significant, it was very weak in both scenarios. This result could be explained by evidence that emerged from the open question included at the end of the survey, which was "Would you have preferred not to provide your e-mail? Try to briefly explain why" (Avresti preferito non fornire la tua e-mail? Prova a spiegarne brevemente il motivo). The answers given by the survey participants were collected and cleaned up, then one or more keywords that could express their meaning were identified for each answer. Thus, through the online tool Visual Thesaurus, a cloud of words was generated that revealed the most frequent reasons why respondents would have preferred not to provide their e-mails. It clearly emerged that privacy, although present among the causes, was not one of the main: the fear of receiving spam and the anxiety of being invaded by unwelcome advertising were the most mentioned reasons for this reticence. This semantic analysis, resulting from open responses, explained the very slight correlation between privacy concern and the willingness to disclose personal information online.

Figure 3.1 - *Reasons for reluctance to disclose personal information online (e-mail)*



Source: Author's elaboration, 2021

3.2.4 Previous interaction with a chatbot and trust

After assessing the significant difference in trust between the two chatbots, an independent sample t-test having as grouping variable " previous interaction with a chatbot", which is a categorical variable, and as dependent variables "FID1" and "FID2" was run. Specifically, the null and alternative hypotheses in this case were the following:

$H0_{FID1}$: Trust of those who have already interacted with a chatbot is NOT larger than trust of those who have never interacted before ($\mu_{y1} < \mu_{n1}$)

$H1_{FID1}$: Trust of those who have already interacted with a chatbot is larger than trust of those who have never interacted before ($\mu_{y1} > \mu_{n1}$)

$H0_{FID2}$: Trust of those who have already interacted with a chatbot is NOT larger than trust of those who have never interacted before ($\mu_{y2} < \mu_{n2}$)

$H1_{FID2}$: Trust of those who have already interacted with a chatbot is larger than trust of those who have never interacted before ($\mu_{y2} > \mu_{n2}$)

The Levene statistics showed that the assumption of homoscedasticity was met, so the null hypothesis of equal variances could not be rejected ($p > 0.05$) and it could be concluded that there was no difference between the variances in the population. The results of the statistical test indicated that trust did not differ between those who had already interacted with a chatbot and those who had never interacted before ($p > 0.05$). It follows that experience and practice did not increase the user's trust in a virtual assistant, but other factors contributed.

__Table 5__ - Independent sample t-test with trust and previous interaction with a chatbot

AS IS

Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze		Test t per l'eguaglianza delle medie						
									Intervallo di confidenza della differenza di 95%	
		F	Sign.	t	gl	Sign. (a due code)	Differenza della media	Differenza errore standard	Inferiore	Superiore
FID1	Varianze uguali presunte	,595	,441	,178	203	,859	,02306	,12974	-,23275	,27888
	Varianze uguali non presunte			,167	82,065	,867	,02306	,13775	-,25097	,29709

HUMANIZED

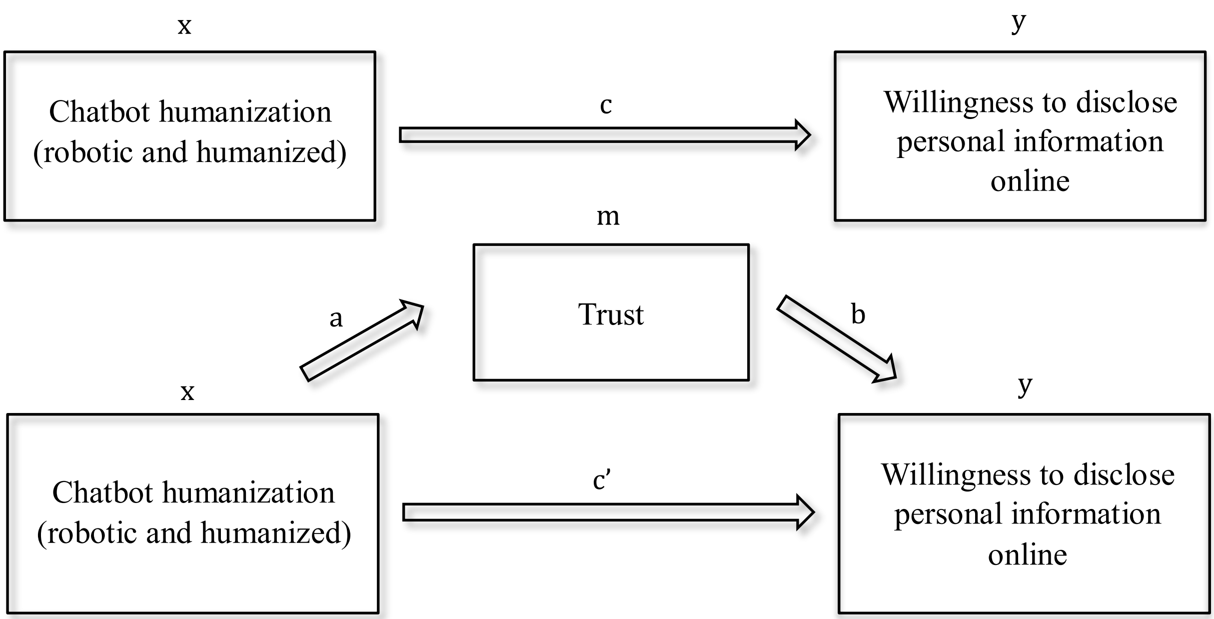
Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze		Test t per l'eguaglianza delle medie						
									Intervallo di confidenza della differenza di 95%	
		F	Sign.	t	gl	Sign. (a due code)	Differenza della media	Differenza errore standard	Inferiore	Superiore
FID2	Varianze uguali presunte	2,217	,138	,362	203	,718	,04523	,12506	-,20135	,29182
	Varianze uguali non presunte			,337	80,834	,737	,04523	,13407	-,22154	,31201

3.2.5 Mediation effect of trust

The main objective of this thesis was to demonstrate a positive effect of a humanized chatbot – compared to a more robotic one (as is chatbot) – on the willingness to disclose personal information online because of trust toward the virtual assistant. To verify this hypothesis, a mediation analysis was carried out through the PROCESS MACRO-MODEL 4 to test that the willingness to disclose personal information online – the e-mail, in this case – increases when respondents interact with a humanized chatbot compared to a more robotic one and that this main effect is mediated by trust. The mediation model with direct and indirect effects is as follows:

Figure 3.2 *- Conceptual model with effects*



c indicates the direct relation between chatbot humanization (x) and the willingness to disclose personal information online (y); *a* indicates the relation between chatbot humanization (x) and trust (m); *b* indicates the relation between trust (m) and the willingness to disclose personal information online (y); *c'* indicates the relation between chatbot humanization (x) and the willingness to disclose personal information online (y) when controlling for trust (m). Since all respondents interacted with both chatbots within the survey, a dummy variable was created, coded as 1 if humanized chatbot and 0 if not humanized. To perform the mediation analysis with a within-subject research design, the columns referring to the variables of interest (FID1, FID2, DAT1 AND DAT2) were exported to an Excel spreadsheet and only two columns were created, each consisting of 205 responses. In this way, the two conditions appeared as if they had been randomized and as if each respondent saw only one stimulus: for this reason, the number of respondents in the mediation analysis output was equal to 410. At this stage it was possible to launch the mediation test.

3.2.5.1 Effects on the mediation variable

The first output table revealed that chatbot humanization (IV) had a significant effect on trust (m) because the p value was lower than the alpha ($p < 0.05$), so the stimulus was significant. The H2 hypothesis (IV => m) had been verified.

Table 6 - *Effects on trust*

```
OUTCOME VARIABLE:
 FIDUCIA

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,1670      ,0279      ,6352    11,7001     1,0000   408,0000      ,0007

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,6322      ,0557    65,2521      ,0000     3,5228     3,7416
STIMOLO       ,2693      ,0787     3,4205      ,0007      ,1145      ,4240
```

3.2.5.2 Effects on the dependent variable

The second output table revealed that trust (m) had a significant effect on the willingness to disclose personal information online (y) because the p value was lower than alpha ($p < 0.05$), so the mediator influenced the dependent variable. The H3 hypothesis (m => DV) had been verified. The stimulus (x) had a non-significant effect on the willingness to disclose personal information online (y) because the p value was higher than alpha ($p = 0.47 > 0.05$), so the independent variable did not influence the dependent variable. The H1 hypothesis (IV => DV) had not been verified.

Table 7 - *Effects on the willingness to disclose personal information online*

```
OUTCOME VARIABLE:
 DATI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4410      ,1945     1,9489    49,1436     2,0000   407,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant       ,9880      ,3297     2,9963      ,0029      ,3398     1,6361
STIMOLO        ,1006      ,1399      ,7193      ,4724     -,1743      ,3755
FIDUCIA        ,8350      ,0867     9,6290      ,0000      ,6645     1,0055
```

3.2.5.3 Direct and indirect effects

These results were confirmed by the third output table of direct and indirect effects of x on y. The direct effect (*c'*) turned out to be not significant when there was a mediation ($p > 0.05$): the humanized chatbot did not have a positive direct effect on the willingness to disclose personal information online. However, to check that there was mediation, it was necessary to demonstrate that the indirect effect was significant.

H0: The indirect effect is equal to 0

H1: The indirect effect is not equal to 0

The indirect effect (*ab*) turned out to be significant since zero did not fall within the confidence interval (0.0926 to 0.3685): the humanized chatbot – compared to the as is chatbot – had a positive effect on the willingness to disclose personal information online because trust was present. Since *c'* was not significant and *ab* was significant, then trust turned out to be a pure mediator because it fully explained the relationship between x and y: it could be concluded that there was total mediation.

Table 8 - *Direct and indirect effects*

```
Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c'_ps
      ,1006      ,1399      ,7193      ,4724     -,1743      ,3755       ,0648

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
FIDUCIA       ,2248      ,0703      ,0926      ,3685

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
FIDUCIA       ,1449      ,0446      ,0596      ,2348
```

3.3 General discussion

This thesis helps investigate how humanization can affect personal data disclosure patterns and what is the role of trust in influencing this behaviour. Specifically, it focuses on chatbots – virtual assistants equipped with artificial intelligence – and analyses the effectiveness of human-like traits to increase perceived anthropomorphism. The research hypothesizes that there is a positive relationship between a humanized chatbot and the willingness to disclose personal information online and that this relationship is mediated by trust. To test this hypothesis, two different chatbots were built: a first robotic model, that reproduces the as is version of the chatbot Elena by Enel Energia, and a second humanized model, which is characterized by anthropomorphic traits such as emojis, natural language, empathy. These two stimuli, with which the survey respondents interacted, generated different interesting results in terms of trust and willingness to disclose personal data, but also in terms of perceived competence and perceived anthropomorphism. Hence, the findings confirmed the main hypothesis by proving that there was a significant trust-mediating effect that explained the relationship between the independent and the dependent variables. It is statistically true that a humanized chatbot increases the user's willingness to disclose personal data compared to a more robotic chatbot and that this relationship can be explained by trust.

3.3.1 Theoretical contribution

Previous studies on virtual assistants have already shown that making a chatbot more anthropomorphic increases perceived trust in this technology. Indeed, human touch is able to create intimacy with the customer and generate positive reactions. For this reason, the chatbot conversational approach is effective in fuelling trust and, if enriched with elements that make it even more empathetic, it can generate a greater sense of closeness and true connection. Other studies on trust have verified that trusted brands and technologies decrease the user’s scepticism and result in greater comfort when providing personal information online. When reassured, customers are more willing to release their data because they trust the partner they interact with. On the one hand, chatbots allow companies to obtain advantages in terms of response times, cost savings and availability: however, it is clear that this communication cannot create the same sense of empathy as a relationship with a human operator. On the other hand, customers want to be understood and listened to, and ask for a close relationship with companies; they also want security and guarantees that their data will be treated in their interest. For this reason, the present study aimed to investigate the effect of humanization in solving the trade-off between efficiency and empathy, between productivity and user care, trying to meet the customer’s needs and expectations.

First of all, this thesis extends literature regarding human-like traits and anthropomorphism in the context of technologies like chatbots. There is a gap concerning the importance of humanization in influencing disclosure and there are no studies that have investigated the direct effect of a humanized chatbot on users' willingness to release their data within the conversation. Hence, the main innovative element of the research is the identification of a new variable coded as "humanization" as a key to incentivize the disclosure of private information such as e-mail. The theory of the uncanny valley, according to which a feeling of discomfort can arise when a robot is so human that it is perceived as disturbing, was also taken into account. Thus, sufficient anthropomorphic elements have been included – emojis, friendly language, human idioms, name request – to stimulate perceived humanization but not to a level that triggers the uncanny valley effect. This type of humanization has been shown to have significant effects on user behaviours.

Second, this research has integrated studies on commitment-trust theory introduced by Morgan and Hunt: they stated that trust and commitment are fundamental elements for creating a bond with consumers. Results displayed that, when the virtual assistant shows that it intends to create a relationship with the user and not just reach a short-term goal, the respondent is more likely to trust it and feel involved in the conversation. One of the main contributions is the analysis of anxiety, which stems from uncertainty and the potential risk associated with anticipated consequences and adverse outcomes, as a predictor of attitudes towards disclosing personal data online. Hence, the second element of innovation concerns the link drawn between humanization, trust and the willingness to disclosure. Few researches have studied trust as a variable that explains the relationship between chatbot humanization and willingness to disclose personal information online, therefore the conceptual model of this thesis included it as a mediating variable.

Finally, one of the most innovative elements is the method of administering the stimulus to the sample. As previously explained, two chatbots were built using the Landbot conversational interface building tool and two links were extracted and then inserted into the survey. The respondent had to click on the link, converse with the chatbot, then go back to answer the related questions. Few previous researchers, such as Smestad (2018), have built a chatbot to make users interact with it within the survey: many others have used static stimuli, such as images or texts. No study has designed chatbots with two levels of anthropomorphism – one of which reproduces the as is version of a brand – and asked respondents to interact with it within a survey.

3.3.2 Managerial implications

People no longer want to be treated as consumer spectators, but they pretend to act as individuals in a dialogue with brands. Conversational marketing, on which chatbots are based, fits into this need and enables companies to communicate with their customers in a more personalized and engaging way (Ramerman, 2021). However, even today virtual assistants are often used in marketing strategies only as tools to speed up customer service or to respond quickly and automatically to customer problems. It is not taken into account that this approach creates distance between brand and customers, who do not like talking to a machine and end up feeling annoyed and unimportant.

The present study provides useful insights to expand the chatbots' potential and create a win-win situation for businesses and consumers. It offers marketers a guide to understand the strategies to implement when refining the design of their virtual assistants and to optimize the results obtained through this communication channel. Practically, this thesis suggests leveraging anthropomorphism to integrate the human aspect into automation, facilitate human-machine interaction and make the exchange more pleasant. First, as the results showed a significant link between humanization and trust, companies could use this evidence to identify the most suitable features to include in their chatbot in order to be perceived as trustworthy and increase customer trust. From a linguistic point of view, techniques such as requesting the customer's name or asking for confirmation before moving on with the next question can simulate a conversation with a human operator and show reliability; from a visual point of view, an avatar and the use of emojis can make the conversation warmer and more informal. These details can help especially those brands operating in sectors with low emotional involvement, such as the energy industry, and struggle to gain customer trust.

Second, trust can be exploited for the sensations it arouses. Indeed, a further result that emerged from this research is the influence of trust in disclosure decisions. When consumers converse with a warm, friendly, human-like virtual assistant, trust seems to come into play to positively influence the propensity to release personal data within the conversation. This means that managers who want to acquire data from their customers to offer them promotions or personalized services should think about techniques to increase trust, knowing that it decreases consumers' anxiety and privacy concern. Assuming that they act with a view to transparency in the consumer's interest and that they adopt measures to protect personal data, companies could declare this information through the chatbot to reassure the customer. Findings show that the humanized chatbot containing a privacy note – which emphasizes that personal data will not be misused or disclosed – received higher scores in terms of willingness to disclose personal information. This highlights that a short and simple sentence in a context of conversation and friendly dialogue can change the customer's attitude of scepticism.

Third, the analysis of the open responses also provided relevant insights into the reasons for resistance to data release: privacy concern is not the only motivation but the fear of receiving unsolicited advertising due to the e-mail provided to the company. For this reason, brands should consider indicating the purpose of the data request, for example by specifying to customers the type of communications they will receive or reassuring them that they will not be bombarded with spam. Naturally, it can be done only if this communication is consistent with the real objective of the brand.

Finally, this research work is particularly relevant for the utility sector: indeed, this thesis analyses and provides suggestions for the chatbot of the Italian energy company Enel Energia. It has been shown that humanization does not only concern highly emotional or impulse buying industries, but also brands that consumers often contact for essential services. Especially for this type of communication, a friendly and empathetic conversation can help achieve performance goals as well as establish a long-term relationship with the target.

3.3.3 Limits and future research

Since it has focused on specific aspects of chatbots, taking into consideration only some variables of the many involved, this study has some limitations. The first limit concerns the stimuli building. Given the impossibility of using complex tools with word recognition systems and artificial intelligence, I used the conversational interface building platform, Landbot, that allowed the user to reply with buttons and to choose only among some pre-existing alternatives. The aim of the research was not to test the bot's ability to understand requests, but its visual and linguistic anthropomorphism; therefore, it was not the user's responses that mattered, but the virtual assistant's words and ways of interacting. However, it would be interesting to develop a study with more complex chatbots to test people's perceptions in a real communication and obtain insights not only from the survey responses, but also from the answers given to the bot.

Still regarding the two chatbots, a second weakness is related to the e-mail request. In both cases, in the last junction of the conversation, the virtual assistant Elena asked the customer if he wanted to leave his e-mail to be updated on Enel services. However, due to practical and privacy reasons, users did not actually release their e-mail after this request. To check for this inconsistency, before showing the chatbot's stimulus, the respondent was told to identify with the context and respond as if it was a real conversation. Future research could allow users to write their e-mail and use it, for example, to give them a contribution or a gift for having taken part in the study.

Another limitation concerns measurement scales, which are pre-validated scales introduced by English-speaking authors. Since the research was carried out on an Italian sample and the object of this study is an Italian chatbot, the items were translated from English into Italian. The reliability of the scale has been tested and found to be reliable, but there may be errors due to the change of language. I suggest using the scales in the original language to check for translation variations and verify the answers according to the nuances of meaning of the original linguistic tongue.

An ultimate limit is the type of target interviewed: 53.7% of respondents were young students in the 20-25 year range. The advantage is that the convenience sample is in line with the audience that uses chatbots the most and is more familiar with technology; however, new studies could broaden the age target to test humanization advantages on older people who are less familiar with technology and virtual assistants. For example, it would be interesting to study whether age or familiarity with virtual assistants could moderate the relationship between chatbot humanization, trust and willingness to disclose personal information online.

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APPENDIX A

Survey

INTRODUCTION

Ciao! Sono Giulia, una studentessa di Marketing, e vorrei chiederti di dedicare **pochi minuti** del tuo tempo al mio progetto di tesi. Questo è uno studio sui **chatbot**, assistenti virtuali in grado di rispondere alle domande delle persone in maniera veloce e automatica grazie all'Intelligenza Artificiale.
La tua opinione è molto importante perché solo un numero limitato di persone partecipa allo studio, perciò cortesemente ti chiedo di rispondere con **attenzione**🙏. Le tue risposte rimarranno ANONIME 😃

Prima di iniziare, solo alcune domande **su di te**.

SOCIO-DEMOGRAPHIC

Sesso:

Maschio

Femmina

Età:

20-25

26-35

36-45

46-55

56-65

66-75

Grado di **istruzione** completato:

- Dottorato
- Laurea magistrale
- Laurea triennale
- Scuola superiore
- Scuola media

Occupazione

- Studente
- Dipendente pubblico/privato
- Libero professionista
- Imprenditore
- Non occupato

PERSONAL

Conosci gli assistenti virtuali?

Si	No

Hai mai **interagito** con un assistente virtuale?

Si	No, ma non avrei problemi a usarlo	No e non lo userei

PRIVACY

Indica il tuo grado di **accordo / disaccordo** con le seguenti affermazioni riguardo la tua privacy.

	Per niente d'accordo 1	2	3	Neutrale 4	5	6	Completamente d'accordo 7
Di solito mi sento **agitato** quando mi vengono chieste le mie informazioni	○	○	○	○	○	○	○
Quando mi vengono chieste le mie informazioni, ci **penso due volte** prima di fornirle	○	○	○	○	○	○	○
Temo che le aziende raccolgano **troppe informazioni** personali su di me	○	○	○	○	○	○	○

STIMULUS 1

Nelle pagine successive troverai **due link**, cliccaci per svolgere due brevi esperienze con l'assistente virtuale Elena. Ti chiedo di prestare **attenzione** perché dopo ogni link ti sarà chiesto di rispondere ad alcune domande👀.

P.S. L'assistente virtuale è stato creato esclusivamente per questa ricerca, ma cerca di **immedesimarti** come se fosse reale. Non verrai davvero messo in contatto con un **operatore** nè dovrai lasciare la tua **email**, ma rispondi come faresti se fosse una vera conversazione.

Clicca sul link qui sotto 👇
https://chats.landbot.io/v3/H-894061-ISQGLW8SKV8PVFPX/index.html

Dopo aver terminato la conversazione, clicca semplicemente **indietro** sul tuo cellulare o pc per tornare quì al questionario.

ANTHROPOMORPHISM 1

Pensando all'esperienza che hai vissuto con l'assistente virtuale Elena, indica il tuo grado di **accordo / disaccordo** con le seguenti affermazioni.

	Per niente d'accordo 1	2	3	Neutrale 4	5	6	Completamente d'accordo 7
L'assistente virtuale mi ha fatto sentire come se stessi comunicando con un **operatore**	○	○	○	○	○	○	○
L'assistente virtuale si è comportato in modo **simile a una persona**	○	○	○	○	○	○	○
L'assistente virtuale si è comportato in modo **naturale**	○	○	○	○	○	○	○

COMPETENCE 1

Anche ora, indica il tuo grado di **accordo / disaccordo** con le seguenti affermazioni.

	Per niente d'accordo 1	2	3	Neutrale 4	5	6	Completamente d'accordo 7
L'assistente virtuale è **competente**	○	○	○	○	○	○	○
L'assistente virtuale è **utile**	○	○	○	○	○	○	○
L'assistente virtuale è **efficace nel risolvere le esigenze**	○	○	○	○	○	○	○

TRUST 1

Pensando ancora all'esperienza che hai vissuto con l'assistente virtuale Elena, indica il tuo grado di **accordo / disaccordo** con le seguenti affermazioni.

	Per niente d'accordo 1	2	Neutrale 3	4	Completamente d'accordo 5
Questo assistente virtuale agisce nel **mio interesse**	○	○	○	○	○
Questo assistente virtuale soddisfa le **mie aspettative**	○	○	○	○	○
Sento di poter **contare su** questo assistente virtuale	○	○	○	○	○
Posso fare affidamento su questo assistente virtuale per **assistenza**	○	○	○	○	○
Posso fidarmi delle **informazioni** presentate da questo assistente virtuale	○	○	○	○	○

WILLINGNESS TO DISCLOSE PERSONAL INFORMATION ONLINE 1

Sempre in base all'esperienza che hai vissuto, indica il tuo grado di **accordo / disaccordo** con le seguenti affermazioni.

	Per niente d'accordo 1	2	3	Neutrale 4	5	6	Completamente d'accordo 7
Mi sarei sentito **a mio agio** nel fornire la mia email	○	○	○	○	○	○	○
Sarebbe stato **seccante** fornire la mia email	○	○	○	○	○	○	○
Mi sarei sentito **rassicurato** nel fornire la mia email	○	○	○	○	○	○	○
Sarei stato **incerto** se fornire la mia email	○	○	○	○	○	○	○
Ero **preoccupato** che mi venisse chiesto di fornire la mia email	○	○	○	○	○	○	○
Avrei preferito **non fornire** la mia email	○	○	○	○	○	○	○
Sarei stato **tranquillo** nel fornire la mia email	○	○	○	○	○	○	○

OPEN QUESTION

Avresti preferito non fornire la tua email? Prova a spiegarne brevemente il **motivo**.

STIMULUS 2

Nella pagina successiva troverai il secondo link. Ti ricordo di prestare particolare **attenzione** per rispondere alle domande successive 👀

P.S. Cerca di nuovo di **immedesimarti** come se fosse reale.

Clicca sul link qui sotto 👇
https://chats.landbot.io/v3/H-894038-3NSZ27ZTUJ5BBJZW/index.html

Dopo aver terminato la conversazione, clicca semplicemente **indietro** sul tuo cellulare o pc per tornare quì al questionario.

DIFFERENCE

Hai percepito **differenze** tra le due esperienze con l'assistente virtuale?

Si

No

Indica quali **caratteristiche** assegneresti a ogni esperienza con l'assistente virtuale:

	Esperienza 1 (primo link)	Esperienza 2 (secondo link)	Entrambi
Empatia	○	○	○
Linguaggio naturale e amichevole	○	○	○
Emojis	○	○	○

ANTHROPOMORPHISM 2

COMPETENCE 2

TRUST 2

WILLINGNESS TO DISCLOSE PERSONAL INFORMATION ONLINE 2

APPENDIX B

Pre-test output

RELIABILITY ANALYSIS

Statistiche di affidabilità

Alpha di Cronbach	N. di elementi
,841	4

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Alpha di Cronbach se viene eliminato l'elemento
In che misura hai percepito l'assistente virtuale Elena come - Simile a una macchina: Simile a un uomo	11,32	6,627	,726	,777
In che misura hai percepito l'assistente virtuale Elena come - Finto:Verosimile	11,17	6,921	,791	,745
In che misura hai percepito l'assistente virtuale Elena come - Artificiale:Realistico	11,40	6,854	,785	,747
In che misura hai percepito l'assistente virtuale Elena come - Impreparato:Preparato	10,52	9,542	,423	,889

INDEPENDENT SAMPLE T-TEST: HUMANIZATION

Statistiche gruppo

	Condizioni	N	Media	Deviazione std.	Media errore standard
UMAN	Stimolo1	30	3,4556	1,05585	,19277
	Stimolo2	30	3,5556	1,01835	,18592

Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze		Test t per l'eguaglianza delle medie						
									Intervallo di confidenza della differenza di 95%	
		F	Sign.	t	gl	Sign. (a due code)	Differenza della media	Differenza errore standard	Inferiore	Superiore
UMAN	Varianze uguali presunte	,194	,661	-,373	58	,710	-,10000	,26782	-,63610	,43610
	Varianze uguali non presunte			-,373	57,924	,710	-,10000	,26782	-,63612	,43612

INDEPENDENT SAMPLE T-TEST: ANTHROPOMORPHISM

Statistiche gruppo

	Condizioni	N	Media	Deviazione std.	Media errore standard
ANTR	Stimolo1	30	5,8250	1,65200	,30161
	Stimolo2	30	7,1333	1,67735	,30624

Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze		Test t per l'eguaglianza delle medie					Intervallo di confidenza della differenza di 95%	
		F	Sign.	t	gl	Sign. (a due code)	Differenza della media	Differenza errore standard	Inferiore	Superiore
ANTR	Varianze uguali presunte	,021	,886	-3,044	58	,004	-1,30833	,42983	-2,16873	-,44794
	Varianze uguali non presunte			-3,044	57,987	,004	-1,30833	,42983	-2,16873	-,44793

Main experiment output

DESCRIPTIVE STATISTICS: GENDER, AGE, EDUCATION

FREQUENCES

Statistiche

		Sesso:	Età:	Grado di istruzione completato:
N	Valido	205	205	205
	Mancante	0	0	0
Mediana		2,00	1,00	3,00
Modalità		2	1	3
Asimmetria		-,432	,868	-,077
Errore standard della asimmetria		,170	,170	,170
Curtosi		-1,831	-,788	-,903
Errore standard della curtosi		,338	,338	,338

Sesso:

		Frequenza	Percentuale	Percentuale valida	Percentuale cumulativa
Valido	Maschio	81	39,5	39,5	39,5
	Femmina	124	60,5	60,5	100,0
	Totale	205	100,0	100,0	

Età:

		Frequenza	Percentuale	Percentuale valida	Percentuale cumulativa
Valido	20-25	110	53,7	53,7	53,7
	26-35	26	12,7	12,7	66,3
	36-45	12	5,9	5,9	72,2
	46-55	26	12,7	12,7	84,9
	56-65	26	12,7	12,7	97,6
	66-75	5	2,4	2,4	100,0
	Totale	205	100,0	100,0	

Grado di istruzione completato:

		Frequenza	Percentuale	Percentuale valida	Percentuale cumulativa
Valido	Dottorato	4	2,0	2,0	2,0
	Laurea magistrale	61	29,8	29,8	31,7
	Laurea triennale	81	39,5	39,5	71,2
	Scuola superiore	58	28,3	28,3	99,5
	Scuola media	1	,5	,5	100,0
	Totale	205	100,0	100,0	

RELIABILITY ANALYSIS

PRIVACY

Statistiche di affidabilità

Alpha di Cronbach	N. di elementi
,746	3

Statistiche degli elementi

	Media	Deviazione std.	N
Di solito mi sento agitato quando mi vengono chieste le mie informazioni	3,37	1,674	205
Quando mi vengono chieste le mie informazioni, ci penso due volte prima di fornirle	4,71	1,788	205
Temo che le aziende raccolgano troppe informazioni personali su di me	4,62	1,715	205

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Alpha di Cronbach se viene eliminato l'elemento
Di solito mi sento agitato quando mi vengono chieste le mie informazioni	9,34	9,313	,554	,682
Quando mi vengono chieste le mie informazioni, ci penso due volte prima di fornirle	8,00	7,750	,686	,518
Temo che le aziende raccolgano troppe informazioni personali su di me	8,08	9,655	,486	,757

ANTHROPOMORPHISM

Statistiche di affidabilità

Alpha di Cronbach	N. di elementi
,883	3

Statistiche degli elementi

	Media	Deviazione std.	N
L'assistente virtuale mi ha fatto sentire come se stessi comunicando con un operatore	4,20	1,838	205
L'assistente virtuale si è comportato in modo simile a una persona	4,51	1,656	205
L'assistente virtuale si è comportato in modo naturale	4,46	1,640	205

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Alpha di Cronbach se viene eliminato l'elemento
L'assistente virtuale mi ha fatto sentire come se stessi comunicando con un operatore	8,97	9,465	,758	,852
L'assistente virtuale si è comportato in modo simile a una persona	8,66	9,961	,833	,782
L'assistente virtuale si è comportato in modo naturale	8,71	10,796	,735	,867

COMPETENCE

Statistiche di affidabilità

Alpha di Cronbach	N. di elementi
,840	3

Statistiche degli elementi

	Media	Deviazione std.	N
L'assistente virtuale è competente	5,00	1,490	205
L'assistente virtuale è utile	5,36	1,467	205
L'assistente virtuale è efficace nel risolvere le esigenze	4,82	1,508	205

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Alpha di Cronbach se viene eliminato l'elemento
L'assistente virtuale è competente	10,19	7,407	,676	,805
L'assistente virtuale è utile	9,82	7,188	,733	,750
L'assistente virtuale è efficace nel risolvere le esigenze	10,36	7,162	,703	,779

TRUST

Statistiche di affidabilità

Alpha di Cronbach	N. di elementi
,862	5

Statistiche degli elementi

	Media	Deviazione std.	N
Questo assistente virtuale agisce nel mio interesse	3,72	1,003	205
Questo assistente virtuale soddisfa le mie aspettative	3,59	,984	205
Sento di poter contare su questo assistente virtuale	3,36	,978	205
Posso fare affidamento su questo assistente virtuale per assistenza	3,50	1,046	205
Posso fidarmi delle informazioni presentate da questo assistente virtuale	3,99	1,043	205

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Alpha di Cronbach se viene eliminato l'elemento
Questo assistente virtuale agisce nel mio interesse	14,44	11,600	,564	,861
Questo assistente virtuale soddisfa le mie aspettative	14,57	10,354	,811	,800
Sento di poter contare su questo assistente virtuale	14,80	10,756	,740	,818
Posso fare affidamento su questo assistente virtuale per assistenza	14,66	10,608	,698	,828
Posso fidarmi delle informazioni presentate da questo assistente virtuale	14,17	11,172	,602	,853

WILLINGNESS TO DISCLOSE PERSONAL INFORMATION ONLINE

Statistiche di affidabilità

Alpha di Cronbach	N. di elementi
,916	7

Statistiche degli elementi

	Media	Deviazione std.	N
Mi sarei sentito a mio agio nel fornire la mia email	4,14	1,875	205
Sarebbe stato seccante fornire la mia email	4,10	2,003	205
Mi sarei sentito rassicurato nel fornire la mia email	3,26	1,671	205
Sarei stato incerto se fornire la mia email	3,95	1,922	205
Ero preoccupato che mi venisse chiesto di fornire la mia email	4,93	1,792	205
Avrei preferito non fornire la mia email	3,60	2,083	205
Sarei stato tranquillo nel fornire la mia email	4,16	1,811	205

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Alpha di Cronbach se viene eliminato l'elemento
Mi sarei sentito a mio agio nel fornire la mia email	24,00	85,152	,782	,899
Sarebbe stato seccante fornire la mia email	24,05	85,400	,711	,907
Mi sarei sentito rassicurato nel fornire la mia email	24,88	90,525	,704	,908
Sarei stato incerto se fornire la mia email	24,20	84,775	,770	,901
Ero preoccupato che mi venisse chiesto di fornire la mia email	23,21	89,424	,681	,910
Avrei preferito non fornire la mia email	24,54	81,867	,783	,899
Sarei stato tranquillo nel fornire la mia email	23,99	86,265	,778	,900

PAIRED SAMPLE T-TESTS

Statistiche campioni accoppiati

		Media	N	Deviazione std.	Media errore standard
Coppia 1	ANTR1	4,3886	205	1,54249	,10773
	ANTR2	5,0650	205	1,43717	,10038
Coppia 2	COMP1	5,0602	205	1,29569	,09050
	COMP2	5,4114	205	1,22046	,08524
Coppia 3	FID1	3,6322	205	,81140	,05667
	FID2	3,9015	205	,78231	,05464
Coppia 4	DAT1	4,0209	205	1,53672	,10733
	DAT2	4,3463	205	1,55325	,10848

Correlazioni campioni accoppiati

		N	Correlazione	Sign.
Coppia 1	ANTR1 & ANTR2	205	,496	,000
Coppia 2	COMP1 & COMP2	205	,704	,000
Coppia 3	FID1 & FID2	205	,677	,000
Coppia 4	DAT1 & DAT2	205	,766	,000

Test campioni accoppiati

		Differenze accoppiate					t	gl	Sign. (a due code)
					Intervallo di confidenza della differenza di 95%				
		Media	Deviazione std.	Media errore standard	Inferiore	Superiore			
Coppia 1	ANTR1 - ANTR2	-,67642	1,49797	,10462	-,88270	-,47014	-6,465	204	,000
Coppia 2	COMP1 - COMP2	-,35122	,97026	,06777	-,48483	-,21761	-5,183	204	,000
Coppia 3	FID1 - FID2	-,26927	,64083	,04476	-,35752	-,18102	-6,016	204	,000
Coppia 4	DAT1 - DAT2	-,32544	1,05705	,07383	-,47100	-,17987	-4,408	204	,000

PERCEIVED COMPETENCE AND TRUST CORRELATION – AS IS CHATBOT

Statistica descrittiva

	Media	Deviazione std.	N
COMP1	5,0602	1,29569	205
FID1	3,6322	,81140	205

Correlazioni

		COMP1	FID1
COMP1	Correlazione di Pearson	1	,744**
	Sign. (a due code)		,000
	N	205	205
FID1	Correlazione di Pearson	,744**	1
	Sign. (a due code)	,000	
	N	205	205

**. La correlazione è significativa a livello 0,01 (a due code).

REGRESSION – AS IS CHATBOT

Riepilogo del modello

Modello	R	R-quadrato	R-quadrato adattato	Errore std. della stima
1	,744[a]	,554	,552	,54306

a. Predittori: (costante), COMP1

ANOVA[a]

Modello		Somma dei quadrati	gl	Media quadratica	F	Sign.
1	Regressione	74,440	1	74,440	252,416	,000[b]
	Residuo	59,867	203	,295		
	Totale	134,308	204			

a. Variabile dipendente: FID1

b. Predittori: (costante), COMP1

Coefficienti[a]

Modello		Coefficienti non standardizzati		Coefficienti standardizzati			Statistiche di collinearità	
		B	Errore standard	Beta	t	Sign.	Tolleranza	VIF
1	(Costante)	1,273	,153		8,307	,000		
	COMP1	,466	,029	,744	15,888	,000	1,000	1,000

a. Variabile dipendente: FID1

CORRELATION – HUMANIZED CHATBOT

Statistica descrittiva

	Media	Deviazione std.	N
COMP2	5,4114	1,22046	205
FID2	3,9015	,78231	205

Correlazioni

		COMP2	FID2
COMP2	Correlazione di Pearson	1	,839**
	Sign. (a due code)		,000
	N	205	205
FID2	Correlazione di Pearson	,839**	1
	Sign. (a due code)	,000	
	N	205	205

**. La correlazione è significativa a livello 0,01 (a due code).

REGRESSION – HUMANIZED CHATBOT

Riepilogo del modello

Modello	R	R-quadrato	R-quadrato adattato	Errore std. della stima
1	,839[a]	,704	,703	,42656

a. Predittori: (costante), COMP2

ANOVA[a]

Modello		Somma dei quadrati	gl	Media quadratica	F	Sign.
1	Regressione	87,914	1	87,914	483,177	,000[b]
	Residuo	36,936	203	,182		
	Totale	124,850	204			

a. Variabile dipendente: FID2

b. Predittori: (costante), COMP2

Coefficienti[a]

Modello		Coefficienti non standardizzati		Coefficienti standardizzati			Statistiche di collinearità	
		B	Errore standard	Beta	t	Sign.	Tolleranza	VIF
1	(Costante)	,991	,136		7,300	,000		
	COMP2	,538	,024	,839	21,981	,000	1,000	1,000

a. Variabile dipendente: FID2

PRIVACY CONCERN AND WILLINGNESS TO DISCLOSE PERSONAL INFORMATION ONLINE

CORRELATION – AS IS CHATBOT

Statistica descrittiva

	Media	Deviazione std.	N
PRI	4,2358	1,40541	205
DAT1	4,0209	1,53672	205

Correlazioni

		PRI	DAT1
PRI	Correlazione di Pearson	1	-,283**
	Sign. (a due code)		,000
	N	205	205
DAT1	Correlazione di Pearson	-,283**	1
	Sign. (a due code)	,000	
	N	205	205

**. La correlazione è significativa a livello 0,01 (a due code).

REGRESSION – AS IS CHATBOT

Riepilogo del modello

Modello	R	R-quadrato	R-quadrato adattato	Errore std. della stima
1	,283[a]	,080	,076	1,47753

a. Predittori: (costante), PRI

ANOVA[a]

Modello		Somma dei quadrati	gl	Media quadratica	F	Sign.
1	Regressione	38,578	1	38,578	17,671	,000[b]
	Residuo	443,169	203	2,183		
	Totale	481,747	204			

a. Variabile dipendente: DAT1

b. Predittori: (costante), PRI

Coefficienti[a]

Modello		Coefficienti non standardizzati		Coefficienti standardizzati	t	Sign.	95,0% Intervallo di confidenza per B	
		B	Errore standard	Beta			Limite inferiore	Limite superiore
1	(Costante)	5,332	,328		16,234	,000	4,684	5,979
	PRI	-,309	,074	-,283	-4,204	,000	-,455	-,164

a. Variabile dipendente: DAT1

CORRELATION – HUMANIZED CHATBOT

Statistica descrittiva

	Media	Deviazione std.	N
PRI	4,2358	1,40541	205
DAT2	4,3463	1,55325	205

Correlazioni

		PRI	DAT2
PRI	Correlazione di Pearson	1	-,192**
	Sign. (a due code)		,006
	N	205	205
DAT2	Correlazione di Pearson	-,192**	1
	Sign. (a due code)	,006	
	N	205	205

**. La correlazione è significativa a livello 0,01 (a due code).

REGRESSION – HUMANIZED CHATBOT

Riepilogo del modello

Modello	R	R-quadrato	R-quadrato adattato	Errore std. della stima
1	,192[a]	,037	,032	1,52813

a. Predittori: (costante), PRI

ANOVA[a]

Modello		Somma dei quadrati	gl	Media quadratica	F	Sign.
1	Regressione	18,123	1	18,123	7,761	,006[b]
	Residuo	474,042	203	2,335		
	Totale	492,165	204			

a. Variabile dipendente: DAT2

b. Predittori: (costante), PRI

Coefficienti[a]

Modello		Coefficienti non standardizzati: B	Coefficienti non standardizzati: Errore standard	Coefficienti standardizzati: Beta	t	Sign.	95,0% Intervallo di confidenza per B: Limite inferiore	95,0% Intervallo di confidenza per B: Limite superiore
1	(Costante)	5,245	,340		15,441	,000	4,575	5,914
	PRI	-,212	,076	-,192	-2,786	,006	-,362	-,062

a. Variabile dipendente: DAT2

PREVIOUS INTERACTION WITH A CHATBOT AND TRUST

INDEPENDENT SAMPLE T-TEST – AS IS CHATBOT

Statistiche gruppo

	Hai mai interagito con un assistente virtuale?	N	Media	Deviazione std.	Media errore standard
FID1	Si	152	3,6382	,78554	,06372
	No	53	3,6151	,88912	,12213

Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze: F	Sign.	Test t per l'eguaglianza delle medie: t	gl	Sign. (a due code)	Differenza della media	Differenza errore standard	Intervallo di confidenza della differenza di 95%: Inferiore	Superiore
FID1	Varianze uguali presunte	,595	,441	,178	203	,859	,02306	,12974	-,23275	,27888
	Varianze uguali non presunte			,167	82,065	,867	,02306	,13775	-,25097	,29709

INDEPENDENT SAMPLE T-TEST – HUMANIZED CHATBOT

Statistiche gruppo

	Hai mai interagito con un assistente virtuale?	N	Media	Deviazione std.	Media errore standard
FID2	Si	152	3,9132	,75245	,06103
	No	53	3,8679	,86908	,11938

Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze: F	Sign.	Test t per l'eguaglianza delle medie: t	gl	Sign. (a due code)	Differenza della media	Differenza errore standard	Intervallo di confidenza della differenza di 95%: Inferiore	Superiore
FID2	Varianze uguali presunte	2,217	,138	,362	203	,718	,04523	,12506	-,20135	,29182
	Varianze uguali non presunte			,337	80,834	,737	,04523	,13407	-,22154	,31201

MEDIATION EFFECT OF TRUST

```
***************** PROCESS Procedure for SPSS Version 3.4 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : DATI
    X  : STIMOLO
    M  : FIDUCIA

Sample
Size:  410

**************************************************************************
OUTCOME VARIABLE:
 FIDUCIA

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,1670      ,0279      ,6352    11,7001     1,0000   408,0000      ,0007

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,6322      ,0557    65,2521      ,0000     3,5228     3,7416
STIMOLO       ,2693      ,0787     3,4205      ,0007      ,1145      ,4240

**************************************************************************
OUTCOME VARIABLE:
 DATI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4410      ,1945     1,9489    49,1436     2,0000   407,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,9880      ,3297     2,9963      ,0029      ,3398     1,6361
STIMOLO       ,1006      ,1399      ,7193      ,4724     -,1743      ,3755
FIDUCIA       ,8350      ,0867     9,6290      ,0000      ,6645     1,0055

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps
      ,1006      ,1399      ,7193      ,4724     -,1743      ,3755      ,0648

Indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
FIDUCIA      ,2248      ,0703      ,0926      ,3685

Partially standardized indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
FIDUCIA      ,1449      ,0446      ,0596      ,2348
```

LUISS

Department of Business and Management

Chair of Web Analytics and Marketing

Humanization builds trust: the effect of human-like chatbots on the willingness to disclose personal information online.

Prof. Matteo De Angelis
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CANDIDATE

Academic year 2020/2021

Index

SUMMARY

INTRODUCTION

Intelligence and emotion is what distinguishes humans from machines. However, the inclusion of emotions in smart systems powered by machine learning and deep learning seems to make artificial intelligence and human intelligence more and more similar: this evidence has given rise to many questions and debates (Bossen, 2020). The aim of this thesis is to study the effects of humanization in chatbots – virtual assistants using AI to simulate human behaviour – and to investigate whether equipping this technology with human-like traits can have positive effects on consumer's trust and willingness to disclose personal data online.

CHAPTER 1 – HUMANIZED CHATBOTS FOR TRUST

1.1 Digital trust is the currency. Humanization is the key

In 2015 Tom Goodwin, senior vice president of strategy and innovation at Havas Media, stated that trust is the most important asset in the new digital world (Goodwin, 2015). Since customers are sceptical, empowered, ask for greater control and give themselves the permission to complain to the brand, building and maintaining trust is becoming more and more important for businesses (Mitchell, 2018). Trust results to be a key factor in a relationship: indeed, while transactional marketing considered the consumer a passive user, relationship marketing takes into account the user's active participation and recognizes that the real goal is not the transaction, but the long-term relationship with the customer (Harker et al., 2006). The history of trust has been complex and fluctuating. Over time, trust in government and institutions decreased both in United States and Europe, while the Internet and digital media has gradually become the primary source for reliable information (Edelman, 2006). Nowadays, trust is no longer taken for granted by role or title but companies should gain it by keeping up with changes and engaging customers (Edelman, 2016). The global Covid-19 pandemic has also marked the history of trust. In this outbreak, scepticism has grown, people have begun to suspect institutions of lies and disinformation while asking brands to take a stand on social issues because demonstrating empathy prevail over advertising, price and product levers in building trust (Edelman, 2021). Thus, integrity, honesty and authenticity are the three pillars on which businesses must leverage because the more communication is perceived as authentic, the more the brand is trusted (Nützel, 2020).

As it is the driving force of the digital age, technology turns out to be the most trusted industry, despite a general decline in trust recorded in 2020 (Edelman, 2021). However, technological innovation creates enthusiasm on the one hand and concern that human capabilities may be jeopardized on the other hand (Salesforce, 2018). Thus, the business has to make technology interpretable by explaining how things work to the lens of the user (Rao & Cameron, 2018). It is clear that technology and digitalization is revolutionizing the way people communicate. Even if they ask for the efficiency of a machine, people still want to be listened to, appreciated and taken into consideration. To satisfy customers, a return to the human touch is needed: AI should be designed considering humanistic qualities such as respect, humour, politeness (Selçuk, 2020). If the man-machine relationship evolved as a social relationship, it would not be necessary to create trust: there would be by default as happens in human-human relationships that deserve it. (Coeckelbergh, 2012).

1.2 Chatbots: advantages, objectives and uses

Conversational marketing can help businesses to be more human. It builds relationships by engaging customers in real-time dialogues to foster direct and customer-centric communication. Chatbots ride this trend by managing interactions within instant messaging apps and establishing a conversational flow with the user (Osservatori Digital Innovation, 2021). A Salesforce research shows that, in 2019, 69% of consumers use chatbots because they deliver quick answers and response time people expect from a chatbot is actually the same as that from a human agent (Sweezey, 2019).

A chatbot can bring numerous benefits to a brand. It offers the opportunity to sell goods through a simple click and a link to an e-commerce, a feature that makes the bot an instant buying tool. In the customer support function, it ensures high responsiveness without cutting down the space for creativity, but including emojis, videos, images, audio files that enrich the answer. The 24/7/365 availability leaves the human agent to dedicate time to more complex activities and allows the brand to know its audience in real-time, learn preferences and offer a personalized experience (Zambito, 2019). Virtual agents can be useful in different industries. Healthcare is leveraging chatbots to improve care delivery by providing empathic aid (Karl, 2020); finance is embracing artificial intelligence to help with expense tracking, online transactions or personalized savings tips. However, the biggest obstacle for using chatbots is the preference of many users to deal with a real assistant: this is why managers are increasingly tending to base their chatbot strategies on the human experience by trying to handle requests with kindness, politeness and emotional connection (Wooler, 2019). Therefore, adding anthropomorphic features to a chatbot design is essential to create a better understanding between machines and humans. Anthropomorphism can be translated into various forms, from appearance to language, and different levels of anthropomorphism can be found in examples of past and current chatbots on the market (Brahnam, 2009). Some bots are represented by the company logo (Parisi, 2017), others emulates humans even visually to the point that its resemblance to a real person is sometimes inconceivable (Maack, 2017). Between these two endpoints, there is a continuum where other more robot or human-like chatbots are placed.

The history of chatbot anthropomorphism is characterized by small successive steps. The first chatbot, ELIZA, launched in 1966, was very basic but still able to generate an emotional attachment that persisted even when the creator revealed the operating mechanism behind it (Pepicq, 2019). Since the first experiment, chatbots have evolved, diversified and proved to be both useful and pleasant for customers (Schwartz, 2019). From ELIZA to Messenger bots the level of humanization has been increasing to redefine the way of communicating with companies, a revolution that Google has taken over with its Google Duplex launched in 2018 (Rita, 2018). Duplex is a voice assistant endowed with AI: it understands conversation nuances and sounds so spontaneous that first tests showed that many did not realize they were interacting with a bot and this prompted them to use the same language they would have used with humans (Leviathan & Matias, 2018).

1.3 Virtual assistants for the energy industry: the case of Enel Energia

Automation, artificial intelligence and chatbots are receiving increasing attention in the utility sector. In particular, the energy industry is the largest user of AI today and the use of chatbots is part of a bigger digitalization process that is changing the control of energy, promoting sustainable consumption and transforming communication with consumers (Booth et al., 2020). There are several benefits a chatbot can bring to an energy provider: at first, call reduction since the bot responds to common queries with 24x7 availability; then, consistency since integration with other touchpoints does not change the quality of the service depending on the operator or the time of the day; finally, advice since digital agents act as consultants to help users with emergencies. Thus, the energy sector benefits from the conversation to make customers feel more connected, informed, and safe. (Harper, 2020).

The energy provider Enel Energia has included AI in its digital strategy because *"it allows you to extract the maximum possible value from data*" explains Giuseppe Amoroso, Head of Enel's Digital Strategy and Governance (Enel, 2019). With a view to transparency, the company has recently integrated a new way of communicating with Enel: the chatbot, Elena, is currently able to independently manage various processes including activating the web bill, inserting self-reading or checking payments (Enel Energia, 2021). Its identity shows affinity with Enel's values: it appears to be professional and reliable, and it speaks to the customer in a precise but empathic way. Since the goal is to offer an increasingly fluid customer experience, the chatbot aims at a greater call deflection – the ability to manage requests in complete autonomy – and a greater understanding of human language to create a relationship of trust between man and technology. This research thesis fits into this scenario and aims to achieve relevant insights that can also be useful to Elena's experimentation and improvement team (Enel Energia, 2021).

CHAPTER 2 – THEORETICAL BACKGROUND AND CONCEPTUAL FRAMEWORK

2.1 Consumer Trust

Studied from many and different perspectives, trust is a complex and manifold multi-sided construct. From a marketing point of view, it is defined as *"a willingness to rely on an exchange partner in whom one has confidence"* (Moorman et al., 1992, p.315) and it has assumed an essential role in establishing and maintaining a long-term relationship between sellers and customers. Young and Albaum defined trust as *"an evolving state including cognitive and affective elements"* (Young et al., 2003, p.255). Cognitive trust is the consumer's willingness to count on a service provider competence and reliability (Moorman et al., 1992), while affective trust is the confidence placed in a brand based on perceived care and concern (Johnson-George et al., 1982). If cognitive trust is based on reasoning, affective trust is based on emotional relationships, but both play a fundamental role and trust implies the coexistence of the two. Much research has also focused on what trust is determined by: provider expertise and product performance have been recognised as antecedents of the cognitive component; sales effectiveness, frequency of interaction and cultural similarity as antecedents of affective trust (Nicholson et al., 2001).

Trust plays a key role in the online world mostly due to the lack of a direct contact and due to greater risks associated with the complexity of the online environment. Empirical studies have studied the effect of key web factors – navigation design, visual design, communication channels and social presence – on trust in online brands (Ganguly et al., 2009). When in a context of uncertainty, users look for shortcuts to ease decision processes and brand trust has been found to be a cognitive shortcut for purchase decisions because it convinces that the chosen brand will be able to meet expectations (Luhmann, 1979). Thus, research highlights that, although trust is related to individual differences and situational factors, brands can invest resources and efforts to build and maintain a climate of trust because customers will feel more comfortable in interacting, transacting and disclosing sensitive information online (Crafter et al., 2013).

Since trust implies by definition the willingness to rely, which pushes the trustee to act and take the risk (Moorman et al., 1993), Morgan and Hunt have established the commitment-trust theory, a model with trust and commitment appearing as mediating variables (Morgan et al., 1994). It explains that, to test if a brand is trustworthy, at first consumers want to see if it is honest and able to keep its promises (Dowell et al., 2013), later if it has the knowledge to complete the requested tasks (McAllister, 1995). As a mediator, commitment has a critical role in long term relationships and, as commitment rises, satisfaction increases (Jap et al., 2000).

2.2 Personal information disclosure

Data allows companies to have accurate and usable insights to personalize content and design new products and services. In the online environment, acquiring consumer information is easier because the way of extracting it is faster and more direct (Zimmer et al., 2010). However, this process is not always immediate. On the one hand, collecting data can be a win-win situation for brands as well as consumers because it allows them to receive personalized offers; on the other hand, consumers are often uncomfortable when sharing information on the Internet (Zimmer et al., 2010). When people act in online exchanges, the urgency to avoid loss becomes stronger than the possibility of pursuing gain (Rieck, 1999). Main concerns for consumers are privacy issues, information misuse or lack of confidence in the brand's ability to solve problems: these beliefs create a perception of vulnerability and have negative effects on disclosure behaviours (Xu et al., 2021).

Evidence shows perceived risk as the main factor limiting the intention to release information online, and trust as what can reduce it. In the marketing literature, risk is often defined as a consumer's belief about potential uncertain negative outcomes (Kim et al., 2008): accordingly, consumers will disclose when perceived risk is offset by trust and when perceived benefits outweigh perceived losses (Foa et al., 1974). The construct of perceived disclosure consequences (PDCs) introduced by White focuses on the user's concerns about the ways companies use personal information and the way data is collected, stored and used by marketers – the so-called "dissemination control" – as well as the kind and the volume of advertising received – the so-called "environmental control" (Phelps et al., 2000). How can brands minimize these effects and work on disclosure avoidance? One of the most effective solutions is found to be relationship building (Derlega et al., 1993): some of the factors positively affecting disclosure are familiarity, commitment and trust as features of close relationships (Fournier, 1998).

The direct and positive relationship between trust and self-disclosure has been confirmed by several studies. Frye and Dornisch found that participants with higher levels of trust tended to report high levels of comfort with disclosure and this comfort was not sensitive to the intimacy of the topic (Frye et al., 2010). The use of trust in disclosing situations – for example when the user is asked to leave his personal e-mail – might shorten the decision making problem by reducing effortful cognitive evaluations (Scholz et al., 1998). Moreover, if they only feel short-term engaged in transactions, consumers are more reluctant to disclose compared to if they feel they have a long-term relationship with the brand (Schoenbachler et al., 2002). This aspect explains the difference between trust and loyalty, which has been discovered to potentially lead to repeat purchases but not real relationships (Oliver, 1999). Literature has suggested that rewards may increase consumer's repurchase intentions, but individuals may consider giving their permission to collect and share personal information just because of the expected reward from the loyalty program (Park et al., 2012). These results show that it is the involvement and the bond with the brand that facilitates the disclosure behaviour.

2.3 Human touch in marketing

Artificial intelligence is gaining a lot of attention thanks to its increasing potential: it allows to optimize and automate many processes with benefits in terms of profit, but with the risk of losing the needed human touch to interact with consumers (Arsenijevic et al., 2019). Instead, especially in the online world, where the absence of face-to-face interactions decreases the degree of consumer trust, human touch is what produces emotional reactions that generate engagement and make the experience memorable (Solnet et al., 2019). The shift from offline to online results in the lack of warmth and sociability due to the absence of social elements (Gefen et al., 2003). Social presence, defined as a medium's capability to express the human sense through a mediated interface (Short et al., 1976), bridges the perceived distance and projects some level of closeness between participants (Cui et al., 2013). In computer-mediated communications emojis, photographs or video clips are some of the elements that supply the missing non-verbal cues such as facial expressions, posture, tone of voice and silences (Basso et al., 2001). This introduces the concept of anthropomorphism, which is the attribution of human-like traits to non-human agents (Epley et al., 2008). Since users tend to anthropomorphize technology, it is important to design media with anthropomorphic traits because the lack of these attributes can trigger the perception of "being teased": distrust could easily be the result (Osei-Frimpong et al., 2018). To increase trust in virtual environments, the practice of re-embedding, which consists in incorporating social cues like photos, videos or text in the online design, allows a brand to reintroduce the perception of face-to-face interactions into a distant approach (Steinbrück et al., 2002).

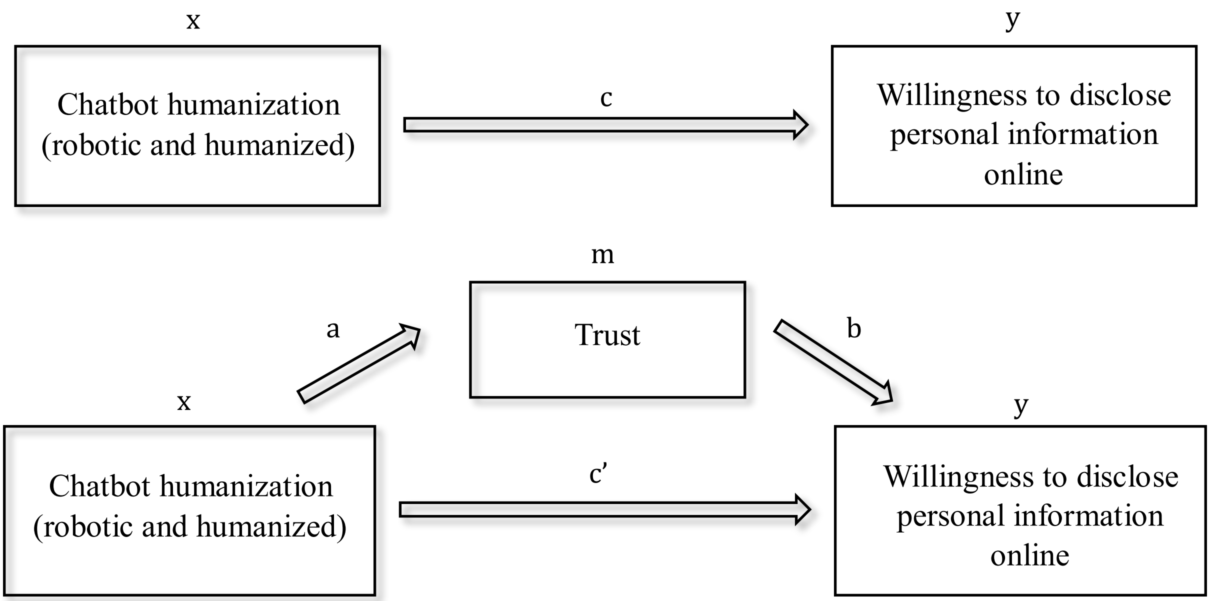
Several studies have highlighted the effectiveness of including human-like traits in chatbots, virtual assistants using AI to create a dialogue with the user (Artemova, 2018), in order to encourage engagement and emotional comprehension that can increase the perception of being heard and understood (Mercieca, 2019). The first step towards humanization is building a chatbot personality: first, the virtual agent must be aligned with the values of the brand; second, it must meet trends, desires and expectations of the target audience; third, the chatbot role must be reflected in the assistant's personality traits and in its tone of voice (Sands et al., 2021). Visual cues are the first that can create a feeling of social presence: a research investigating the effects of three types of chatbot appearance – a logo, an animated human and a human picture – confirmed that, although companies tend to use the organizational logo, a human picture leads to a better user experience (Assink, 2019). Linguistic cues make the chatbot use a human-like language to create a smooth experience: humour, for example, can alleviate boredom and boost engagement (Smestad, 2018). Vocal cues include the tone of voice, the cadence, the pace and the interlayers (Sotolongo, 2018): research revealed the persuasiveness of voice-enabled chatbots by stressing the effectiveness of the social role of a friend with an informal language style (Rhee et al., 2020). Based on these findings, it should be taken into consideration to what extent humanizing chatbots produces successful results and what is the threshold beyond which the uncanny valley effect occurs. Introduced by the Mori's theory, it is the feeling of discomfort arising when a robot is so human that the user perceives it as disturbing (Mori, 1970). This effect highlights the caution in the humanization of virtual agents and the urge to avoid pretending them to appear too human.

2.4 Theoretical model and hypothesis

This research aims at bridging gaps in existing literature and making a contribution to studies on virtual assistants with a focus on the role of trust in human-digital agent interactions. First, past studies have explored how human-like traits in chatbots can boost trust in the brand (Ciechanowskia et al., 2018), but much research is localized – it studies these effects in restricted geographic contexts – or focuses on analyzing one social cue at a time, such as a photo, humour or emojis. Second, there are no studies that investigate the direct effect of a humanized chatbot compared to a more robotic one on the users' willingness to provide their data within a chat. Third, trust has never been used as a mediating variable explaining the relationship between humanized chatbots and willingness to disclose personal information online.

Thus, this thesis seeks to answer the following two research questions: *How a humanized chatbot (vs a more robotic chatbot) influences consumers' willingness to disclose personal information online?* and *Does trust* *mediate this effect?* In particular, it seeks to demonstrate that a humanized chatbot has positive effects on the user's propensity to release even sensitive data during a conversation with a virtual agent. Moreover, it hypothesizes that chatbot humanization increases the user's trust in the virtual agent. Finally, it hypothesizes that trust leads the consumer to have greater comfort in releasing personal and sensitive information.

Fig. 1 *– Conceptual model*



Source: Author's elaboration, 2021

CHAPTER 3 – EMPIRICAL RESEARCH: STUDY, RESULTS AND CONTRIBUTION

3.1 Method

The conceptual framework consisted of a within-subject factorial design with an independent variable manipulated on two levels (x = humanized chatbot vs robotic chatbot), a measured mediator (m = trust) and a measured dependent variable (y = willingness to disclose personal information online). It proposed a *main effect* between the independent (x) and the dependent variable (y) and a *mediating effect* of the mediator (m) which explains this relationship. The hypotheses were tested through an experimental study carried out through an online questionnaire generated with Qualtrics software.

A pre-test was performed to experiment whether respondents perceived the difference between the two stimuli. The short online survey consisted of two images showing two possible conversations with a chatbot that simulates Elena, the virtual assistant of the Italian energy company Enel Energia. In both conditions, only the chatbot humanization varied, with the same communication, length, buttons and type of request managed. The first image represented a functional, formal and more machine-like chatbot; the second image represented a friendly, empathetic and human-like chatbot. Results showed that there was a statistically significant difference between the mean anthropomorphism for stimulus1 ($M_{stimulus1}$ = 5.82) and the mean anthropomorphism for stimulus2 ($M_{stimulus2}$ = 7.13): the manipulation was satisfactory.

The main experiment aimed at assessing the influence of a humanized versus robotic chatbot on the users' willingness to disclose personal information online as well as the mediating effect of trust. To measure these variables, the main study manipulation consisted of two simulations of the virtual agent inspired by the virtual assistant of Enel Energia, which was created using the conversational interface builder Landbot. In both cases the agent managed the same requests and had the same personality, it was named Elena and appeared to be professional, polite and reliable. However, the first scenario consisted of a more robotic chatbot with a cold and formal communication, which aimed to resemble the AS IS version of Enel Energia. There were no visual representation and no visual cues such as emojis or GIFs, the language did not show empathy because it was in line with a goal of providing information and notifying the user. When the customer was asked for his e-mail, no information was given on the personal data protection policy. The second scenario consisted of a more humanized chatbot characterized by a warm and informal communication to connect with users on an emotional level. It was graphically represented as a female avatar, and emojis and human-like expressions acquired by human-human conversations were employed. To get familiar with the respondent, Elena asked for his first name and the e-mail request was incorporated with a privacy note stressing that personal data would not be misused: this detail was added to give users a valid reason to trust the virtual agent.

A within-subject design was adopted for the main study. The reason for this choice lies in the willingness to reduce errors associated with individual differences that could impact the experiment's validity. Furthermore, fewer participants were required to get statistically significant results because the same respondents provided data for both conditions. These advantages had been valued greater than the benefits of a between-subject design since, in this case, effects of individual differences were considered more important to control than learning effects that the between-subject design can prevent.

The final sample of 205 Italian participants, extracted through a non-probabilistic convenience sampling, is a mix of men and women (Male = 39.5%; Female= 60.5%), with the highest concentration in the 20-25 year range (53.7%). Results showed that 87.8% is familiar with virtual assistants and 74.1% has already interacted with a virtual assistant before the experience proposed in the survey.

3.2 Results

3.2.1 Differences in perceived anthropomorphism, perceived competence, trust and willingness to disclose personal information online between the two chatbots

The first element of analysis concerned perceived anthropomorphism, which was investigated through the use of a seven-point Likert scale adapted from Han (2021). The reliability analysis showed that all items of the scale appeared to be worthy of retention, thus two factors were created – one for each set of items – called "ANTR1" and "ANTR2". The paired-sample t-test showed that the mean of "ANTR1" ($MEAN_{ANTR1} = 4.38$) was statistically different from the mean of "ANTR2" ($MEAN_{ANTR2} = 5.06$), and that the second scenario ("ANTR2") was perceived as more anthropomorphic than the first ("ANTR1"). The same procedure was also employed for three other variables: perceived competence, assessed through a seven-point Likert scale adapted from Roy and Naidoo (2021); trust, studied through two five-point Likert scales adapted from Li and Yeh (2010) and Gulati, Sousa and Lamas (2018); willingness to disclose personal information online, investigated through a seven-point Likert scale adapted from Robinson (2018). All the scales reached a good reliability ($\alpha = 0.84$; $\alpha = 0.79$; $\alpha = 0.89$), therefore the factors "COMP1" and "COMP2", "FID1" and "FID2", "DAT1" and "DAT2" were created. The paired sample t-tests showed that all the means for the first scenario (as is chatbot) were different from those for the second scenario (humanized chatbot) and that the second chatbot was perceived as more competent ($MEAN_{COMP1} = 5.06$; $MEAN_{COMP2} = 5.41$), it was more trusted ($MEAN_{FID1} = 3.63$; $MEAN_{FID2} = 3.90$) and had a greater effect on the willingness to disclose personal information online ($MEAN_{DAT1} = 4.02$; $MEAN_{DAT2} = 4.34$). A surprising fact emerged: the anthropomorphic chatbot was able to change the user's perception of competence, although both agents responded to the same requests and had the same level of expertise.

3.2.2 Perceived competence and trust

Given the differences between the two chatbots, a correlation analysis was conducted between "COMP1" and "FID1" and between "COMP2" and "FID2". The matrices indicated that "COMP1" was positively correlated with "FID1" ($r = 0.744$) and "COMP2" was positively correlated with "FID2" ($r = 0.839$) and both correlations were statistically significant ($p < 0.05$). However, the correlation was stronger in a positive sense for the humanized chatbot, indicating that humanization resulted in a greater connection between the variables. In addition, two linear regressions showed that chatbot's perceived competence had a significant positive effect on trust for both chatbots ($b1_{COMP1} = 0.46$; $b1_{COMP2} = 0.53$) and that this positive effect was stronger for the humanized chatbot.

3.2.3 Privacy concern and willingness to disclose personal information online

Because there was a significant difference in the willingness to disclose personal information online between the two chatbots, these variables ("DAT1" and "DAT2") have been correlated with privacy concern. After assessing the reliability of the scale, the factor privacy concern (PRI) was created. The correlations matrices displayed that "PRI" was negatively correlated with "DAT1" ($r = -0.283$) and with "DAT2" ($r = -0.192$) and both correlations were statistically significant ($p < 0.05$). However, it resulted that the correlation was stronger in a negative sense for the first chatbot: as privacy concern increases, the willingness to disclose personal information online decreases and humanization weakens the negative link between the two variables. Although the correlation was significant, it was very weak in both scenarios. This slight correlation could be explained by evidence that emerged from the open question, which was "Would you have preferred not to provide your e-mail? Try to briefly explain why". It emerged that privacy, although present among the causes, was not one of the main: the fear of receiving spam and the anxiety of being invaded by unwelcome advertising were the most mentioned reasons for this reticence.

3.2.4 Previous interaction with a chatbot and trust

After assessing the significant difference in trust between the two chatbots, an independent sample t-test having as grouping variable " previous interaction with a chatbot" and as dependent variables "FID1" and "FID2" was run. The results indicated that trust did not differ between those who had already interacted with a chatbot and those who had never interacted before ($p > 0.05$). It follows that experience and practice did not increase the user's trust in a virtual assistant, but other factors contributed.

3.2.5 Mediation effect of trust

The main objective of this thesis was to demonstrate a positive effect of a humanized chatbot versus a more robotic one (as is chatbot) on the willingness to disclose personal information online because of trust toward the virtual assistant. To verify this hypothesis, a mediation analysis was carried out through the PROCESS MACRO-MODEL 4. Since all respondents interacted with both chatbots within the survey, a dummy variable was created, coded as 1 if humanized chatbot and 0 if not humanized. To perform the mediation analysis with a within-subject research design, the columns referring to the variables of interest (FID1, FID2, DAT1 AND DAT2) were grouped: in this way, the two conditions appeared as if they had been randomized.

The direct effect (*c'*) turned out to be not significant when there was a mediation ($p > 0.05$): the humanized chatbot did not have a positive direct effect on the willingness to disclose personal information online. The indirect effect (*ab*) turned out to be significant since zero did not fall within the confidence interval (0.0926 to 0.3685): the humanized chatbot – compared to the as is chatbot – had a positive effect on the willingness to disclose personal information online because trust was present. Since *c'* was not significant and *ab* was significant, then trust turned out to be a pure mediator because it fully explained the relationship between x and y: it could be concluded that there was total mediation.

3.3 General discussion

This thesis investigates how humanization affects personal data disclosure and what is the role of trust in influencing this behaviour. Findings statistically confirmed that a humanized chatbot, compared to a more robotic one, increases the user's willingness to disclose personal data and that this relationship can be explained by trust.

3.3.1 Theoretical contribution

Previous studies on virtual assistants have already shown that making a chatbot more anthropomorphic increases perceived trust in this technology. Other studies on trust have verified that trust decreases user's scepticism and results in greater comfort when providing personal information online. The present study aimed to investigate the effect of humanization in solving the trade-off between chatbot efficiency and empathy in order to meet the customer's needs and expectations.

First of all, this thesis extends literature regarding anthropomorphism in the context of chatbots. There are no studies that have already investigated the direct effect of a humanized chatbot on users' willingness to release their data: thus, the main innovative element of the research is the identification of a new variable coded as "humanization" as a key to incentivize disclosure. The uncanny valley theory, according to which a feeling of discomfort can arise when a robot is perceived to be too human, was also taken into account: anthropomorphic elements were included but not to a level that triggers the uncanny valley effect. Second, this research has integrated studies on the commitment-trust theory introduced by Morgan and Hunt: they stated that trust and commitment are fundamental elements for creating a bond with consumers. Results displayed that, when the virtual assistant intends to create a relationship with the user, the respondent is more likely to trust it. One of the main contributions is the analysis of anxiety as a predictor of attitudes towards disclosure. Few researches have studied trust as a variable explaining the relationship between chatbot humanization and willingness to disclose personal information online: therefore, the conceptual model of this thesis included it as a mediating variable. Finally, one of the most innovative elements is the method of administering the stimulus. Few previous researchers have let users interact with a virtual assistant within the survey and many had used only static stimuli, such as images or texts. Hence, for this research two chatbot simulations were built and respondents were asked to converse with each chatbot, then answer related questions.

3.3.2 Managerial implications

The present study provides useful insights to expand the chatbots' potential and create a win-win situation for businesses and consumers. Practically, this thesis suggests leveraging anthropomorphism to integrate the human aspect into automation, facilitate human-machine interaction and make the exchange more pleasant.

First, as the results showed a significant link between humanization and trust, companies could use this evidence to identify the most suitable features to include in their chatbot to be perceived as trustworthy: from a linguistic point of view, techniques such as requesting the customer's name or asking for confirmation can show reliability; from a visual point of view, an avatar and emojis can make the conversation warmer and informal. These details can especially help those brands operating in sectors with low emotional involvement, such as the energy industry. Second, it emerged that, when consumers converse with a human-like virtual assistant, trust seems to come into play to positively influence the propensity to release personal data within the conversation. This means that managers who want to acquire data from their customers should think about techniques to increase trust, knowing that it decreases consumers’ anxiety and privacy concern. Third, the analysis of open responses has provided evidence that the fear of unsolicited advertising is the main cause for resistance to data release. For this reason, brands should consider indicating the purpose of the data request and reassure users that they will not be bombarded with spam. Finally, this research is particularly relevant for the utility sector and provides suggestions for the Italian energy company Enel Energia. It has been shown that humanization concerns also low emotional industries and brands that consumers contact for essential services. Especially for this type of communication, a friendly and empathic conversation can help establish a long-term relationship with the target.

3.3.3 Limits and future research

The first limit of this study concerns the stimuli building. Given the impossibility of using tools with word recognition and artificial intelligence, a basic conversational interface building platform was used: indeed, the aim was not to test the bot's expertise, but its visual and linguistic anthropomorphism. It would be interesting to test people's perceptions in a real chatbot conversation and obtain insights from the answers given to the bot. A second weakness is related to the e-mail request: due to practical and privacy reasons, users did not actually release their e-mail after the request but the respondent was told to respond as if it was a real conversation. Future research could allow users to write their e-mail and use it to give them a contribution for having taken part in the study. Another limitation concerns measurement scales: since the research was carried out on an Italian sample, the items were translated from English into Italian. The reliability of the scale has been tested and found to be reliable, but I suggest using the scales in the original language to verify the answers according to the nuances of meaning of the original linguistic tongue. An ultimate limit is the target interviewed: 53.7% of respondents were young students in the 20-25 year range. New studies could broaden the age target to test humanization on older people who are less familiar with technology. For example, it would be interesting to study whether age or familiarity with virtual assistants could moderate the relationship between chatbot humanization, trust and willingness to disclose personal information online.

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