Genders' Fascinations and Fears Towards the Use of Cognitive Computing

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Abstract

Cognitive computing are intelligent systems that have been designed by companies in order to enhance customer experiences by providing personal advice and guidance for the everyday life buying decisions. The ability of cognitive computing systems to analyze huge amount of consumer data and their ability to learn from experience by machine learning systems, will revolutionize the interaction between consumers and companies. Therefore it is important to determine the major factors that impact the consumers' willingness to use cognitive computing systems. The objective of our research is to determine the perception and preferences of consumers regarding cognitive computing systems based on gender. The results of an online survey show that the two genders have more similarities than differences in the perception of cognitive computing. However women tend to be more reluctant to cognitive computing systems, as they don't know the processes behind the system and they don't have a control over the information shared with the intelligent system. These results are in accordance to previous research and they have important implications for the implementation of cognitive computing systems and for future research.

Keywords: cognitive computing, artificial intelligence, cognitive virtual assistants, data, consumer.

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Introduction

As new technologies emerge, information remains a valuable resource of power for companies and consumers (Gupta, et al., 2018). The new technological developments allow the exchange and creation of data through virtual communication, information transferring, media transmission, sharing and all access to different kinds of data, but simply collecting and storing data is not enough, as data has to be transformed into information. In itself, data actually only represent raw material that has to be further processed and understood. Researchers agree on the fact that both computing power, and analytical methods, allow this at an unprecedented level (Huang and Rust, 2018; Holmlund, et al., 2019; Zaki, 2019; Wiener, Saunders and Marabelli, 2020).

The complexity and diversity of the existing data types combined with the increased volume and delay in the analysis and processing by human forces, makes data analysis a time-consuming and tiring activity (Gupta et al., 2018). In addition, existing human behavioral distortions and cognitive biases (Chen, Elenee Argentinis and Weber, 2016) contribute as further inhibitors. At this point, however, the so-called concept of cognitive computing (cc) and the underlying computer-aided methods of automated data analysis and data base analysis come into play (Civita, 2017) and remove the existing human limitations. In this regard, both cognitive computing and big data are related and are to be characterized by the same 5V-characteristics often acknowledged by literature: Volume, Variety, Veracity, Velocity and Value (Fosso-Wamba et al., 2015; Grover and Kar, 2017; Gupta et al., 2018; Hurwitz, Kaufman and Bowles, 2015; Pelau and Barbul, 2021). According to Chen, Elenee Argentinis and Weber (2016), these five main data properties are also to be seen as five inherent challenges that need to be overcome with the help of advanced technology and analytics.

Given the consistent and wide applicability of cognitive computing and of its derived cognitive computing systems, the present work aims to investigate the consumer experiences with the help of cognitive computing. The focus of the research is put on the perception of consumers regarding the ability of intelligent systems to consumer profiling as well as their ability to determine the deriving preferences of the consumer and to deliver suitable product recommendations and contouring the consumer experience when interacting with companies. In the following sections of the present article, we discuss the concept of cognitive computing, with regard to its meaning for multiple, diverse data streams and types. We then empirically investigate consumers' enthusiasm for cognitive systems and especially for the so-called cognitive virtual assistants (CVAs). The present paper also assesses consumers' fear of intrusion of cognitive systems into their private spheres. In this regard, we discuss based on a discriminant analysis the differences in perceptions between two gender groups (male and female).

1. Literature review on Cognitive Computing

Cognitive computing systems are thinking, reasoning and remembering systems, designed to work together with humans in order to provide them with helpful advice in making decisions. Cognitive computing systems are used by companies in order to provide customers with a personalized online shopping capability that makes it easy to find what they are looking for online. Previous research almost always connects the concept of cognitive computing to the concept of (big) data (Reynolds, 2015). As a synergy between data science and cognitive science, cognitive computing was developed as an interdisciplinary approach and become the field of study that incorporates both research areas into advanced computer technologies (Hurwitz, Kaufman and Bowles, 2015; Varadarajan, et al., 2020). In search for a solution to manage the above-described volume of data and to keep up with the still ongoing data generation, the concept of cognitive computing came to life. Not only do cognitive systems solve these two problems, but in addition they try to unlock and find meaning of data in all its varieties and contexts, eliminating unwanted data noise. Furthermore, human incapacities, such as biases and time limitations are obstructed, allowing faster, more accurate data processing.

Chen, Elenee Argentinis and Weber (2016) describe the concept of cognitive computing as a subset of AI-technology that has the ability of mimicking specific human cognitive behavior (e.g. sensing, observing, interpreting, learning adapting and reasoning). In this regard, the cognitive technologies find their main deployment in problem-solving and assisting humans for decision-making processes. Cognitive computing is therefore shortly to be described, as a comprehensive approach to assess data challenges (Ogiela and You, 2013; Chen, Elenee Argentinis and Weber, 2016; Gupta, et al., 2018; Pramanik, Pal and Choudhury, 2018). Without an actual formal agreement on its definition, researchers seem to only partially agree on the meaning of cognitive computing (Reynolds, 2015). Probably the most accurate definition simply unveils the ability of such technologies to create cognition (Appel, Candello and Gandour, 2017). Gupta et al. (2018) have explained the resemblance, even the subordination of cognitive computing to artificial intelligence (AI). While technologies based on AI are working under specific parameters and rules, cognitive technologies work by detecting commands, asserting presumptions, and suggesting possible solutions (Gupta, et al., 2018). Cognitive systems use AI in their core, in order to break down and understand different data sets. These kinds of systems try to find connections between countless streams and types of structured and unstructured data, to carry out in-depth analyses, to formulate predictions and to convey insights to people in a comprehensible way.

As a fundamental component of cognitive systems, the wide applications of machine learning represent an innovative method for data mining of large databases and for creating accurate predictive models. Machine learning is based on the idea that a system can learn from data, recognize patterns on its own, and make decisions with minimal human intervention (Chahal and Gulia, 2019). Fast and precise the automated models of machine learning enable a more detailed analysis of the aforementioned huge databases and the surrounding big data characterized by the 5Vs (Cui, Wong and Lui, 2006). As sub-areas of machine learning, deep learning methods and artificial neural networks further enable the automation and digitization of human-like tasks. Advances in deep learning are to be observed in numerous AI-driven activities, ranging from gaming and precise computer vision to speech and pattern or problem recognition by machines. Deep learning methods and programmed algorithms inspired by the human brain are actually able to learn from large amounts of data, work and adapt by gaining experience and thus solve complex problems faster than actual people (Quinto, 2020, p. 289). Artificial neural networks are based on studies of biological models and relate directly to the cognitive process for mimicking the processes and capabilities of the human brain. This means that complex structures, interactions and non-linearities can be investigated and recognized as patterns by machines and be further used in the decision-making process (Cui, Wong and Lui, 2006).

According to many studies (e.g. Reynolds, 2015; Chen, Elenee Argentinis and Weber, 2016; Gupta, et al., 2018; Zaki, 2019), cognitive systems, which are built with the help of the operating technologies discussed above, take data from their environment, convert them into information with the help of pre-programmed learning algorithms, and furthermore use the generated information to create valuable knowledge, just like humans do. The act of gaining experience leads to influencing and improving the performance of both people and computers. In the same way as the human thinking process, cognitive systems invest their self-built knowledge in a certain pre-defined goal and thus in the direction of an exact performance in the environment from which they collect the data (Dietterich and Langley, 2007). Respectively, cognitive learning systems and algorithms are able to convert what they have learned into a problem-solving process and lead to precise, evidence-based results (Dietterich and Langley, 2007).

Often used as an overall description of several technologies, such as IT infrastructures, software solutions and algorithms, cognitive computing aims to make problems that are characterized by ambiguity and uncertainty more approachable and thus also solvable by machines and computers. Cognitive systems are able to deal with natural language through natural language processing and possess the necessary specialist knowledge so that they can learn, understand and evaluate content by themselves. As mentioned earlier, the most important aspect of the cognitive system is the ability to learn on its own. The cognitive computing-based services in the background are characterized by adaptability, interactivity and contextuality, with the help of cognitive algorithms, in which imprecise, controversial situations are formulated in an understandable manner (Baumbach and Ketterer, 2017). In addition, developed with regard to technologies of neuromorphic computing and neural network accelerators, cognitive systems can cope with the processing challenges caused by noisy, unstructured surrounding data (Gudivada, 2016) and obtain valuable information out of such data.

Having the above-mentioned characteristics und underlying technologies in mind, research concludes (e.g. Fosso-Wamba, et al. 2015; Appel, Candello and Gandour, 2017; Gupta, et al. 2018; Lytras, et al. 2020) that cognitive systems are suitable for the investigation of various data sets, including rich media and texts, the identification of conflicting data, information discovery, pattern recognition, clarification of ambiguous situations, creation of complex solution alternatives in the big data environments and not only. It is therefore fair to admit that cognitive computing offers a new approach to uncovering the potential of data (Reynolds, 2015), with data being perceived right from its context, with temporal, spatial and personal characteristics directly influencing the meaning and consistency of the information.

Perhaps the most common form of cognitive systems is the Cognitive Virtual Agent (CVA), which has a human-like, intelligent digital assistant function and cognitive abilities in order to understand the diverse relationships in the environment. By definition, cognitive assistants and CVAs are generally software agents that can interpret and process text, speech, gestures or visual inputs. They have different abilities to understand the data input provided, to interpret it and, with step-by-step programmed logic, to check the user for the intention and context of a conversation and to provide information as a result or to carry out the intended task (Sabharwal, et al., 2020, p. 3). The wide applicability for cognitive agents and assistants ranges from the finance and investment sector to the healthcare industry and to the education sector. Examples therefore include: monitoring and analyzing physical health, assisting medical staff for problem diagnosis, screening and suggesting appropriate treatment, simulating human conversation, understanding and responding to customers' needs and desires, responding to questions and offering support.

2. Consumer experiences using cognitive computing

Cognitive systems are continually evolving based on new information, results, and undertaken actions, so they act as advisory systems by presenting human users the information and suggesting a range of options. More and more companies use cognitive computing to generate insights and to implement fundamental business changes (in areas such as marketing, consumer support, and product development) (Davis, et al., 2016). As previously established, cognitive systems are able to capture the human thinking process, imitate it and also learn from mistakes made over time (Gupta, et al., 2018). Numerous companies from data-driven industries (e.g. healthcare, retail, financial services, education, marketing, social media etc.) have integrated cognitive systems into their processes. There is no doubt that cognitive systems, like for instance IBM Watson, have extensive application potential. The fact that they are used to help launch new products and draw conclusions about how people in different geographic and demographic groups will respond consists in a precious advantage. This enables the product alignment to be adapted and facilitates direct addressing of the appropriate target group throughout the marketing campaign.

With the help of advanced cognitive computing systems, companies are provided with meaningful insights derived from the abundance of data and are thus facilitated with relevant information for future strategic and economic decisions. It is only fair to say that cognitive computing systems have fastened the anticipation of global trends of today's newly defined experience economy (Dziewanowska, 2015). The transition to a cognitive-based/optimized consumer experience lays important ground for research in terms of the whole re-design of consumer experience, as in interaction, perception, emotion (McColl-Kennedy, et al., 2019; Lytras, et al., 2020). The complexity of collected data proves the hard work companies have to do, in order to meet the consumer expectations. In terms of data-driven initiatives by companies, marketers need to focus on meeting consumers exactly where and how they want to get involved in long term relationships (Glass and Haller, 2017; Stanescu, Pelau and Barbul, 2021).

Current advances in the field of cognitive computing in the retail industry are not actually just a fad, but an increasing trend, an actual necessity, as cognitive systems demonstrate in many situations efficiency and time advantages, as well as service quality over human employees. This is due to extended data storage functions, high processing speeds and precise personalization capabilities. From an operational perspective, AI and cognitive devices can substantially lower costs by increasing operational efficiency and effectiveness and by also reducing the workload of human employees (West, Clifford and Atkinson, 2018). As mentioned, and also proven, cognitive APIs have human-like intelligence. In addition, these cognitive systems are designed to interact and manage relationships with consumers just like regular employees. They have functional, social and emotional pre-programmed capacities (Lu, Cai and Gursoy, 2019), with performance advantages such as accuracy, reliability, efficiency and consistency of communication and marketing structures being brought to the fore (Gursoy, et al., 2019).

Currently, most people have a hard time understanding how and why exactly intelligent, cognitive systems do what they do. As industries are still transitioning to the so-called cognitive era, making more and more room for cognitive systems, both companies and consumers need to further adapt to this increasing trend. It is therefore important to examine and assess the coexistence of the consumers and the cognitive systems from different perspectives, see the extent to which it is recognized and desired and also what attitudes exist about it. Accordingly, our research results in this direction it will be presented in the following sections.

3. Methodology

Acknowledging the ongoing trend and increasing implementation of different forms of cognitive computing in interaction with customers in various contexts, the focus of the present study is to determine the attitude of consumers towards cognitive systems from a more personal point of view. The conducted empirical research aims to offer some meaningful insights into consumers' enthusiasm for cognitive systems as well as to investigate the consumers' response towards the intrusion of cognitive systems into their private spheres. In order to test these objectives, a questionnaire has been developed containing 50 questions about the attitude of consumers regarding cognitive computing and data protection. The above-mentioned items have been measured via an online questionnaire, with Likert Scale questions, having values between 1 (total disagreement) and 7 (total agreement). A total of 140 randomly chosen respondents, profiled by different characteristics, such as age, gender, education and income have been involved in our study. The Cronbach Alpha coefficient of $\alpha = 0.894$ shows the good reliability and internal consistency of the used scale. For the purpose of the study, the results of the survey have been concluded based on a discriminant analysis conducted with the help of IBM SPSS Statistics 25, in order to determine significant differences between the two sample groups: male and female. The sample includes a total of 63 males and 77 females.

4. Results and discussions

Our research mainly focuses on the difference between the two genders of consumers. Both previous and present results show that in the case of cognitive computing, which is still a rather unfamiliar set of interacting and interactive technologies for most consumers, there are only average significant differences (Pelau and Barbul, 2021), as can also be observed in the Table 1. Results marked in bold writing show where significant differences arise in the comparison between female and male perception regarding the tested aspects related to cognitive computing.

After performing the discriminant analysis on the data set for the items listed in table 1, regarding the independent gender-variable four significant differences emerged. First, female respondents seem to be generally more affected by their lower understanding of what actually lays behind cognitive systems (question 4, where $\overline{x}_{women}=4.34$ and $\overline{x}_{men}=3.17$). Accordingly, women tend to be more worried than men for this reason (question 5). This behavior is proven by significant differences between the two groups ($F_4=16.249$, $p_4=0.000$ and $F_5=7.031$, $p_5=0.009$). While both sample groups wish to understand the technology behind CCS, the lack of knowledge on how these technologies work seem to be a source of concern for women. This could cause worries that CCSs may seem to overtake their capabilities, as one may not be able to evaluate competences of cognitive computing.

Regarding the fear of invasion of privacy, as already expected, some differences between men and women occur. Considering the security of an interaction with a CVA (question 11), the two groups assess and behave differently with regard to personal data communication (F_{11}=4.280, p_{11}=0.040). Female respondents show higher feelings of uncertainty in this regard, compared to male respondents. Likewise, when evaluating item 13, significant gender differences emerge between gender occur (F_{13}=8.247, p_{13}=0.005). While men tend not to be manipulated by such systems or are less likely to worry about it - women, on the other hand, show more vulnerability or awareness towards the power of influence CVAs are likely to pursue. As also previously observed and discussed, the fact that women show to some extent a tendency to feel insecure, even inferior, towards cognitive systems also holds true with the evaluation of statement 13. Compared to the male side of the sample, women are more likely to show concern, anxiety and awareness towards the idea that they can be manipulated by cognitive computing. This could also be caused by the fact that they somehow feel overwhelmed by cognitive systems, probably unsecure or exposed in the presence and during the interaction with such systems. An interesting direction of investigation would be to analyze the possible reasons for the different behavior of the two genders in this context and the underlying causes.

Table no. 1. Discriminant analysis regarding the perception of consumers regarding cognitive computing

Item	$\bar{x}$ Male	$\bar{x}$ Female	$\bar{x}$ Total	F	p-Va-lue
1. I am pleasantly impressed by the technology of cognitive computing systems.	4.89	5.23	5.08	1.810	0.181
2. I am fascinated by the possibility of human-computer interaction.	5.23	5.08	5.15	0.337	0.563
3. I want to be able to understand the technology behind cognitive computing systems.	5.25	5.32	5.29	0.068	0.794
4. I believe that cognitive computing systems are beyond me, because I do not understand what is exactly behind them.	**3.17**	**4.34**	**3.81**	**16.249**	**0.000**
5. The fact that I do not understand what is hidden behind cognitive computing systems worries me.	**2.38**	**3.13**	**2.79**	**7.031**	**0.009**
6. The evolution and applicability of cognitive computing systems seem to me to be areas that need to be further exploited.	5.98	5.92	5.95	0.095	0.758
7. I believe that cognitive computing systems must not be absent from companies' interaction with consumers.	4.78	5.13	4.97	1.642	0.202
8. I believe that cognitive computing systems are important for shaping companies' relationships with customers.	4.61	5.03	4.84	2.546	0.113
9. I consider that cognitive computing systems can maintain my private sphere.	4.50	4.26	4.37	0.588	0.444
10. It bothers me that cognitive computing systems use my data.	4.25	4.44	4.35	0.382	0.538
11. I consider that the transmission of personal data to a CVA (Cognitive Virtual Assistant) in the dialogue with a company is uncertain.	**3.58**	**4.19**	**3.91**	**4.280**	**0.040**
12. I believe that interacting with a CVA (Cognitive Virtual Assistant) can invade my private sphere.	4.05	4.04	4.04	0.001	0.981
13. I consider that the suggestions received from a CVA (Cognitive Virtual Assistant) influence my purchasing decisions in a direct way that I do not want.	**3.17**	**3.97**	**3.61**	**8.247**	**0.005**
14. I consider that the purpose of cognitive computing systems applied in interaction with consumers is to control consumers.	3.70	3.79	3.75	0.071	0.790
15. I believe that the purpose of cognitive computing systems applied in interaction with consumers is to help firms move towards coherent processing of large volumes of data.	5.72	5.70	5.71	0.006	0.940

Source: Authors' own research

Overall, both men and women show enthusiasm and fascination toward cognitive systems and human-CC interaction, with no significant differences between the two groups. On one side, both female and male respondents agree that cognitive computing systems seem need to be further exploitation and acknowledge the fact that such kind of systems are important for shaping companies' relationships with customers. On the other side, both groups show some concern regarding their private sphere and privacy in connection to CC. However, the majority of respondents show strong believe that the purpose of cognitive computing systems applied in interaction with consumers is to help firms move towards coherent processing of large volumes of data and not to control consumers.

Conclusions

With clear advances being made towards implementation of cognitive computing in various consumer interactive contexts, unlimited possibilities for further research arise. Although the present research only addresses a very brief part of the whole discussion, it underlines some differences in perception between men and women, reaching the conclusion that the two groups are related in many more aspects, than they are differentiated. Consumers in general need to familiarize themselves with the concept of cognitive computing and with the idea and actual interaction with cognitive virtual assistants. As our study shows, consumers' perceptions of cognitive systems are now somewhere near the middle point (on a scale from 1 to 7) with an answering tendency of little above or around the middle scale point – but this could of course also be attributed to a common central tendency bias respondents often face when confronted with a not so familiar concept or subject. Although there are not many differences between the two genders, it can be observed that women are more reluctant to these new systems as they don't know and don't control the systems behind them. Moreover women worry more about providing their personal data to these cognitive systems in comparison to men. As the results reveal, women fear more that their buying decision might be influenced in undesired way. This result is in accordance with previous research, where the willingness of providing data to intelligent systems is predicted by the consumer's control over the data (Stanescu, Pelau and Barbul, 2021). This study confirms that women are more concerned about not having control over the intelligent or cognitive system they interact with. This result has important implications for the development of intelligent cognitive systems, as developers should consider the need of the consumer to control at least to a certain degree the data shared with the system. Letting the consumers know the general principle on which the cognitive system is based on, will increase their acceptance in the everyday life of consumers and it will increase the frequency of using intelligent cognitive systems.

It may seem now that there is little evidence of significant differences between men and women, but as awareness of such technologies rises, so will the contrasts between sample groups. Considering the rapid technological developments and the dynamics of reshaping consumers' experiences, further studies need to be undertaken, in order to keep research on consumers' perception up to date. The more cognitive computing is used by companies to interact with consumers, the more relevant it is to assess the differences between different consumer groups and their various impressions and understandings of this concept.

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