

The Impact of Conversational Agents on Humans in Services: Research Questions and Hypotheses

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Abstract

The research focused on conversational agents and chatbots is dominated by perspectives specific to computer science, engineering and social sciences. The fields of business, management and decision sciences are almost not represented. This paper aims to provide a starting point to the research on the impact of conversational agents on humans in services. To accomplish this purpose, several questions are raised and hypotheses are formulated for the research community. The approach of the topic is conceptual. The need for this perspective was uncovered by means of a literature survey that answered the question: “*Did researchers studied the impact of conversational agents on humans in services?*”. The findings showed that researchers have not published yet such studies. The paper formulates research questions and hypotheses in four major domains in which conversational agents impact humans in services. These domains are: human capital of service companies, service customer behaviour towards conversational agents, service customer interviewing; decision-making in service companies. The questions and the hypotheses formulated in this paper provide potential directions for further research in the field of services. This paper is among the first to formulate questions and hypotheses related to the impact of conversational agents on humans in the field of services with the aim to serve further research.

Key words: conversational agents, chatbots, artificial intelligence, cognitive systems, services

JEL classification: M15, M31, L89, O14, O39.

1. Introduction

Conversational agents are systems that imitate the communication between humans. They interpret and respond to statements made by users in natural language (Lester *et al.*, 2005). A conversational agent is defined as “a software that accepts natural language as input and generates natural language as output, engaging in a conversation with the user” (Griol *et al.*, 2013). Conversational agents may be used for various applications among which customer service, help desk, website navigation, guided purchasing and technical support.

An example of conversational agent is the chatbot. This is a computer program that interacts with users by means of natural language (Shawar & Atwell, 2007), especially over the Internet (Oracle, 2017).

Conversational agents use channels such as: mobile applications, Web applications, messaging platforms (Facebook Messenger, Twitter, Twilio, Slack etc.), personal assistance devices (Amazon Echo, Google Home, Siri of Apple etc.). Recently, Facebook announced that 300,000 messenger bots are active monthly (Kraus, 2018). Researchers envisage that future artificial intelligence (AI) which will be embedded in various objects and in the walls of the rooms will communicate with humans in natural language (IBM, 2017a).

The history of conversational agents spans over more than half a century. It started with the text-based chatbots Eliza in the 1960 and Parry in the 1970s. Further, conversational agents evolved to task completion systems in the years 2000s, intelligent personal assistants (such as Siri) in the 2010s and to social chatbots like Microsoft's Xiaolce (Shum *et al.*, 2018). The conversational agents progressed from simple rule-based chatbots to AI-infused assistants and will continue with the development of cognitive conversational agents. The human interaction with the conversational agents shifted from typed text towards talking to machines. Nevertheless, there is still a long way until the artificial general intelligence (AGI) will be developed by researchers and will be associated with conversational agents.

The quasi-totality of the research on conversational agents and chatbots is dominated by perspectives specific to computer science, engineering, mathematics and social sciences. The fields of business, management and decision sciences are almost not represented.

This paper is among the first to provide a conceptual perspective of the impact of conversational agents on humans in services. The research questions and associated hypotheses formulated on this topic aim to contribute to the launch of further research.

2. Taxonomy of conversational agents

Conversational agents differ in terms of their *dialog domain*. According to this criterion, two major categories of agents exist. The former focuses on closed domain and the latter on open domain.

The closed-domain agents are task-oriented or goal-driven. Research on this category was the first to evolve. The communication medium between the human user and the agent is text or speech. Such a goal-driven system was approached in a dialogue problem as a partially observable Markov decision process (POMDP) (Young *et al.*, 2013; Young *et al.*, 2010). Neural network models were also applied (Henderson *et al.*, 2014).

The open domain agents do not aim to effectively and rapidly accomplish a specific task. They are oriented towards conversations relative to a range of issues, respectively to a sequence of questions and answers on different topics. Natural language interactions raise specific challenges to these dialog systems (Perez-Marin & Pascual-Nieto, 2011).

The open domain agents may be classified according to the *method applied* to formulate a response to the questions of the human user. Research identified two main categories of methods (Wu *et al.*, 2018). One consists in the retrieval-based methods that select a reply from a pre-built index (Zongcheng *et al.*, 2014) and use a large chat corpus. The second encompasses the generation-based methods. Researchers approached the open domain response generation by means of phrase-based statistical machine translation (Ritter *et al.*, 2011), a knowledge base of interactions (corpus built from movie subtitles) to deal with out-of-domain requests (Ameixa *et al.*, 2014), vector space model (Banchs & Li, 2012) and lately by means of neural networks (Serban *et al.*, 2016; Shang *et al.*, 2015; Sordoni *et al.*, 2015, Vinyals *et al.*, 2015).

The development of the deep learning technology will open new research directions related to conversational agents (Io & Lee, 2017).

Another classification criterion is *embodiment*. Conversational agents may be embodied or disembodied (Araujo, 2018). Chatbots are disembodied agents that communicate by means of a messaging-based interface. The embodied agents have a human-like body or face and communicate with people not only by means of natural language (text or speech), but also by non-verbal cues.

3. Approach

Decisions to adopt conversational agents in services should be based on a thorough evaluation of the impact on humans, not only on productivity or cost criteria.

This paper focuses on the potential research questions and hypotheses relative to the impact of conversational agents on humans in services. In order to assess the need to approach this topic, a literature survey was designed and implemented. The survey aimed to answer the following question:

- **LSQ: Did researchers studied the impact of conversational agents on humans in services?**

To answer this question the following main search string was created: (impact OR effect) AND ("conversational agent" OR chatbot) AND (human OR user OR individual) AND services. Several additional search strings were developed from the main string in order to focus on specific services: medical services; insurance and legal services.

Four prominent international databases were surveyed: Emerald Insight, Science Direct, Scopus and Web of Science Core Collection. The search encompassed all published documents, irrespective of their type (articles published in peer-reviewed journals, conference papers, book chapters etc.); publication status (already published or “in press”/“Earlycite” articles); availability (abstract only or full-text) or language. The key terms were sought in the title, abstract or keywords of the documents. The survey was achieved on 14 September 2018. The use of the search strings in the four databases led to 17 distinct documents. After screening and filtering these documents, only two may be considered related to the impact of conversational agents on humans in services (Chung & Park, 2018; Tielman *et al.*, 2017).

Literature survey findings reveal that researchers have not published such studies yet. Until now, researchers that investigated conversational agents did not focus on the impact in services. The paper aims to contribute to the launch of future research on this topic by suggesting potential questions and hypotheses in four major domains in which conversational agents impact humans in services. These domains are: human capital of services companies, service customer behaviour towards conversational agents, service customer interviewing; decision-making in service companies.

4. Impact of conversational agents

The future evolution of conversational agents is based on AI, respectively on machine learning, deep learning, natural language processing, understanding and generation, as well as on cognitive computing.

4.1. Impact of conversational agents on human capital in services

Companies and employees in the service sector are preoccupied of the effects these new technologic trends will have on human capital. A legitimate research question may be raised:

➤ **RQ1: What impact will conversational agents have on human capital in services?**

A set of set of sub-questions and hypotheses related to this major research question are formulated hereinafter.

The first research sub-question is:

- **RQ1.1:** *Will conversational agents totally displace humans in services?*

Experts give warnings that human labour will be displaced by automation, robotics and artificial intelligence (World Economic Forum, 2017).

Based on the current demonstrated technology, in the US, the McKinsey Global Institute (MGI) estimates that 60% of all occupations have at least 30% potentially automatable activities (McKinsey Global Institute, 2017). Nevertheless, according to the MGI, there are occupations with a technical automation potential close to 0%, such as psychiatrists and legislators.

The first hypothesis is the following:

- **H1.1:** *In services, the adoption of conversational agents will displace some activities accomplished by human employees, especially the repetitive tasks and the activities that do not require high-level thinking and empathetic skills.*

The second sub-question derived from the major research question RQ1 is:

- **RQ1.2:** *What changes in the employee skills will be required by the use of conversational agents in services?*

Many disruptive trends will drive changes in the future work skills at the horizon 2020. Some of these drivers (Institute for the Future, 2011) are the following: *rise of smart machines and systems* (that leads to workplace automation and to replacing humans for the repetitive tasks); *development of the computational world* (based on the use of sensors and on increased processing power); *new media ecology* (that will impact attention and cognition, as well as sensitivity towards reality and truth); *emergence of superstructured organisations which focus on collaboration at large scale* (that will change the value creation by means of new

communication technologies and social media); *globally connected world* (that will require competitive adaptation to various markets and consumers).

According to the Institute for the Future (2011), ten skills will be necessary for the future workforce: *sense-making* (higher-level thinking skills that are not owned by learning machines and determine the deeper meaning of communication); *social intelligence* (ability to socially and emotionally interact with other people, which is necessary to develop collaboration and trustful relationships); *novel and adaptive thinking* (proficiency at thinking and providing responses beyond those based on rules, when faced with unexpected circumstances); *cross cultural competency* (ability to work in diverse cultural settings); *computational thinking* (ability to make sense of large volumes of information by applying simulations, models and statistical analysis); *new media literacy* (ability to use new media and generate content for engaging and persuasive communication); *transdisciplinarity* (ability to deeply understand a specific discipline and to communicate in other disciplines); *design mindset* (ability to develop tasks, processes and environments leading to the desired outcomes); *cognitive load management* (ability to filter information in function of its importance and to use tools and techniques to maximize cognitive function); *virtual collaboration* (ability to work as an active member of a virtual team).

The future of the workforce will be marked by skill shifts. Automation and artificial intelligence are the main drivers of changes in the employee skills. Research conducted by McKinsey Global Institute (2018) revealed that during the period 2016-2030, there will be a growth in the demand for advanced technological skills (such as programming), social and emotional skills (e.g. leadership and managing others) and higher-level cognitive skills (especially creativity). In parallel, the need for basic cognitive skills (for example, basic data input and processing) will decline (McKinsey Global Institute, 2018).

Based on the above-mentioned aspects, the second hypothesis may be formulated as follows:

- **H1.2:** *In services, the future development of conversational agents will drive changes in the employee skills, requiring abilities like sense making, novel and adaptive thinking, creativity, social and emotional skills etc.*

The third sub-question related to the major research question RQ1 is:

- **RQ1.3:** *What new tasks and jobs will emerge in services following the use of conversational agents?*

New types of jobs will be necessary to build and maintain proper relationships between humans and conversational agents. A survey made by Accenture (among 1,075 process professionals from large companies that use artificial intelligence technologies in at least one business process) identified the emergence of three new types of jobs that will be accomplished by humans only (Accenture, 2018). According to this study, these jobs are: trainer, explainer and sustainer. Trainers will teach the AI systems (including chatbots/conversational agents) to better understand the meaning of the customer communication, going beyond the literal significance of the words. The training will be necessary to ensure a proper tone of the conversation and an empathetic response of the AI systems in their dialogue with humans/customers. As AI systems become more sophisticated due to the progress in machine learning and deep learning, the explainers will facilitate communication between the AI technology specialists on one side and the decision makers, non-technical professionals and consumers on the other side. The sustainers will ensure that AI systems deployed will fulfil their mission and the unintended outcomes will be promptly addressed. They will maintain the confidence in the AI in terms of safety and respect of ethical values. New job titles will appear (Wilson *et al.*, 2017). Examples are: customer-language tone and meaning trainer, transparency analyst, AI usefulness strategist, machine relations manager.

Thus, the following hypothesis may be developed:

- **H1.3:** *In services, the adoption of the conversational agents will create the need for new tasks or new jobs focused on training, explaining and sustaining the new AI-powered systems.*

The fourth sub-question that emerges from the major research question RQ1 is the following:

- **RQ1.4:** *In services, will the use of AI in conversational agents be able to solve only complex customer problems?*

Research shows that collaboration between humans and machines leads to higher performance levels than teams made of humans only or of machines only (Wilson *et al.*, 2018). Consequently, companies should develop a new mindset and a new culture that rely on the idea that humans and machines have complementary not competitive roles.

The collaboration “human +machine” has a multiplier effect on the key performance indicators (KPIs) of companies. Complementarity may improve the values of KPIs up to 6.5 times compared to the situation when there is no collaboration between employee and machine (Wilson *et al.*, 2018).

There is a need for workforce reskilling in the context of the collaboration between employees and machines. The employees must renew and adapt their skills in order to ensure complementarity with the AI systems in delivering customer experience. (McKinsey Global Institute, 2017). Conversational agents will become the co-workers of humans, within organisations.

At present, a new era begins for human kind – the cognitive era. Experts underline that “boundaries between people and technology become blurred” (IBM & Globoforce, 2016). This new era is made possible by the development of machine learning, natural language processing, understanding and generation, as well as of cognitive computing. The employee experience and customer experience will be strongly impacted by the cognitive trends.

Cognitive computing is able to improve business performance by expanding the expertise of the employees and providing valuable support for decision making. In essence, the cognitive systems have three major capabilities, respectively to understand, reason and learn (IBM, 2017b). The understanding capability consists in processing large volumes of unstructured information in order to identify existing patterns based on keyword frequency, tone and sentiment. The reasoning capability refers to the ability of the cognitive systems to formulate relevant responses based on the identification of underlying concepts, on the development of hypotheses, on inferences and idea extraction. A distinct capability of the cognitive systems is learning. They are able develop a knowledge base with updated and meaningful information from various sources of data and an extremely large number of interactions (e.g. conversations between customers and the human agents of call centres etc.).

The new concept “augmented intelligence” was developed to underline the role of the artificial intelligence to assist humans. The AI is designed to enhance and not to replace human intelligence. IBM suggest the term “intelligence augmentation” (IA).

The concept of intelligence augmentation may be applied to the relation between humans and cognitive conversational agents.

From the perspective of IBM, customer service and call centres may benefit from cognitive systems that are accessed through conversational agents (Costa, 2017). A specific share of the total number of customer calls will be answered by the conversational agent, the rest of the calls being turned over to the human agent. The employee of the call centre will enjoy advantages such as improved performance and higher job satisfaction. The customers are satisfied because their problems are quickly addressed.

The use of technology to augment frontline employees instead of replacing employees is a business decision that is triggered by the objective to increase customer satisfaction not only to decrease costs and increase efficiency (Marinova *et al.*, 2017).

An additional hypothesis may be developed:

- **H1.4:** *In services, providing solutions to complex customer problems will require augmented intelligence or intelligence augmentation instead of artificial intelligence only.*

The final sub-question raised in relation to the major research question RQ1 is:

- **RQ1.5:** *What feelings do employee have towards conversational agents in the service domain?*

Intelligence augmentation is a relevant concept. However, its implementation requires the support from the employees.

In the European Union, the population of the countries considered digital front-runners (Norway, Finland, Sweden, Denmark, Estonia, Ireland, Netherlands, Luxembourg and Belgium) have a positive view of automation and AI. A survey organized in these nine countries showed that overall, 60% of the population has a fairly positive view and 15% a very positive view (McKinsey & Company, 2017).

Recent survey research made by IPSOS in seven countries (France, Germany, Spain, United Kingdom, United States, Canada and China) revealed that respondents (18 years old and over) have mixed feelings about the consequences of AI on own work in the coming years (IPSOS, 2018). The most widely spread feeling is curiosity, being expressed by 60% of the interviewees, while concern reaches 40%, optimism 35%, indifference 21%, confidence 17%, anxiety 15% and rejection 12%. At least one positive feeling is associated with AI by 78% of the respondents, compared to 52% that cite at least one negative feeling. According to the findings of this study, only 18% of the respondents working in services stated that AI-enabled tools are already in use, compared to 82% that declared that none are in use. The expectations relative to the effects of the AI on work efficiency are the following: reducing the time spent performing certain tedious tasks (72% of respondents); enhancing own abilities to meet deadlines and do things faster (68%); reducing the risks of error (67%); increasing the time spent on tasks with the most added value (64%); enhancing the quality of own work (63%); reducing the danger associated with certain tasks (61%); enhancing ability to innovate in own work (61%). Respondents associate several risks (negative consequences) with the AI-enabled tools: more control and surveillance (76% of respondents); job losses due to a reduced workload (68%); work dehumanizing and less social cohesion (65%); ethical problems related to personal data protection (64%). The users of AI-enabled tools envisage higher risks than the other respondents. Less than one third of the employees expect that AI will revolutionize their workplace in the next five years. In addition, about 70% of the current users of AI think that in the next ten years, AI will have profound transformational consequences at the level of own job (71% of the respondents that use AI) own profession (70%) and own company/organization (71%).

These aspects lead to the following hypothesis:

- **H1.5:** *In services, employees will have overall positive feelings about the use of AI cognitive conversational agents, while some concerns will still exist.*

These hypotheses reflect an optimistic perspective of the profound impact of conversational agents on human capital.

4.2. Impact on the behaviour of service customer relative to conversational agents

At present, researchers study the “service encounter 2.0”. In essence this is defined as “any customer-company interaction that results from a service system that is comprised of interrelated technologies (either company or customer owned), human actors (employees and customers), physical/digital environments and company/customer processes” (Larivière *et al.*, 2017). Integral part of the “service encounter 2.0” are the interactions between humans and conversational agents in the service domain.

In this context, the following major question is suggested for further research:

➤ **RQ2: What response will customers have to the use of conversational agents in services?**

The sub-questions derived from this major research question and the suggested hypotheses are presented below.

The first research sub-question is:

- **RQ2.1:** *Would people treat conversational agents differently from humans when interacting with them in the service domain?*

Chatbots as conversational agents progressed from the initial script-based Eliza created by Weizenbaum (1966). However, their conversational capabilities do not fully reach the complexity and sophistication of human-to-human dialogue. This state of fact is reflected by the experiment made by Shah *et al.* (2016) on a sample of 100 respondents that included males and females, people speaking English as native language or not, aged between 13 and 64 years old. The participants were invited to compare five modern chatbots (Ultra Hal, Elbot, Cleverbot, Eugene Goostman and JFred) to an online version of Eliza. The findings showed that all the five chatbots received a conversational ability mode score of 50, meaning *good conversation, but still machinelike*. The maximum score 100 = *human-like* was received as follows: Ultra Hal 2.6% of the time; Elbot 4.4% of the time; JFred 5.8% of the time; Eugene Goostman 13.8% of the time and Cleverbot 14.8% of the time.

People consider computers as social actors (Nass *et al.*, 1994). Based on the results of five experiments, Nass *et al.* concluded that individual's interactions with computers are fundamentally social. The explanation of researchers for this perception is that social responses to computers are commonplace and easy to generate. They consider that social responses are neither the result of conscious beliefs that computers are human/human-like nor the effect of user's ignorance or psychological or social disfunctions.

Reeves and Nass (1996) formulated the *media equation*: "media equals real life". Their studies led to the conclusion that humans perceive their interactions with computers, TV and new communication technologies as identical to the real social relationships and to the navigation of the real physical space. Their research findings uncovered that people are polite to computers, but treat them differently depending on their female or male voice. Also, findings showed that people perceive large faces on a screen as invading their personal body space. In addition, the physical responses of humans are similar in the case that motion is seen on screen or in real-life. Thus, people treat computers and television as social actors and they apply the same rules to interactions irrespective of their type, respectively with other people or with media.

A review of several experimental studies uncovered that individuals mindlessly apply social rules and expectations to computers (Nass & Moon, 2000). Four distinct sets of studies were identified in terms of their main topic and findings. The first set reveals that individuals apply gender stereotypes and ethnic identification to computers. According to the second set of studies, politeness and reciprocity are social behaviours manifested towards computers. A third set of studies refers to premature cognitive commitments. The fourth set refers to the response of individuals to computer "personality".

Based on the above-mentioned aspects, the following hypothesis is formulated:

- **H2.1:** *In services, customers tend to equate interactions with conversational agents to interactions with people and mindlessly apply social norms and expectations to these agents.*

The second sub-question related to the major research question RQ2 is the following:

- **RQ2.2:** *How will the human-like appearance of conversational agents influence the affinity of people towards such agents used in services?*

The reaction of humans towards conversational agents emerged as an important topic of study. In this context, researchers often refer to the concept of "uncanny valley". This term is a

translation found in the book of Reichardt (1978). The original wording in Japanese was introduced by Masahiro Mori in his essay of 1970 (Mori, 1970). The created word “shinwakan” used by Mori generated translation difficulties and was associated with the English words “familiarity,” “likableness,” “comfort level,” and “affinity” (Hsu, 2012). A revised translation was suggested by MacDorman and Kageki (Mori, 2012), respectively “a valley in one’s sense of affinity”.

Mori formulated the hypothesis according to which the response of a person towards a human-like robot would shift from empathy to revulsion as the robot approaches but fails to attain the lifelike appearance. The affinity towards a robot increases as the robot appears more human, but it abruptly decreases when individuals experience an eerie sensation when they realize that the robot that looked real is in fact artificial.

- **H2.2:** *In services, the affinity of customers towards conversational agents will increase as agents are more human-like, but will decline if customer realize that a gap exists between their expectations and reality in terms of agents’ human-like representation.*

The third sub-question related to the major research question RQ2 is:

- **RQ2.3:** *What influence will similarities between service customers and conversational agents have on the attitude and response of individuals towards such agents?*

Guadagno *et al.* (2007) investigated the extent to which gender and behaviour of an embodied agent (“virtual human”) influence the change in attitude of humans that listen to the agent’s persuasive communication in a virtual environment. Results showed greater change in the attitude of the participants when the embodied agent was of the same gender as them. These researchers also studied the influence of behavioural realism on attitude change in function of the belief that the other is an embodied agent or an avatar (an online representation of an actual person). According to the findings of the study, the agents in high behavioural realism condition are more influential/persuasive when participants believe they interact with an embodied agent. This influence is moderated by the gender of the “virtual human” and of the human participant in the research. The male agent was more persuasive when the participant believed that he interacted with a computer-controlled agent (not a human), the opposite being found in the case of female agents.

In their research, Moreno *et al.* (2002) investigated whether people apply stereotypes to animated agents based on visually apparent social group memberships. Research results indicated that participants applied social stereotypes based on sex. However, they did not apply stereotypes based on ethnicity.

In contrast, the empirical research of Pratt *et al.* (2007) found that computer users are more likely to change their actions based on input from a computer agent with the same ethnicity as theirs. The participants in the experiment received advice from two personified computer agents, one of African American and one of European/ Caucasian American ethnicity.

Based on two experimental studies Baylor and Kim (2004) found that transfer of learning was positively influenced by the more realistic images of the agents and the non-traditional representation of “expert” agents (as Black versus White). The pedagogical agents were animated, delivered the same messages and had computer-generated voices.

Behrend and Thompson (2011) studied the similarity effects in online training related to computerized trainer agents. Similarity in terms of appearance and feedback-giving style were assessed objectively by the researchers and subjectively by the trainees based on their perceptions. The findings of the study uncovered that in the case of objective similarity, the trainees scored higher on a declarative knowledge test and the trainees liked more their computerized trainer. Subjective similarity improved the trainees’ reaction to and engagement in training, as well as the liking of the trainer. Researchers concluded that subjective similarity is more important than objective similarity in predicting training outcomes.

A hypothesis can be formulated:

- **H2.3:** *In services, the attitude and response of customers towards conversational agents will be positively influenced by the similarities between customers and agents (e.g. in terms of gender, appearance, ethnicity etc.).*

The fourth sub-question derived from the major research question RQ2 is:

- **RQ2.4:** *What factors moderate the influence of facial similarity on the response of service customers?*

Similarities do not always lead to positive reactions to conversational agents. The study of Van Vugt *et al.* (2010) revealed a negative response. Researchers investigated the effects of facial similarity between users and embodied conversational agents. The variables manipulated during the experiment were facial similarity and agent helpfulness. Research findings showed that male participants had negative responses to the similar-looking agent when it was perceived as being unhelpful. More specifically, the male participants were less inclined to use again an obstructing agent that is facially similar, in comparison to an obstructing agent that is facially dissimilar. A facially similar obstructing agent affected the intention of individuals to use it again, in the case of male users, but not in the case of female participants.

A hypothesis reflecting this situation in services could be the following:

- **H2.4:** *In services, gender is one of the factors that moderate the relationship between the unhelpfulness of the conversational agent and the customer's intention to use it again.*

The fifth sub-question related to the major research question RQ2 is:

- **RQ2.5:** *What influence will anthropomorphic design cues have on the perceptions of service customers towards conversational agents and service company?*

The mindful or mindless nature of agent anthropomorphism is also a relevant topic of study. There are different viewpoints on what anthropomorphism is. As defined by Nass and Moon (2000, p. 93, 82), anthropomorphism involves the “thoughtful, sincere belief that the object has human characteristics” and it consists in “the assignment of human traits and characteristics to computers”. According to Sundar (2004), it is a mindless tendency towards long-term social relationships with computers, being a strong predictor of “hard-core” loyalty to computers.

Mindful anthropomorphism consists in the conscious evaluations made by individuals whether the conversational agent is human-like or machine-like. In contrast, mindless anthropomorphism refers to the unconscious attribution of human characteristics to the agent. The experiment designed by Kim and Sundar (2012) aimed to investigate if anthropomorphism is mindful or mindless. The experimental variables were the presence/absence of the human-like agent and the low/high interactivity on a health website. These variables served as anthropomorphic cues. Researchers found evidence of mindless anthropomorphism.

Recent research made by Araujo (2018) focused on the influence that anthropomorphic design cues and communicative agency framing have on the people's perceptions about conversational agents and companies. The study referred to the disembodied conversational agents that are available in social media and in messaging applications. The findings revealed that use of human-like language and name enhanced people's perception that agent is human-like. These results were obtained in the case of both mindful and mindless anthropomorphism. In the research of Araujo, no difference was found in terms of social presence between human-like and machine-like agents. As defined by Heeter (1992), social presence is “the extent to which other beings (living or synthetic) also exist in the world and appear to react to you”. Besides the personal presence and the environmental presence, the social presence is one of the dimensions of the subjective experience of presence.

According to the findings of Araujo, framing the conversational agent as intelligent diminishes the perceptions of mindless anthropomorphism for the machine-like agent, but not for the human-like agent. In addition, research results uncovered that designing conversational agents

with human-like cues positively influences relationship building and the emotional connection between the individual and the company that uses the agent.

Another hypothesis is issued:

- **H2.5:** *In services, the use of anthropomorphic design cues would positively influence individuals' perceptions about disembodied conversational agents and would favourably impact relationships between the individuals and the service company.*

The next sub-question evolving from the major research question RQ2 is:

- **RQ2.6:** *Does the attribution of mental capabilities to the conversational agent explain the feelings of eeriness that service customer could experience in the communication with that agent?*

The research of Gray and Wegner (2012) aimed to identify the causes of the “uncanny valley of the mind” which they named “the unnerving nature of human-like robots”. Their explanation for the “uncanny valley” is the attribution of mind to robots, respectively the attribution of experience (capacity to feel and sense) rather than agency (capacity to act and do). The attribution of experience was considered one of the factors that drive the “uncanny valley”, besides the facial features, threat avoidance and general perception of categories.

Recently, the experiment of Stein and Ohler (2017) introduced a virtual reality chat program to a group of participants. A pre-recorded 3D scene with two digital characters engaged in an emotional and emphatic dialogue was presented. The characters expressed their own emotions and empathized with the mental state of each other. In the experiment, the manipulated variables were the type of character (human-controlled avatars vs. computer-controlled agents) and the character autonomy level (scripted vs. self-directed). Researchers found that participants experienced the strongest feelings of eeriness when they perceived the characters as being autonomous artificial intelligence, social beings with their own mind. In conclusion, the “uncanny valley of mind” is based on the attribution of emotion and social cognition to the computer-controlled agent.

The hypothesis developed for this sub-question is:

- **H2.6:** *In service, customers could experience an “uncanny valley of mind” when they associate emotions and social cognition to the conversational agent.*

The final sub-question related to the major research question RQ2 is:

- **RQ2.7:** *Do effects of the uncanny valley (the valley in one's sense of affinity) depend on the type of interface between service customers and conversational agents?*

The experiment made by Ciechanowski *et al.* (2018) revealed the affective responses of humans to different types of interfaces used when they interact with a chatbot. Two types of chatbots were used, respectively a simple text chatbot and a more complex animated chatbot. Research findings uncovered that uncanny effects were lower and the affective responses were less negative when participants interacted with the text chatbot, compared to the animated chatbot. The psychophysiological reactions were less intense in the case of the text chatbot.

The following hypothesis is developed:

- **H2.7:** *In services, the effects of the uncanny valley (valley in one's sense of affinity) depend on the type of interface used for the interaction between the consumer and the conversational agent.*

The hypotheses associated with the major research question RQ2 underline the multi-faceted impact of conversational agents.

4.3. Impact of conversational agents on the interviews with service customers

In the service sector, conversational agents can potentially play the role of interviewer in various situations. For example, agents could ask customers for feedback relative to the service

experience, could question respondents on various market research topics or could interview patients to accomplish the health screening in the medical field.

Computer-assisted interviewing and the use of survey platforms became commonplaces in market research. Face-to-face interviewing progressively loses ground in front of modern techniques applied in the virtual environment.

Conversational agents are able to provide new opportunities for customer interviewing, especially for data collection from various types of subjects. The relevance of conversational agents as interviewers will depend on the reaction of individuals towards the “AI-powered” interviews. Consequently, a major question may be raised for further research:

➤ **RQ3: How will conversational agents impact the interviews with humans in the service sector?**

Several sub-questions that evolve from this major question and the suggested hypotheses are presented hereinafter.

The first sub-question derived from the major research question RQ3 is:

- **RQ3.1:** *Will response rate and efficiency be the differential advantages of the interviews led by conversational agents compared to those led by humans in services?*

Researchers studied the use of conversational agents to interview respondents in the virtual world. This approach represents a new stage in the evolution of surveys in the online environment. Several other interviewing methods preceded this stage, such as computer assisted self-interviewing (Couper & Nicholls, 1998) and the automated online interviewing via the instant messaging service ICQ (Stieger & Reips, 2008). In the social online environment Second Life, bots (computer-controlled agents) were used to collect data, engage in simple interactions and achieve simple automated experiments (Friedman *et al.*, 2007), as well as to interview human avatars on their opinion about genetically modified tomatoes (Van Vliet *et al.*, 2009).

The experiment conducted by Hasler *et al.* (2013) assessed the use of embodied survey bots to automate data collection in 3D virtual worlds such as Second Life. A comparison was made between a bot (software-controlled avatar) and a human-controlled avatar. Participants were asked about their religion. The findings showed that in comparison with the survey bot, the human-controlled avatar led to a higher response rate (65.6% against 30.9%) and more negative answers. However, the embodied survey bot is more cost-effective than a human interviewer, due to two main reasons. Firstly, it contacted a larger number of respondents than the human-controlled avatar within the same time interval. Secondly, it carried out interviewing in an automated manner, without the need for monitoring or maintenance. The findings of this research support the use of bots as virtual research assistants for interviewing avatars in large scale surveys in social online environments.

The hypothesis issued for the RQ3.1 is:

- **H3.1:** *The use of conversational agents to interview service customers (on their experience with the service company, its brands and employees) will be cost-effective, but the response rate will be lower than that of a human-controlled avatar interviewer.*

The second sub-question related to the major research question RQ3 is:

- **RQ3.2:** *What changes will incur conversational agents as interviewers in comparison with human interviewers in the communication with service customers?*

In their research, Hill *et al.* (2015) compared 100 instant messaging conversations to 100 exchanges with the chatbot Cleverbot. In comparison to a conversation with a human, they found that communication with a chatbot has longer duration, shorter messages, lower vocabulary richness and greater profanity (use of more banned words of different levels of intensity). The researchers considered that an explanation for this situation could be the adaptation of individuals to the communication style of the chatbot. On average, individuals were inclined to send to the chatbot two times more messages than to another human. The

number of words per message varied between 2 and 13 in the human-chatbot communication and between 2 and 25 in the human-human communication. In addition, the results highlighted a 30-fold average increase in profanity in the human-chatbot communication compared to the human-human conversation.

The hypothesis based on these findings is:

- **H3.2:** *The communication of service customers with a conversational agent differs from a conversation with humans in terms of duration, message length, vocabulary richness and level of profanity.*

The third sub-question related to the major research questions RQ3 is:

- **RQ3.3:** *What differences exist between the human-agent and the human-human communication as regards the attitude of the service customer towards self-disclosure?*

The research of Mou and Xu (2017) focused on studying whether individuals during their initial interaction with a chatbot would disclose their personality traits and communicative attributes differently from an interaction with humans. The researchers investigated the communication of individuals with the chatbot Xiaolce (of Microsoft) and with humans on the social media platform WeChat. According to their findings, users tended to be more open, more agreeable, more extroverted, more conscientious and self-disclosing when interacting with humans than with the chatbot. In their communication of Xiaolce, users had a higher level of neuroticism. In essence, individuals demonstrated more desirable traits in the communication with humans than in the conversation with the chatbot. There were no significant differences in the level of control over social interaction between the communication with humans and communication with the chatbot.

The hypothesis developed for the sub-question RQ3.3 is:

- **H3.3:** *Service customers tend to be more open to disclose their personal traits in the initial communication with a person rather than with a chatbot.*

The fourth sub-question entailed by the major research question RQ3 is:

- **RQ3.4:** *How will the use of conversational agents as interviewers impact the disclosure of highly sensitive personal information by service customers?*

Richman *et al.* (1999) achieved a meta-analysis of the social desirability distortion in three types of surveys, respectively based on computer questionnaires, paper-and-pencil questionnaires and face to face interviews. The comparison of these surveys showed there is less social desirability distortion in computerized surveys compared to surveys based on paper-and-pencil questionnaires and to the face-to-face interviews.

Based on a laboratory experiment, Lind *et al.* (2013) found that respondents tend to disclose more information in audio computer-assisted self-interviewing (ACASI) than in other types of interviews such as face-to-face interview and automated interviewing systems with more or less facial movement (even if the virtual interviews involved the computerized self-administration of the questionnaire). The researchers concluded that the absence of facial representation in ACASI was the reason for the higher level of disclosure.

An exploratory study made by Pickard *et al.* (2016) investigated the influence of topic sensitivity on the preference of individuals to disclose personal information to a human interviewer or to an embodied conversational agent. Research findings uncovered that individuals prefer to be interviewed by an embodied conversational agent when the topic is highly sensitive or evokes negative self-admission. In contrast, the preference for a human interviewer is associated with topics that are low in sensitivity or evoke positive self-admissions. The reason for such preferences is the fact that individuals feel being judged/evaluated by a human interviewer, but not by an embodied conversational agent.

In the service sector, several topics may be perceived as highly sensitive by customers. People could be less eager to disclose information on aspects such as specific health problems, addiction situations, financial difficulties etc. Thus, they would prefer an AI interviewer.

In medical context, Gratch *et al.* (2014) studied the impact of virtual humans on the disclosure of personal information by patients, during the health screening procedure. In the experiment, participants interacted with two types of *virtual humans* – one being teleo-operated by humans (“Wizard-of-Oz”) and the other controlled by artificial intelligence (fully automated). Lower resistance to self-disclosure, lower impression management and higher system usability were reported by the participants who believed that interacted with an automated system than by those who believed that interacted with a human operator.

The laboratory experiment of Schuetzler *et al.* (2018) examined the influence of conversational relevance and embodiment on socially desirable responding (respectively on answers given by individuals to sensitive and non-sensitive questions). Responses to three types of interviews were compared: interaction with a conversational agent, face-to-face interview and web-based survey. In the case of sensitive questions (related to alcohol consumption), the human interviewer elicited responses with a higher social desirability than the chatbot interviewer. The potential explanation suggested by researchers was the social presence specific to the face-to-face interviews. When interviewed by a conversational agent with better conversational abilities (i.e. that provides more relevant responses), individuals tend to provide more socially desirable responses. The influence of the agent embodiment had no significant influence on the responses to sensitive questions.

These findings lead to the following hypothesis for the sub-question RQ3.3:

- **H3.4:** *Service customers would prefer to disclose highly sensitive personal information to a conversational agent rather than to a human interviewer, especially when the conversational relevance of the agent is low or moderate.*

The hypotheses related to the major question RQ3 reflect opportunities for the use of conversational agents in research context for service customer interviewing.

4.4. Future impact of conversational agents on decision-making in service companies

The advancement of research in cognitive computing within the field of artificial intelligence will open new opportunities for the use of conversational agents in the decision-making process within service companies.

A major question for further research can be raised:

➤ **RQ4: How will conversational agents support business decision-making in service companies?**

Cognitive computing refers to “systems that learn at scale, reason with purpose and interact with humans naturally” (Kelly, 2015). These systems have the ability to learn from the interactions with humans and environment. Thus, the capabilities of the cognitive systems improve by means of training and use.

Such systems are also able to make sense of the unstructured data that represents the overwhelming majority of world’s data. The core capabilities of cognitive systems are the following: *to create deeper human engagement* – based on the detailed data about individuals (geolocation data, Web interactions, transaction history, electronic medical records etc.); *to scale and elevate expertise* – through the access to professional knowledge/expertise; *to infuse products and services with cognition* – with the support of the Internet of Things; *to enable cognitive processes and operations* - for the enhancement of operational effectiveness; *to enhance exploration and discovery* - in order to identify patterns, opportunities and to formulate actionable hypotheses (Kelly, 2015).

The first sub-question derived from the major research question RQ4 is:

- **RQ4.1:** *What contribution will conversational agents based on cognitive computing have to decision-making in service companies?*

Experts envisage a partnership in decision-making between humans and artificial intelligence. The role of conversational agents will be to augment human capabilities. This will be possible

due to cognitive services like: locating knowledge, pattern identification, natural language recognition, machine learning and eliminating bias (Michiels, 2017). The cognitive systems will provide information to help humans make decisions. The contribution of cognitive computing to decision-making will depend on the capabilities to facilitate the effective search of large and relevant volumes of knowledge, as well as to process natural language related to the human queries (Cognizant, 2017).

Research demonstrated that combined predictions made by humans collaborating with intelligent agents (artificial neural network agents) are more accurate and robust compared to predictions made only by groups of humans or only by agents (Nagar & Malone, 2011). The combined approach is recommended when identifying patterns in data is difficult, data cannot be easily codified and unexpected changes occur.

The IBM Watson for oncology (WFO) cognitive system provides evidence-based treatment options for the decisions made by oncologists. The options are presented in three categories: “recommended”, “for consideration” and “not recommended” (Zhou *et al.*, 2017).

The hypothesis formulated for the RQ4.1 is:

- **H4.1:** *In service companies, conversational agents based on cognitive computing will help decision-makers to locate and analyse knowledge, identify patterns, make predictions and better understand the alternative options.*

The second sub-question corresponding to the major research question RQ4 is:

- **RQ4.2:** *What specific types of services will benefit from the support of conversational agents based on cognitive computing in the decision-making process?*

In the healthcare field, the increasing data complexity and the fact that universal solutions are not effective for all the patients open the way to mobile health services provided by a chatbot with a knowledge base for cloud computing (Chung & Park, 2018).

Human pathology benefits from new screening techniques based on artificial intelligence. Experiments show that top pathologists reach 96% accuracy in detecting cancer cells in biopsy samples, while an AI screening technique developed by a Harvard-based team reaches 92%. When the same top pathologists collaborate with the AI, the level of accuracy increases to 99.5% (Wanijek, 2016). To ensure high accuracy, the algorithms must be trained by “deep learning,” using thousands of images of cancer cells in order to better recognize and diagnose them.

In insurance, cognitive computing is already applied for customer self-service, call centre representative assistance, underwriting and claims tools, regulatory policy compliance management (IBM, 2017c). With cognitive systems, underwriters will be able to make informed decisions based on the assessment of each customer risk by means of weather data, geolocation data and other types of data. In addition, in claims management, the cognitive systems will be able to recognize the relevant text from various documents (IBM, 2015).

The legal field is also a domain of potential application of AI. An example is ROSS – an AI supported platform for legal services, an advanced research tool provided by the company ROSS Intelligence. Compared to the traditional Boolean search tools, the ROSS platform provides better performance in information retrieval, respectively: 40% more relevant authorities cited, 30% decrease in search time; an annual revenue increase of \$8,466 to \$13,067 per attorney (based on a 25% conversion of unbillable time into billable time) (Chang, 2018). An algorithm developed by Katz *et al.* (2017) predicted the behaviour of the Supreme Court of the United States for the period 1816-2015. The prediction accuracy was 70.2% at the case outcome level (for 28,000 cases) and 71.9% at the justice vote level (for 240,000 votes).

The hypothesis developed for the sub-question RQ4.2 is:

- **H4.2:** *All the types of services will benefit from the support of conversational agents based on cognitive computing, especially the medical, insurance and legal services.*

The third sub-question evolving from the major research question RQ4 is:

- **RQ4.3:** *At what managerial levels will conversational agents based on cognitive computing support decision-making in service companies?*

An experiment made by the Massachusetts Institute of Technology uncovered that decision-making groups assisted by AI perform better by at least 17% than teams that are not supported by AI (Tikka, 2018). However, there is extremely few information relative to the experience acquired by companies in involving conversational agents in decision-making.

In 2014, the Hong Kong-based venture capitalist fund Deep Knowledge Ventures (DKV) included the software VITAL (Validating Investment Tool for Advancing Life Sciences) as an AI-member of the management team (PRWeb, 2014). The aim was to make more logical decisions of investment in biotechnology, sector marked by a very high failure rate (96% of the drugs being unsuccessful in clinical trials). In 2017, the fund stated that VITAL helped to avoid bankruptcy (Burridge, 2017). VITAL 2.0, the new version of the algorithm will rely on diversified data sources such as scientific literature, grants, patent applications, clinical trials and even the biographies of individual team members of companies in which DKV is interested.

Tieto, the Finnish software and service company listed on OMX - the Nordic Stock Exchange ranged among the first companies that promoted a conversational agent to a senior management position (Tieto, 2016). Named Alicia T., the conversational agent is full-member of the management of the data-driven business unit and also has voting rights. Alicia T. assists the business unit in data-driven decision-making. The role of Alicia T. is to support “truly data-driven decision-making and innovate new data-driven ideas” (Järvelä, 2016). This conversational agent is based on natural language processing and supervised learning. Thus, Tieto will study the impact of human-robot teams on decision-making (Tieto, 2016).

Artificial intelligence was also “hired” by the advertising agency McCann-Erickson Japan (McEleny, 2016). Created by the McCann Millennials Taskforce, the AI-CD β holds the position of creative director. AI-CD β is able to give creative directions on ads for various real accounts. Its capabilities are based on data about TV shows and the winners of the All Japan Radio & Television Commercial Confederation’s CM Festival. In addition, AI-CD β becomes more effective by learning from the results of the campaigns it directed.

The hypothesis for the RQ4.3 is:

- **H4.3:** *In service companies, conversational agents based on cognitive computing can support decision-making at different managerial levels, including the board of directors.*

The hypotheses related to the major research question RQ4 consider the development in the capabilities of conversational agents due to cognitive computing. Nevertheless, the idea that such an agent is member of the board of directors could have not only raving fans, but also serious opponents.

5. Discussion

The topic of this paper emerged in the context of the active debate on the effects that artificial intelligence (AI) will have on individuals and society. Opinions range from very optimistic to very pessimistic with various degrees of intensity. Illustrative examples are the optimism of Mark Zuckerberg, the CEO of Facebook, and the pessimism of Elon Musk, the CEO of Tesla, both being prominent supporters of the AI (Jones, 2017). To answer questions like “Should we fear AI?”, experts engage in scientific foresight (Metzinger *et al.*, 2018) or use models to analyse the implications (Berg *et al.*, 2018).

The optimistic approach relative to the artificial intelligence recognizes the future shifts in labour due to the accession of the AI, but states that humans will still be part of the equation (Davenport & Kirby, 2016). While knowledge workers will be affected by the development of

intelligent technologies, humans will have to learn how to play a significant role augmenting their capabilities by means of AI.

Within this context of mixed viewpoints, the perspective of this paper is founded on the favourable future foreseen by experts for conversational agents. In 2018, Gartner estimated that 25% of customer service operations will use virtual customer assistants or chatbot technology by 2020, compared to less than 2% in 2017 (Gartner, 2018). Gartner experts also predict that by 2020 over 50% of medium to large enterprises will have deployed product chatbots (Goasduff, 2018).

The approach specific to this paper is based on the expected evolution of conversational agents from chatbots to the cognitive dimensions. According to Forrester, one of the top emerging technologies of the period 2017-2021 will be the intelligent agents coupled with AI/cognitive technologies that will automate engagement and solve tasks (Hopkins, 2016). Over the next ten years, AI technologies will be the most disruptive class of technologies (Panetta, 2017). The main factors that will contribute to this trend will be the augmentation in the computational power, big data and the development of the deep neural networks.

6. Conclusions

The aim of this paper is to contribute to the conceptual approach of the impact of conversational agents on humans in services. The literature survey in several prominent databases revealed that such topic has almost not been addressed by researchers.

The actual contribution of the paper consists in raising a set of major questions for further research. Each question focuses on a distinct domain related to humans in services. Overall, four impacted domains were targeted: human capital of services companies, service customer behaviour towards conversational agents, service customer interviewing; decision-making in service companies.

In each domain, several hypotheses were developed. They were formulated to serve the study of the impact of conversational agents on humans in services.

This conceptual approach has several limitations. It refers only to the impact on humans. Other perspectives can also be considered such as the impact on the organizational structure, company performance, personal data protection, business customers and overall society.

The direct implications of the paper for further research emerge from the sub-questions and hypotheses suggested in each of the four domains. They represent an invitation to analyse the new opportunities and challenges generated by the artificial intelligence under the form of conversational agents.

Future studies may consider a more granular view of the impact of conversational agents on humans in services. Each domain may be studied in-depth, hypotheses may be reviewed and refined.

Even if the present narrow AI is sometimes below the expectations of users and if AGI (artificial general intelligence) has not become reality yet, humans have to make decisions on how to act and position themselves towards the new forms of artificial intelligence. Conversational agents are an integral part of this (r)evolution.

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