ICIS 2020 Proceedings

Implementation and Adoption of Digital Technologies

Dec 14th, 12:00 AM

Understanding Individuals' Perceptions Regarding Cognitive Computing Systems

Maximilian Welck
University of Augsburg, maximilian.welck@wiwi.uni-augsburg.de

Ingrid Julia Derdak
University of Augsburg, ingrid.j.derdak@gmail.com

Daniel Veit
University of Augsburg, daniel.veit@wiwi.uni-augsburg.de

Understanding Individuals' Perceptions Regarding Cognitive Computing Systems

Short Paper

Maximilian Welck
University of Augsburg
Chair of IS and Management
Universitaetsstr. 16
86135 Augsburg, Germany
mw.research@welck.de

Ingrid Derdak
University of Augsburg
Chair of IS and Management
Universitaetsstr. 16
86135 Augsburg, Germany
ingrid.j.derdak@gmail.com

Daniel Veit
University of Augsburg
Chair of IS and Management
Universitaetsstr. 16
86135 Augsburg, Germany
daniel.veit@wiwi.uni-augsburg.de

Abstract

Artificial Intelligence based Information Systems (AI-based IS) play an increasingly important role in everyday life of individuals, and for organizations that invest substantially into such systems, e.g., to transform and optimize their business processes. These AI-based IS can aggregate such capabilities as knowing, reasoning and autonomously (re)acting, hence, a considerable amount of capabilities that are human-like. In addition, the most current AI-based IS, also referred to as, cognitive computing systems (CCS), are capable to process unstructured data, such as audio-visual inputs, enabling these systems to mimic human-cognition in ways not seen in previous IS. These systems challenge long standing assumptions, about how humans use IS and how these IS generate outcomes. In this study we endeavor to better understand what factors affect individuals' perception regarding these CCS. Based on sixteen semi-structured interviews, we propose nine preliminary factors, that appear to influence individuals' perceptions regarding CCS.

Keywords: Cognitive Computing Systems; Artificial Intelligence; Interpretive Qualitative Study

Introduction

Artificial Intelligence based Information Systems (AI-based IS) play an increasingly important role for individuals' daily lives (Rai 2020) and for the many organizations that substantially invest into such systems (Pumplun et al. 2019). The reasons why individuals and companies use such systems are diverse, e.g., to increase competitiveness (Zaki 2019), to advance digital transformation and efficiency (Vial 2019), etc. Yet, organizations often struggle to motivate employees to make sufficient use of these systems, although IS literature provides plenty of studies that improve our understanding regarding how to mitigate IS underutilization (Ali et al. 2016; Craig et al. 2019).

What is more, the recent development that AI-based IS are capable to process unstructured data adds a whole new level of complexity to this issue: When looking at the chronological development history of AI-based IS, Schuetz and Venkatesh (2020) distinguish four systems that continuously received better, and increasingly human-like capabilities: decision support systems; expert systems; intelligent agents; and cognitive computing systems. While the first two AI-based IS still rely on human decision makers, intelligent agents and cognitive computing systems do not. Moreover, these last two kinds of AI-based IS aggregate capabilities such as knowing, reasoning and autonomously (re)acting, hence, they possess a considerable amount of capabilities that are human-like (Schuetz and Venkatesh 2020). In addition, cognitive computing systems are also capable to process unstructured data, such as audio-visual inputs, which enables these systems to mimic human-cognition in ways not seen in previous IS (Schuetz and Venkatesh 2020).

This development, manifested in cognitive computing systems, challenges long standing assumptions, such as "how we as IS researchers think about how humans use IT artifacts and how IT artifacts generate outcomes" (Schuetz and Venkatesh 2020, p. 461) or the prevalent conception that humans are users and IT artifacts are merely tools that produce consistent outcomes (Demetis and Lee 2018; Schuetz and Venkatesh 2020). Additionally, the aggregation of human-like capabilities in AI-based IS makes these systems also somewhat fuzzy and, indeed, only few people appear to have a clear understanding of what these systems are capable of (Schuetz and Venkatesh 2020).

This research endeavor attempts to shed light on this development, by trying to answer the research question: **What factors influence the perceptions of individuals regarding cognitive computing systems?** To address this exploratory research question, we conduct a series of interviews (currently 16) with individuals from the banking, IT and the healthcare industry, and inquire about their perceptions regarding AI-based IS. Our preliminary results shed light on nine factors that appear to influence employees' perceptions regarding cognitive computing systems and how individuals attribute meaning to such systems. Thus, this research endeavor contributes to IS literature by improving our understanding about factors affecting individuals' openness and reservation towards the use of AI-based IS. Our findings will also serve practitioners by pointing out important aspects that should be consider by managers who plan to take advantage of cognitive computing systems.

Theoretical Background

While no commonly accepted definition of AI-based IS exists, most definitions concerning such systems explain what these try to achieve, yet, usually without conclusively determining AI-based IS as such (Rzepka and Berger 2018). The majority of these definitions can, accordingly, be categorized into systems that (A) think like humans; (B) act like humans; (C) think rationally, or (D) act rationally (Russel and Norvig 2010; Rzepka and Berger 2018). Similarly, Rai and colleagues recently defined artificial intelligence as "the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity" (Rai et al. 2019, p. iii). We adopt this notion for what we refer to as AI-based IS.

Research finds that users tend to make anthropomorphic attributions (i.e., awarding human characteristics) to AI-based IS (Beran et al. 2011) and that users also judge these systems based on their attributions (Edwards et al. 2014). Nonetheless, despite these anthropomorphic attributions, users tend to treat IS differently (mostly worse) than they treat fellow humans beings (Mou and Xu 2017). What is more, anthropomorphic attributions can also lead to threat perceptions (Rosenthal-Von Der Pütten and Krämer 2014), just like a system's counter-attitudinal advice appears to often lead to threat perceptions (Elkins et al. 2013).

In the IS literature, Rzepka and Berger (2018) identified four particularly important characteristics of AI-based IS, these are system capabilities; system transparency; human-like appearance; and gestural and conversational behavior. Perceived capabilities of AI-based IS, such as the capability to function autonomously (Chao et al. 2016) can positively affect usage intentions. Yet, at the same time, such capabilities can also entail negative consequences, as they can cause risk perceptions (Chao et al. 2016) and identity threats (Złotowski et al. 2017). Apart from a system's capabilities, increasing transparency regarding why a certain decision has been taken, can have positive effects on users' general perceptions towards a system (Gregor and Benbasat 1999; Xu et al. 2014) and its recommendation quality specifically (Wang and Benbasat 2016). Regarding human-like vis-à-vis machine-like appearance, research finds that more is not always better, as, after a certain point, increased perceived humanness can indeed cause the perception of threat – a phenomenon that is also referred to as the uncanny valley (Cresswell et al. 2018; Rosenthal-Von Der Pütten and Krämer 2014). In the same vein, Gaudiello et al. (2016) find that users appear to generally trust AI-based IS more in the context of functional tasks than in the context of social tasks.

Apart from these system characteristics, also user, and context characteristics play a vital role, e.g., the fear to be replaced by an AI-based IS appears to negatively affect its usage (Johnson and Verdicchio 2017). Even if individuals do not fear to be replaced by AI-based IS, such systems can be perceived as a threat to one's professional role (Elkins et al. 2013; Jussupow et al. 2018). On the contrary, AI-based IS that produce explanations, which are perceived to fit to the user's cognition, appear to be perceived as being of superior quality (Shmueli et al. 2016). Similarly positive effects entails the perception that an AI-based IS increases work efficiency (Tauchert and Mesbah 2019). Moreover, catchy articles and headlines in the media, preconceptions about AI from science-fiction (Aleksander 2017; Cresswell et al. 2018) and expressed concerns regarding AI by public figures can trigger anxiety towards AI-based IS (Johnson and Verdicchio 2017).

However, as previously mentioned, cognitive computing systems (CCS) are incommensurable to the just discussed AI-based IS for at least five reasons: First, the interaction between users and CCS is bilateral, since, unlike previously, these systems are interactive and users may receive or react to stimuli from these systems; Second, CCS can process unstructured input making them aware of their environment and capable to interact with it in new ways; Third, CCS are adaptive and functionally less consistent than previous AI-based IS, so that user-system interaction likely changes over time; Fourth, the functionality of these systems may be opaque, that is, these systems are so complex that it is often not possible for its user to understand how the CCS arrived at its outcome; Fifth, the user of a CCS does not necessarily need to be aware that he/she is in fact interacting with such a system and not a fellow human being (Schuetz and Venkatesh 2020). Taken together, this discussion makes it salient that insights gained in the context of systems other than cognitive computing systems cannot easily be applied to contexts with cognitive computing systems, which both, justifies and necessitates this research endeavor.

Methodology

Our approach to address our research endeavor is a hermeneutic interpretative one, and is based on qualitative data (Klein and Myers 1999; Stahl 2014; Walsham 2006). Thus, "What we call our data are really our own constructions of other people's constructions of what they and their compatriots are up to" (Geertz 1973, p. 9; found in Walsham 2006). Stahl (2005) explains that an interpretive researcher tries to understand phenomena. Yet, the researcher needs to be aware that these phenomena result from individuals' perceptions, and that these individuals create meaning through interaction, throughout their lives. Thus, as Stahl (2005) argues, understanding this meaning demands a circular engagement. What is more (and contrary to positivist research), an interpretivist research does not aim to explain the world in terms of falsifiable laws, he/she instead aims to understand it by clarifying the motives and life-worlds of individuals.

Consequently, we attempt to accesses the meaning that individuals ascribe to AI-based IS as such, and cognitive computing systems in particular, without attempting to find an 'objective truth'. To do so, we chose to remain rather outside observers (without understanding our stance as 'objective' observers) and to rely on interviews as our source of data. We do so, as interviews permit us to access the interpretations of our respondents regarding the events surrounding them and their intra- and interpersonal views (Walsham 1995). At this point we would like to allude that, while the previous literature review served as an initial orientation, we do not attempt to validate or falsify any of the insights gained from it. We deem this approach to be suitable for researching a type of AI-based IS that remains largely unexplored to date.

Research Context and Design

For this research we chose to interview individuals working either in IT, banking or healthcare. Our rationale is that we assume that individuals working in these industries are likely to have some touch-points with AI-based IS and thus a basic understanding regarding such systems. Yet, although we deliberately chose these three industries, our unit of analysis is the individual. Here, we attempt to maximize variability (Sandelowski 1995) by conducting interviews with individuals from diverse backgrounds in terms of experience with AI-based IS and cognitive computing systems, work experience, age and job roles. Thus, we consider individuals working in either of these industries, to be both somewhat typical for the context of this study and to provide more diversity than if we would focus at one industry only. Together, this shall substantiate our purposive sampling strategy that aims to increase variation (Sandelowski 1995).

We conducted our interviews in the form of semi-structured interviews (c.f. e.g., Orlikowski 1993), thus we prepared an interview guideline with open-ended questions to gather the maximum possible input from the subjective views of our respondents. These interview questions revolved around four foci: perceptions of employees regarding AI-based IS in general, e.g., "Please describe your everyday encounters with AI"; AI in the professional environment, e.g., "In the context of which tasks during your daily work, do you come into contact with AI, and what is your opinion about the use of AI then?"; AI in the private environment, e.g., "Which technologies with AI do you use in your private everyday life and why", "Which AI technologies would you currently avoid in your private life and why?"; and personality related questions, such as work experience, typical work routines, etc. In order to ensure the appropriate formulation of the questions, we thoroughly discussed the preliminary guideline with a senior radiologist and a senior manager from an IT company. These discussions helped us to improve the guideline. E.g., instead of constantly asking for "… AI with human-like capabilities …", we reworded the questions to ask merely for "AI", and decided to estimate through follow-up questions what kind of human-like capabilities the AI offered and if/how these were adopted/perceived. After these adaptations, we conducted two further interviews in a think aloud fashion, with individuals with work experience in IT companies. That is, our respondents were asked (and repeatedly reminded throughout the interviews) to speak out whatever they were currently thinking. This helped us to organize the sequence of questions, and to time the progress of our interviews.

Data Collection

Sandelowski (1995) and Morse (1994) suggest to include at least six participants for studies, such as this one. For good measure, we plan to conduct interviews with at least eight individuals per industry (i.e., min. 24 in total). At the point of write-up of this paper, we conducted, transcribed and coded 16 semi-structured interviews (c.f. table 1 for an overview of the respondents).

IT							
I1 Male 27 (i.e., age) IT support specialist	I2 Female 25 Online-Marketing consultant	I3 Female 29 Web design apprentice	I4 Male 35 IT project manager	I5 Male 51 CEO	I6 Female 28 Web developer	I7 Male 30 IT project manager	I8 Female 23 Web developer apprentice
Banking							
B1 Male 28 (i.e., age) Commercial customer advisor	B2 Female 25 Private customer advisor	B3 Male 35 Divisional director	B4 Male 43 Sales director	B5 Female 19 Bank clerk apprentice	B6 Male 26 Real estate broker	B7 Female 23 Service consultant	B8 Female 23 Private customer advisor

Table 1. Overview of Interview Partners

We conducted eight interviews with individuals from an IT background and eight with employees with a banking background – we are still conducting interviews with individuals with a healthcare background (i.e., individuals working in the radiology department of a large maximum care hospital), but decided not to draw from these interviews for this study, as we may not have reached saturation for individuals with this background yet. The 16 interviews have been conducted between January and March 2020 in German, the participants' mother tongue. The interviews lasted about 30 min. (the longest 72 min.), were audio recorded and transcribed afterwards.

Data Analysis

For this data analysis, we attempted to learn from the data, while being conscious that we are predisposed to resort to our prior knowledge, as depicted in the literature review above. We hence followed the suggestion of Walsham (2006) and analyzed our data according to the elucidations of Strauss and Corbin (1990). We did so with the help of the program MAXQDA for qualitative analyses. As recommended, in our first visit of the data (i.e., open coding), we read through the interviews line-by-line to identify meaning units to which we assigned comprehensible codes (Strauss and Corbin 1990). During this initial visit to the data a long list of unique codes evolved that we subsequently structured into higher-level abstractions to establish code categories. In this second step, we reread the interviews with the goal in our minds to identify relationships between different code categories (Strauss and Corbin 1990). This step helped us to identify emerging patterns, inconsistencies and to gain an initial understanding of the connections between various code categories. We continued to conduct interviews until we perceived to have reached an initial level of saturation (Corbin and Strauss 1990) – initial as we lack the interviews with healthcare personnel. We perceived to have reached this point after 12 interviews, but conduced 4 further interviews, for good measure.

Preliminary Findings

Table 2 depicts those nine factors that appear to us to be (most) grounded at this point of time in our research endeavor and that we identified to impact individuals' perceptions regarding AI-based IS and cognitive computing systems. Given the preliminary nature of this study, we will subsequently elaborate only those factors and refrain from presenting a theoretical model. – Please note, consistently with our initial definition, AI-based IS are systems that are capably of certain human-like cognitions, but are not capable to process unstructured data, while cognitive computing systems (CSS) are systems that process unstructured, for the most part CSS refer to Amazon's Alexa hereinafter.

Most respondents, who revealed that they avoided AI-based IS with human-like capabilities (such as Amazon's Alexa), reasoned their decision with the fear of being **surveilled** – without wanting to hide something from others. It is simply about the invasion into one's privacy, which evokes discomfort and anxiety: *"I think it is scary that this recording device [Alexa] is always able to record all conversations. I do not want that. I do not think that it is about having something to hide, but infringing my privacy." - (Private customer advisor, 25).* This quote depicts how the mere potential capacities of a cognitive computing system can deter individuals from using such systems. It also appears that individuals ascribe these surveillance capabilities to cognitive computing system only, since all our respondents stated to use smartphones without mentioning the fear to be potentially surveilled.

The factor **high hopes**, results from respondents' vivid anticipations that AI-based IS with human-like capabilities will offer unprecedented opportunities for disadvantaged individuals. One respondent, for example, hoped for autonomously driving vehicles that would provide increasing mobility for elderly people: *"Considering my grandparents, they always need someone, who drives them [around]. And if there were autonomously driving cars, these would increase mobility and quality of life" - (Private customer advisor, 23).* This statement expresses the high hopes that individuals attach to CCS.

#	Factor	Definition of the Factor
1	Perceived surveillance	Individuals perception to be constantly watched.
2	High hopes	Hopes that individuals ascribe to AI-based IS.
3	Helpfulness	Perceived utility, practical worth or applicability of AI.
4	Customization-centered work tasks	Employees' set of tasks at work that require customized solutions.
5	Type of clients	Characteristics that employees attribute to their customers.
6	Fear of inertia	Fear to become dull from relying excessively on AI-based IS.
7	Perceived exchangeability	Employees' set of tasks at work that are substitutable through AI.
8	Robustness	Perceived quality of AI not to break or fail.
9	Inner conviction	Individual's strong persuasion or belief.

Table 2. Factors influencing Individuals' Perceptions (preliminary)

Multiple respondents emphasized the **helpfulness** and practical value of AI-based IS. A recurring theme that our respondents mentioned, refers to how AI-based IS helped them make their lives easier, e.g.: *"[There is] a lot [about AI-based IS] that makes daily routines easier. Being reminded about things one neglected in the recent past, for example." - (Web developer, 28).* This statement exemplifies how individuals appreciate the helpfulness that AI-based IS bring about their daily routines.

The fourth factor that we identified is labeled **customization-centered work tasks**. It refers to the fact that an individual's average type of work tasks can affect how he or she perceives AI-based IS. A number of participants mentioned, for example, that their usual work tasks would be so customer focused that they could not imagine to be replaced by AI-based IS or CCS. They, consequently, do not perceive AI-based IS to threaten their jobs, as it can be seen in the following quote: *"I still think [...] that the advisory function, which we represent [...], cannot be replaced by artificial intelligence and will be needed." - (Online marketing consultant, 25)*. This statement shows that the employee is attentive to the possibility that AI-based IS could, in parts, threaten her job. Nevertheless, she is confident that her tasks as customer advisor are unlikely to be replaced by AI-based IS. A very similar thought was voiced by multiple respondents, e.g.: *"I don't think that my job is threatened by AI, because we offer very individual solutions to our customers. As long as I am working, and not retired, no computer will be able to do the work that I do." - (IT project manager, 35)*. Many respondents with jobs requiring to deliver customized solutions, appeared confident that AI-based IS are unlikely to interfere with their professional careers. Our respondents often compared their skills as a human with those skills that they think that AI-based IS are capable of, anytime soon.

Many of our respondents also referred to the type of their **clients**, when they thought about how AI-based IS might affect their professional careers. Many had the opinion that their customers would always prefer to talk to humans and not to AI-based systems: *"Banking businesses are businesses that are based on trust, particularly in the case of larger matters, and in such cases personal relationships with humans will always be superior to humans' trust in a machine." - (Divisional director, 35).* This quote depicts how the type of customer, in this case borrowing customers affect how individuals think about the potential consequences of AI-based IS. (Other respondents also mentioned high quotas of elderly people that would be unlikely to prefer IS over real humans.)

Many respondents voiced that cognitive computing systems would likely lead individuals to become, not only reliant on these systems, but that they feared to become **inert** due to excessive reliance on these systems: *"So, the risk of AI is that individuals will delegate many decisions to a computer and that the individual becomes lazier and more stupid." - (IT project manager, 35)*. This quote illustrates, how certain individuals are sensible about, on the one hand, that cognitive computing systems simply daily lives, yet, on the other hand, that these are also concerned that such simplifications could lead to become inert.

While we previously mentioned that certain individuals would not fear to be made redundant, due to the type of clients they served or due to the level of customization that was inherent to their work tasks, other respondents clearly articulated their fear that AI-based IS might adversely affect their professional careers. Respondents feared in particular that their economic efficiency might lack behind the efficiency of AI-based IS and the feeling of being **interchangeable**: *"I might look at another job somewhere else, where one needs more of me as a human being, [...] because otherwise I might feel a bit interchangeable and then I'm also afraid of how things might continue to evolve." - (Private customer advisor, 25).* This quote makes it apparent that some employees indeed perceive AI as serious competition, not only to one's workplace, but even to one's existence as a valuable human being.

Some interviewees were also concerned that AI-based IS might not meet their standard of **robustness** that they expected from such systems. For example, one respondent expressed that he would not use smart home technology because he would not be able to control the system in case of a malfunction:

> *"We have a friend who implemented smart home technology and now has technical problems with it. If there is a power cut, then he is no longer able to open or close the windows. [...] I could imagine to use an Alexa, if it has an apparent added value for me. As, if there is a box at home with which I can talk to and which does not control my life, that would be fine." - (Divisional director, 35).*

This quote highlights how distrustful some individuals are towards the robustness of smart home technologies. Particularly the loss of control over the system, and consequently, the loss of control over his life in case of a malfunction appears to be a major concern for this respondent.

Many respondents presented quite clear **inner convictions** to reason their attitude towards AI. One individual, for example, stated that she would always support progress and consequently supports also the use of AI-based IS and cognitive computing systems: *"I always support progress. That is why I feel more positive regarding a future with [cognitive computing systems], yes." - (Web developer apprentice, 23)*. This statement depicts how she remains true to her principles of always supporting progress. In the same vein, another individual states how he believes that one does not to talk to robots, which is reason enough for him to reject any cognitive computing systems: *"I do not really like AI in my job. In my opinion, a human should talk to a human and not with a robot." - (Real estate broker, 26)*. This quote elucidates how strongly the real estate broker's inner conviction, that humans should talk to humans and not to systems, affects his personal attitude.

Discussion

We commenced this study as we aim to improve our understanding regarding what motivates individuals to make use or to refrain from taking advantage of AI-based IS with human-like capabilities. A first noteworthy finding is that while our respondents voiced a number of very different points of view regarding AI-based IS, we did not notice that these views, voiced by individuals working in the banking sector, were systematically different from those, voiced by individuals working in the IT sector.

In addition, our preliminary findings suggest that individuals perceive AI-based IS, with which one interacted based on unstructured means, e.g., through voice commands, very differently from AI-based systems, with which one interacted in more structured ways, e.g., by means of touchscreens. We explained this finding with the argument by Schuetz and Venkatesh (2020) that these two types of IS are incommensurable. In particular, we found that many participants refuse to use cognitive computing systems that (almost) exclusively rely on input from unstructured data, such as voice commands, as they are afraid of being surveilled. Many interviewees state that they perceive discomfort by the thought to introduce such a system into their sphere of personal privacy. While at same time they freely admitted to use other forms of AI-based IS, such as private and/or company provided smartphones. A similar factor that appears to affect individuals in their motivation to interact with cognitive computing systems refers to their robustness. Respondents reported reluctance to engage with such systems in situations that may affect one's well-being, simply as they are suspicious regarding the robustness of these systems (e.g., autonomous parking, or extensive smart home systems).

Participants often attached own experiences or observed interactions with cognitive computing systems with labels such as "spooky", "scary" or "terrifying". This finding could be explained by the suggestions of Schuetz and Venkatesh (2020), who find that cognitive computing systems, such as Alexa, Siri, Cortana etc., disrupt individuals' belief of what machines can do or cannot do. They argue that individuals are used to interact with systems via artificial interfaces, while they are not used to interact with IS based on more natural, human-like means, such as voice command (Schuetz and Venkatesh 2020). Nonetheless, we found that other personal-level factors appear to play a larger role when individuals consider making use of cognitive computing systems: In particular we found that individuals' inner convictions, high hopes and fear to become inert play an important part. Multiple individuals would use or not use cognitive computing systems, based on their inner convictions, such as the conviction that speech needs to be reserved for human-human interactions. Then again, some respondents also voiced reservations regarding cognitive computing systems, as they feared that they will likely make one excessively inert.

Moreover, our preliminary findings suggest that individuals assess the likelihood of being replaced by AI-based IS, depending on how customization-centered their work tasks are and the type of clients they served. A number of individuals, for example, stated that they did not consider AI-based IS to interfere with their professional careers, as their work was too customization-centered, i.e., centered towards realizing products that are individually customized to the wishes of their clients. Similarly, many respondents also stated that the clients they served would not want rely on AI-based IS, but interact with human agents. In both instances, the individuals welcomed the introduction of AI-based IS at work, and emphasized their willingness to educate themselves to be able to efficiently use such systems.

Finally, we found that many of our respondents appeared to be widely unaware that they were already using AI-based IS until we specifically discussed their personal everyday IS usage behaviors. Furthermore, all our respondents showcased rather positive attitudes towards AI-based IS.

Anticipated Contributions and Next Steps

Upon the completion of our study, we anticipate to contribute to IS research in the following ways: First, our research will contribute to IS literature by identifying and providing a deeper understanding regarding how individuals perceive the capability of IS to autonomously process unstructured data. As previously argued, IS that rely on autonomously processing unstructured data are systematically different from previous IS, in various terms (Schuetz and Venkatesh 2020). We will thereby also contribute to IS research by identifying factors that motivate and demotivate individuals to make use of AI-based IS as such, and cognitive computing systems in particular (Rzepka and Berger 2018; Wagner and Schramm-Klein 2019). Furthermore, as we conduct our study across different industrial contexts, we anticipate our findings to provide means to understand comparable situations in different contexts. Our study will also serve practitioners, as we will provide insights into important aspects that managers need to consider when they aim to take advantage of new AI-based IS and likewise to vendors and developers of such systems. – We are planning to proceed with our data collection, to produce a complete study that we aim to publish.

References

Aleksander, I. 2017. "Partners of Humans: A Realistic Assessment of the Role of Robots in the Foreseeable Future," *Journal of Information Technology* (32:1), pp. 1–9.

Ali, M., Zhou, L., Miller, L., and Ieromonachou, P. 2016. "User Resistance in IT: A Literature Review," *International Journal of Information Management* (36:1), pp. 35–43.

Beran, T. N., Ramirez-Serrano, A., Kuzyk, R., Fior, M., and Nugent, S. 2011. "Understanding How Children Understand Robots: Perceived Animism in Child–Robot Interaction," *International Journal of Human-Computer Studies* (69:7–8), pp. 539–550.

Chao, C.-Y., Chang, T.-C., Wu, H.-C., Lin, Y.-S., and Chen, P.-C. 2016. "The Interrelationship Between Intelligent Agents' Characteristics and Users' Intention in a Search Engine by Making Beliefs and Perceived Risks Mediators," *Computers in Human Behavior* (64), pp. 117–125.

Corbin, J. M., and Strauss, A. 1990. "Grounded Theory Research: Procedures, Canons, and Evaluative Criteria," *Qualitative Sociology* (13:1), pp. 3–21.

Craig, K., Thatcher, J. B., and Grover, V. 2019. "The IT Identity Threat: A Conceptual Definition and Operational Measure," *Journal of Management Information Systems* (36:1), pp. 259–288.

Cresswell, K., Cunningham-Burley, S., and Sheikh, A. 2018. "Health Care Robotics: Qualitative Exploration of Key Challenges and Future Directions," *Journal of Medical Internet Research* (20:7), pp. 1–11.

Demetis, D., and Lee, A. S. 2018. "When Humans Using the It Artifact Becomes It Using the Human Artifact," *Journal of the Association for Information Systems* (19:10), p. 5.

Edwards, C., Edwards, A., Spence, P. R., and Shelton, A. K. 2014. "Is That a Bot Running the Social Media Feed? Testing the Differences in Perceptions of Communication Quality for a Human Agent and a Bot Agent on Twitter," *Computers in Human Behavior* (33), pp. 372–376.

Elkins, A. C., Dunbar, N. E., Adame, B., and Nunamaker, J. F. 2013. "Are Users Threatened by Credibility Assessment Systems?," *Journal of Management Information Systems* (29:4), pp. 249–262.

Gaudiello, I., Zibetti, E., Lefort, S., Chetouani, M., and Ivaldi, S. 2016. "Trust as Indicator of Robot Functional and Social Acceptance. an Experimental Study on User Conformation to ICub Answers," *Computers in Human Behavior* (61), pp. 633–655.

Geertz, C. 1973. *The Interpretation of Cultures: Selected Essays by Clifford Geertz*, (Vol. 5019), New York, NY, USA: Basic books.

Gregor, S., and Benbasat, I. 1999. "Explanations from Intelligent Systems: Theoretical Foundations and Implications for Practice," *MIS Quarterly* (23:4), pp. 497–530.

Johnson, D. G., and Verdicchio, M. 2017. "AI Anxiety," *Journal of the Association for Information Science & Technology* (68:9), pp. 2267–2270.

Jussupow, E., Spohrer, K., Heinzl, A., and Link, C. 2018. "I Am; We Are - Conceptualizing Professional Identity Threats from Information Technology," in *Proceedings of the 39th International Conference on Information Systems*, R. Baskerville and R. Nickerson (eds.), San Francisco, California, USA, pp. 1–17.

Klein, H. K., and Myers, M. D. 1999. "A Set of Principles for Conducting and Evaluating Interpretive Field Studies in Information Systems," *MIS Quarterly* (23:1), pp. 67–94.

Morse, J. M. 1994. "Designing Funded Qualitative Research," in *Handbook of Qualitative Research*, N. K. Denzin and Y. S. Lincoln (eds.), Thousand Oaks, California, USA: Sage Publications, pp. 220–235.

Mou, Y., and Xu, K. 2017. "The Media Inequality: Comparing the Initial Human-Human and Human-AI Social Interactions," *Computers in Human Behavior* (72), pp. 432–440.

Orlikowski, W. J. 1993. "Case Tools as Organizational Change: Investigating Incremental and Radical Changes in Systems Development," *MIS Quarterly* (17:3), JSTOR, pp. 309–340.

Pumplun, L., Tauchert, C., and Heidt, M. 2019. "A New Organizational Chassis for Artificial Intelligence - Exploring Organizational Readiness Factors," in *Proceedings of the 27th European Conference on Information Systems (ECIS)*, P. Johannesson, P. Ågerfalk, and R. Helms (eds.), Stockholm-Uppsala, Sweden, pp. 1–15.

Rai, A. 2020. "Explainable AI: From Black Box to Glass Box," *Journal of the Academy of Marketing Science* (48:1), pp. 137–141.

Rai, A., Constantinides, P., and Sarker, S. 2019. "Next-Generation Digital Platforms: Toward Human–AI Hybrids," *MIS Quarterly* (43:1), pp. iii–ix.

Rosenthal-Von Der Pütten, A. M., and Krämer, N. C. 2014. "How Design Characteristics of Robots Determine Evaluation and Uncanny Valley Related Responses," *Computers in Human Behavior* (36), Elsevier, pp. 422–439.

Russel, S. J., and Norvig, P. 2010. *Artificial Intelligence: A Modern Approach*, (3rd ed.), Upper Saddle River, New Jersey: Pearson Education Inc.

Rzepka, C., and Berger, B. 2018. "User Interaction with AI-Enabled Systems: A Systematic Review of IS Research," in *Proceedings of the 39th International Conference on Information Systems*, R. Baskerville and R. Nickerson (eds.), San Francisco, California, USA, pp. 1–17.

Sandelowski, M. 1995. "Focus on Qualitative Methods: Sample Size in Qualitative Research," *Research in Nursing and Health* (18:2), pp. 179–183.

Schuetz, S., and Venkatesh, V. 2020. "Research Perspectives: The Rise of Human Machines: How Cognitive Computing Systems Challenge Assumptions of User-System Interaction," *Journal of the Association for Information Systems* (21:2), pp. 460–482.

Shmueli, L., Benbasat, I., and Cenfetelli, R. 2016. "A Construal-Level Approach to Persuasion by Personalization," in *Proceedings of the 37th International Conference on Information Systems*, B. Fitzgerald and J. Mooney (eds.), Dublin, Ireland, December, pp. 1–19.

Stahl, B. C. 2005. "A Critical View of the Ethical Nature of Interpretive Research: Paul Ricceur and the Other," in *Proceedings of the 13th European Conference on Information Systems (ECIS)*, Regensburg, Germany, May.

Stahl, B. C. 2014. "Interpretive Accounts and Fairy Tales: A Critical Polemic Against the Empiricist Bias in Interpretive IS Research," *European Journal of Information Systems* (23:1), Taylor & Francis, pp. 1–11.

Strauss, A., and Corbin, J. M. 1990. *Basics of Qualitative Research: Grounded Theory Procedures and Techniques.*, Los Angeles, CA: Sage Publications, Inc.

Tauchert, C., and Mesbah, N. 2019. "Following the Robot? Investigating Users' Utilization of Advice from Robo-Advisors," in *Proceedings of the 40th International Conference on Information Systems*, H. Krcmar and J. Fedorowicz (eds.), Munich, Germany, December, pp. 1–17.

Vial, G. 2019. "Understanding Digital Transformation: A Review and a Research Agenda," *The Journal of Strategic Information Systems* (28:2), pp. 118–144.

Wagner, K., and Schramm-Klein, H. 2019. "Alexa, Are You Human? Investigating Anthropomorphism of Digital Voice Assistants – a Qualitative Approach," in *Proceedings of the 40th International Conference on Information Systems*, H. Krcmar and J. Fedorowicz (eds.), Munich, Germany, pp. 1–17.

Walsham, G. 1995. "Interpretive Case Studies in Is Research: Nature and Method," *European Journal of Information Systems* (4:2), Taylor & Francis, pp. 74–81.

Walsham, G. 2006. "Doing Interpretive Research," *European Journal of Information Systems* (15:3), pp. 320–330.

Wang, W., and Benbasat, I. 2016. "Empirical Assessment of Alternative Designs for Enhancing Different Types of Trusting Beliefs in Online Recommendation Agents," *Journal of Management Information Systems* (33:3), Routledge, pp. 744–775.

Xu, J. (David), Benbasat, I., and Cenfetelli, R. T. 2014. "The Nature and Consequences of Trade-Off Transparency in the Context of Recommendation Agents," *MIS Quarterly* (38:2), Management Information Systems Research Center, University of Minnesota, pp. 379–406. (https://doi.org/10.2307/26634931).

Zaki, M. 2019. "Digital Transformation: Harnessing Digital Technologies for the Next Generation of Services," *Journal of Services Marketing* (33:4), pp. 429–435.

Złotowski, J., Yogeeswaran, K., and Bartneck, C. 2017. "Can We Control It? Autonomous Robots Threaten Human Identity, Uniqueness, Safety, and Resources," *International Journal of Human-Computer Studies* (100), pp. 48–54.