6-18-2022

"Feel, Don't Think" Review of the Application of Neuroscience Methods for Conversational Agent Research

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“FEEL, DON’T THINK!” REVIEW OF THE APPLICATION OF NEUROSCIENCE METHODS FOR CONVERSATIONAL AGENT RESEARCH

Research Paper

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Abstract

Conversational agents (CAs) equipped with human-like features (e.g., name, avatar) have been reported to induce the perception of humanness and social presence in users, which can also increase other aspects of users’ affection, cognition, and behavior. However, current research is primarily based on self-reported measurements, leaving the door open for errors related to the self-serving bias, socially desired responding, negativity bias and others. In this context, applying neuroscience methods (e.g., EEG or MRI) could provide a means to supplement current research. However, it is unclear to what extent such methods have already been applied and what future directions for their application might be. Against this background, we conducted a comprehensive and transdisciplinary review. Based on our sample of 37 articles, we find an increased interest in the topic after 2017, with neural signal and trust/decision-making as upcoming areas of research and five separate research clusters, describing current research trends.

Keywords: Conversational Agents, Neuroscience, NeuroIS, Literature Review

1 Introduction

Through recent advancement in artificial intelligence, especially natural language processing, the application of conversational agents (CAs) has become widespread (Berg, 2015; McTear, 2017; McTear et al., 2016). CAs are “software-based systems designed to interact with humans using natural language” (Feine et al., 2019, p. 1) and common examples include Alexa und Siri. Besides voice-based CA (e.g., Alexa and Siri), text-based CA, so called chatbots, are applied in many contexts. For instance, in 2018, 300,000 different chatbots were available on Facebook alone (Kraus, 2018).

Besides improving the technology for CA, one central aspect of developing effective CAs is their human-like design (e.g., giving it a name and gendered avatar), which has been reported to improve the users’ perception of a CA and its provided service (Araujo, 2018; Feine et al., 2019; Seeger et al., 2018). In this context, research has shown that users react to human-like designed CAs similar to a social actor (e.g., a human being) because of the perceived humanness and social presence (Nass & Moon, 2000). Recent studies report that this perception of humanness and social presence can increase the enjoyment (Diederich et al., 2020), service satisfaction (Gnewuch et al., 2018), and trustworthiness (Araujo, 2018) associated with a CA and its service. Consequently, research on the human-like design of CAs and how it leads to affective, cognitive, and behavioral responses by users is an important area of research with high practical relevance (Diederich et al., 2022; Feine et al., 2019).

However, the complexity of human-likeness and human-to-CA interaction has led to wide variety of different and sometimes contradicting results. For instance, an increase in social presence and humanness was reported to increase customer satisfaction (Araujo, 2018; Feine et al., 2019). In contrast, Hadi (2019) reported the opposite effect. Currently, CA studies employ primarily a questionnaire-based research approach, i.e., users are self-reporting their experience. This self-reporting has been shown to be prone to errors, including self-service biases (Moon, 2003), socially desired responding (Fisher & Katz, 2000; Krumpal, 2013), anchoring bias (Santhanam et al., 2020), and negativity bias (Thomas & Diener, 1990). Also, despite best efforts of the developing researchers, not all constructs and related items lead to valid and comparable results (Ho & MacDorman, 2010; Lu et al., 2021). For instance, from our own research experience, different set of items for perceived humanness and related constructs (e.g., social presence or anthropomorphism) lead to different results. There is a present need for an objective way to measure the responses of users to different CA designs.

Against this background, neuroscience methods (i.e., methods measuring responses of the central nerve, peripheral nerve or hormone system (Riedl & Léger, 2016)), such as encephalography (EEG) or function magnetic imaging (fMRI), should provide a valuable and complementary approach for studying the effects CAs have on users. Within the neuro information system (NeuroIS) community, adapting and applying such methods for various information systems (IS) related research topics has led to new and innovative discoveries (Riedl et al., 2020). For instance, Dimoka (2010) utilized fMRI to show that trust and distrust are separate concepts and not different ends of the same scale. This leads us to the question regarding the current extend researchers (either within the IS community or as part of other scientific communities) have adopted neuroscience methods to investigate CA design and related affective, cognitive, and behavioral responses of users, which we summarize in the research question of this study:

RQ: *What is the current status-quo of conversational agent research via neuroscience methods?*

To answer this question, we conducted a structure literature review, gathering and analyzing 37 papers. Specifically, we conducted a time series analysis and cluster analysis, leading to the identification of trends and five clusters. Overall, our results reveal five distinct clusters describing the current state of research.

2 Research Background

2.1 Design and Application of Conversational Agents

In the last few years, CA have found mainstream application in various contexts, ranging from traditional customer service (Barrett et al., 2015) to healthcare (Laranjo et al., 2018). This success is based on the recent technological advancements, primarily in natural language process (Berg, 2015; McTear, 2017; McTear et al., 2016), and the ability of CAs to serve users at any time and at any place, paired with a comfortable and convenient user experience (Verhagen et al., 2014). Common services of CAs include searching for information, writing emails (Gnewuch et al., 2018; Marinova et al., 2017), helping with stress management, and supporting healthy eating (Laranjo et al., 2018).

Overall, CAs have advantages over traditional systems (e.g., web forms) because of the option to equip CA with social cues (Feine et al., 2019), such as a human name, avatar and using emoticons (Seeger et al., 2018). These social cues can significantly alter users’ perception of the CA and its service (van Doorn et al., 2017; Verhagen et al., 2014). Driven by this potential and the widespread application of CAs, research has engaged this timely and relevant research topic. The most extensive framework to classify CA and research into CAs was provided by Diederich et al. (2022). The framework consists of the dimensions, human, context, agent, perception, and outcome and has shown great utility for structuring CA research. This paper follows a modification of this framework, focusing on context, agent, and outcome.

2.2 Human-like Design of Conversational Agents

In general, humans attribute objects with human-like characteristics because of their innate anthropomorphism bias (Howard & Kunda, 2000). It is part of human nature to associate objects, like animals (e.g., smiling monkey) and cartoon characters (e.g., mickey mouse), with human characteristics (Epley et al., 2007). This process of searching for human-like features and attributing corresponding characteristics is carried out mindlessly and also applies to users of computers, including CAs (Nass & Moon, 2000). In this context, Nass et al. (1994) formulated the “Computers are Social Actors” (CASA) paradigm. Following CASA, users are mindlessly assigning the computer a level of humanness, despite knowing mindfully that the computer is an object and not an human (Nass & Moon, 2000). Subsequently, users apply social norms (e.g., gender and related stereotypes) to the computer (Lang et al., 2013; Nass et al., 1994; Nass & Moon, 2000).

Furthermore, following the social response theory (Nass & Moon, 2000), a CA equipped with human-like features triggers an automatic social response by users (Feine et al., 2019; Nass & Moon, 2000). In effect, users experience the interaction with CAs similar to the communication with a human being (Gnewuch et al., 2017) and the intensity of this experience and related behavior is associated with the human-like appearance of the CA (Gong, 2008). For instance, researchers found that users respond with politeness and gratitude to a CA quipped with human-like features (e.g., users thanking Alexa) (Lopatovska & Williams, 2018). Furthermore, this perception of humanness can be related to increased levels of enjoyment (Lee & Choi, 2017), social presence (Kim & Sundar, 2012), and trustworthiness (Araujo, 2018).

In this context, Seeger et al. (2018) propose three main types of social cues for CA design: human identity, verbal cues, and non-verbal cues. Human identity consists of cues like name (Cowell & Stanney, 2005), avatar (Gong, 2008), and gender (Nunamaker et al., 2011). Verbal cues include elements like turn-taking (Gong, 2008), syntax and word variability (Seeger et al., 2018), and self-reference (e.g., “I think …”) (Schuetzler et al., 2018). Lastly, examples for non-verbal cues are dynamic response delays (Gnewuch et al., 2018), gestures (Cassell et al., 1994; Hartmann et al., 2005), facial expressions (Cassell et al., 1994), and the use of emoticons (Feine et al., 2019).

CA research, providing the needed new insights and theories into CA design, would benefit from the application of a divers set of methods. However, IS research in general does rely on a limited selection thereof. With a recent survey of the employed methods in the basket of eight, giving the percentage of papers employing the top four methods (survey, mathematical modelling, case study, qualitative research, and literature review) at 68,1% (Mazaheri et al., 2020). Likewise, the majority of studies into CAs utilizes a small set of methods and is mainly based on self-reported values. This assessment is based on our reanalysis of the literature sample of Diederich et al. (2022). To supplement this research, utilization of methods based on objective measurements is needed (e.g., neuroscience methods).

2.3 Neuro Information Systems Research Methods

Human behavior, including interactions with a CA, is not only influenced by the conscious mind, but also the subconscious (Lieberman, 2007). Therefore, investigative techniques, such as interviews or questionnaires, who only rely on the conscious reflection, will not give the full picture (Riedl & Léger, 2016). To understand the human interaction with any IS construct in its entirety, therefore, requires exploring the subconscious mind of the user. In this context, the needs of the IS community merged with the methods of neuroscience research to form the emergent field of NeuroIS (Riedl et al., 2014, 2020). Neuroscience methods, such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG), measure the neural activity or a direct marker thereof to gain insight into the basis of action and behavior (Kandel et al., 2000). They allow an insight into the mind, that is not filtered through the subject’s consciousness.

This is of particular interest to CA research. CAs are, both by design and reception, the embodiment of the concept of CASA (Nass et al., 1994). Unfortunately, social actions and reactions of humans are primarily based on the subconsciousness (Strack & Deutsch, 2004). It follows, that an application of neuroscience methods to CAs would give invaluable insight into the perception and use of CAs. However, to best of our knowledge, it remains unclear to what extend these methods have been applied for research of CAs.

3 Research Approach

Our research design is based on the structured literature review (Webster & Watson, 2002) and content analysis (Arnott & Pervan, 2012) approaches. We apply a three-step research process to analyze the extent of how CA research has utilized neuroscience methods. The goal is to identify how future research could further contribute to the ongoing discourse regarding the influence of CA on users' perception, affection, cognition, and behavior. In the following sub-chapters, each phase will be described in greater detail.

3.1 Phase 1: Gather Literature

The objective of the first phase was to gather a comprehensive set of articles on the topic of CA, which apply neuroscience methods. The gathering of literature (including searching and filtering) was conducted in July 2021. Overall, the process consisted of two parts.

First, we searched for publication by performing a keyword search in leading and established databases. Specifically, we included PubMed for neuroscientific and medical research, APA PsycArticle for psychological research, ACM for computer science research, and Scopus as a general data base, which includes IS research. For our search, we excluded white papers, opinions pieces, and books. Furthermore, we limited our literature search to studies and articles published after 2011, to focus our review on the most recent research. Furthermore, research on CA has gained mainstream research attention after 2011 (Diederich et al., 2022), supporting out decision. We used the following search string for our full text search:

((Conversational OR Interactive OR Virtual) AND Agent) OR Chatbot OR Digital Assistant))

AND

(PET OR fMRI OR fNIRS OR EEG OR TMS OR tDCS OR (ECG OR EKG) OR (pupil AND (dilation OR diameter)) OR hormone OR (galvan AND skin) OR EMG)*

The search string consists of two main parts. The first part ensures that only studies concerned with CA research were included. The terms were adapted from Diederich et al. (2022) and include synonyms for the term CA. The second part is based on the comprehensive list of neuroscience methods utilized in NeuroIS research (Riedl et al., 2020; Riedl & Léger, 2016), ensuring that studies using neuroscience methods were selected. In this step a total of 4,941 articles were gathered, after removal of duplicates 3,177 remained.

Second, we filtered the initial literature set of articles. To be included, publications must fulfil the following two criteria to be considered: first, the publications must be about a study on CA. Hence, research that only addresses CA in passing or developed conceptual contributions were excluded. This criterion also filtered out review studies. Second, a study must employ one or multiple neuroscience methods (e.g., EEG, MRI) to be included. Hence, studies based on other methods (e.g., survey, online experiments, interviews) were not considered.

The filtering was conducted by two of the authors. One of the authors has a background in business information systems and the other has background in neurobiology. First, articles were selected by title, keywords and abstract. This process resulted in a filtered sample of 417 articles. The remaining articles were then reviewed by both authors independently until it was clear, if they belonged into the final sample. Second, the filtering results were compared and discussed until both authors agreed upon a unified set of articles. In the end, our final sample consisted of 37 articles.

3.2 Phase 2: Code Literature

To compare and summarize the publications present in our research database, we coded them along dimensions related to CA research and neuroscience methods (see Table 1). The dimensions related to CA were identified along the CA research framework of Diederich et al. (2022), which consists of the components: human, context, agent, perception, and outcome. We selected this framework because it is holistic and developed based on recent CA publications and is, therefore, suitable to classify state-of-the-art research.

Furthermore, the neuroscience methods dimensions are based on Riedl & Léger, (2016) and Riedl et al. (2020). The two authors coded the literature sample independently, discussing inconsistencies to reach a common understanding and consistent coding. Before discussing and adapting the coding, a high level of similarity was already achieved (over 95% matching coding), indicating that the coding guidelines were consistently and adequately formulated.

Dimensions	**Characteristics**			
Method	PET	fNIRS	TMS	tDCS
	fMRI	EEG	ECG	Pupil dilation
	GSR	Hormones	EMG	Other
Measurement	Neural signal	Stress/Relaxation	Emotion/Attention/Arousal	
	Trust/Decision making	General biosignal	Task demand	
Context	Professional task support	Customer interface	Team collaboration	Individual task support
	Health	Education	Generic	Other
Embodiment	Virtual	Physical	None	
	Fully embodied	Partially embodied		
CA Type	Text	Voice	Both	
Design	Human identity	Verbal communication	Non-verbal communication	Combination

Note the characteristics are not mutually exclusive.

Table 1. Coding Dimensions and Characteristics

We extracted from the works of Riedl & Léger (2016) and Riedl et al. (2020) a comprehensive set of state-of-the-art neuroscience **methods**, which are already used in the context of IS research**,** including: positron emission tomography (PET), heart rate measurements (EKG or ECG), galvanic skin response (GSR, some authors (e.g., Katada et al. (2020), Leite et al. (2013) and Blankendaal et al. (2015)) also use the term electrodermal activity EDA), functional magnetic resonance imaging (fMRI), functional near infrared spectroscopy (fNIRS), electroencephalogram (EEG), transcranial magnetic stimulation (TMS), transcranial direct current stimulation (tDCS), pupil dilation, hormonal reaction, and electromyogram (EMG). All those neuroscience methods measure a response of either the central or peripheral nervous system (Riedl et al., 2020). For example, EEG is recording the changes in the electrical field at the scalp, caused by the changes in neural activity of the brain area beneath the recording site (Berger, 1929).

Since different physiological and psychological parameters can be evaluated via different neuroscience methods (e.g., stress can be extracted from heart rate variability (Marques et al., 2010) and/or galvanic skin response (Setz et al., 2010)), we included the **measurement** as an additional dimension for our analysis. This dimension was iteratively developed based on the measurements found in our literature sample. We grouped different concepts together based on the underlying physiological reaction. For example, emotion/attention/arousal were grouped together, since arousal is a dimension of the emotional spectrum (Russell, 1979), as well as interlinked with attention (Pribram & McGuinness, 1975). Besides emotion/attention/arousal, the included dimensions are neural signal, stress/relaxation, trust/decision making, task demand, and general biosignal.

When considering the **context** of CA application, we followed the separation into professional and private as described in Diederich et al. (2022). On the professional side, we have the usage of the CA to function as an interface to the customer and provide a service (Diederich et al., 2021; Vaccaro et al., 2018; Wuenderlich & Paluch, 2017), internal task support (Bittner & Shoury, 2019; Fast et al., 2018), and team collaboration (Bittner et al., 2019; Seeber et al., 2020). In the private context, CAs can be used for individual task support (Porcheron et al., 2018), education (Graesser et al., 2017), or personal health (Yokotani et al., 2018). Additionally, we grouped articles using CAs, whose only purpose was to engage the user in a conversation, as 'generic' and all CAs, which could not be classified using the above characteristics, as 'other'.

Embodiment describes the presentation of the CA to the user. With the CA being either embodied in physical form, virtual form, or have no embodiment (Diederich et al., 2022). Additionally, we grouped the embodiment after the extend of the embodiment. CAs embodied in a whole anthropomorphic body visible to the user, including at least the head, arms, and torso, were classified as fully embodied. CAs with a lower extend of embodiment (e.g., only the head and shoulders) were classified as partially embodied. If the CA did not have a visible representation (e.g., a pure text-based chat window, or an unseen voice commentor), the CA was classified as none in this dimension.

CA type addresses the mode of interaction with the user. Human language can be separated into written and spoken word. This separation translates into CA design, with different approaches using either text (Schroeder & Schroeder, 2018), voiced speech (Cowan et al., 2015), or both (Cho, 2019) to interact with the user. Accordingly, we grouped the communication method of the examined CAs into text, voice, or both.

Lastly, the dimension **design** describes which part of the CA interaction the study focused on. Based on Seeger et al. (2018), design can be categorized into 'human identity,' 'verbal communication,' 'non-verbal communication,' and 'combination.' For instance, if the CA used gestures to reengage the users, when a drop in attention was recorded, it was classified as 'non-verbal' (e.g. Szafir and Mutlu (2012)) and 'verbal' if speech was employed (e.g. Large et al. (2018)). If the study focused on the representation regarding the identity of the CA (i.e., if the CA presented itself as human or included features to appear less or more human), it was classified as 'human identity'. If the study employed multiple different CA interaction manipulations, it was classified as 'combined'.

3.3 Phase 3: Analyze Literature

We analyzed our literature sample via three methods. We applied a structured literature analysis, followed by a time series analysis and a cluster analysis.

For the **structure literature analysis**, we constructed a concept matrix. A concept matrix enables viewing literature from a thematic- / concept-centric position (Arnott & Pervan, 2012). Based on this perspective, research can be understood beyond the scope of descriptive summary of the written content of each article (Webster & Watson, 2002). Furthermore, it helps to quantify the distribution of characteristics within theoretical dimensions (see section 3.2).

In the **time series analysis**, we looked at the number of publications each year (similar to Leukel et al., 2014). We conducted the time series analysis by plotting the number of publications both by outlet and coding dimensions. Trends in the data were identified by visual inspection. In general, CA research is an evolving research field (Diederich et al., 2022) and understanding trends and shifts is important to understand the direction research is going.

Lastly, we applied a **cluster analysis** to identify groups (clusters) of articles that share similar characteristics. Articles within a cluster have to be as similar as possible and have to be as dissimilar as possible from articles of other clusters (Kaufman & Rousseeuw, 2005). Clusters built from research publications help identify predominant forms of research within a research domain. We applied a two-stage approach (Punj & Steward, 1983; Remane et al., 2016). First, we identified five clusters as suitable separation by using hierarchical clustering (shortest distance algorithm with hamming distance as implemented in MATLAB R2021b) and reviewing the dendrogram. Second, we applied k-means clustering (hamming distance and 100,000 iterations as implemented in MATLAB R2021b to construct the five clusters).

4 Results and Findings

In the following sections, we will present the results of our analyses. First, we will present the developed concept matrix, providing a descriptive account of the distribution of characteristics within our sample. Second, we will outline the identified trends (or lack thereof) based on our time series analysis. Lastly, we will present and summarize the emerged research clusters.

4.1 Results of Structure literature Analysis

In this section, we will present the results of the structured literature analysis, summarized, and illustrated in form of a concept matrix (see Table 2). Considering the context of the employed CAs, we found the health context and generic conversation as the most common with 27% of all examined articles. The second most common context is education (16%), followed by individual task support (14%). 11% of the articles fall outside of our classification and are classified as ‘other.’ Only a few articles deal with customer interactions (5%) and professional task support (3%). We did not find a research article with the ‘team collaboration’ context.

The examined research is dominated by CAs utilizing voice conversation with 76%. Text based CAs represent 16% of the research and 8% utilize both. Research into verbal communication design elements is the most often represented type of the design with 43%. 27% use a combination, while 24% examine the effects of human identity. Only 3% utilize non-verbal communication. Fully embodied and not embodied CAs present the majority of the research with 43% and 35% respectively. Partially embodied CAs are employed in 19% of the articles.

When considering the employed neuroscience methods, we find ECG as the most often used with 30%, followed by EEG with 27%. 22% are outside our classification schema (e.g., emotion recognition from video recording such as in Doumanis and Smith (2014), or relaxation from breath patterns in Shamekhi and Bickmore (2018)). GSR and fMRI are used in 16% in of the examined articles respectively. Pupil dilation is used in two articles representing 5%, while hormonal measurements and EMG are used exactly once each. We did not observe the usage of PET, TMS, tDCS or fNIRS.

Considering the measured signal, 27% of articles examine emotion/attention/arousal and 19% measure either neural signals or stress and relaxation. General biosignals are collected in 16% of the research articles. Trust and decision making as well as task demand are measured in 14% of the reviewed research.

4.2 Results of Time Series Analysis

The investigated articles show a distinct distribution over time with a steady level of about two publications per year until 2015 (see Figure 1). In 2016 only one publication was recorded. However, in 2017, we see a strong increase in publications, peaking in the year 2019. This increase in publications closely follows the reported development regarding publications investigating CAs in IS research (Diederich et al., 2022). We see a decline of the number of publications in 2020 and 2021.

While the reduced number of 2021 is explained by the fact, that the literature collection took place in July of 2021, and, therefore, not all publications of 2021 could be included.

	Method								Measurement						Context							Embodiment					CA type			Design				
Publication	fMRI	EEG	ECG	pupil dilation	GSR	Hormones	EMG	other	neural signal	stress/relaxation	emotion/attention/arousal	trust/decision	general biosignal	task demand	professional task support	customer interface	individual task support	health	education	generic	other	virtual	physical	none	fully	partially	text	voice	both	human identity	verbal	non-verbal	combination	Cluster membership
(Rauchbauer et al., 2019)	x								x											x			x			x		x			x			4
(Ehrlich & Cheng, 2018)		x							x												x		x		x			x					x	2
(Lydakis et al., 2017)							x			x								x				x			x		x				x			3
(De Visser et al., 2017)						x						x									x	x			x			x		x				1
(Bellos et al., 2014)			x										x					x						x			x							3
(Schneeberger et al., 2021)			x							x								x				x			x			x			x			1
(Shamekhi & Bickmore, 2018)			x					x		x								x				x			x			x					x	1
(Chaminade et al., 2015)					x								x							x				x				x		x				4
(Gupta et al., 2019)		x	x		x							x		x			x							x				x			x			5
(Heard et al., 2019)			x											x	x								x					x					x	1
(Alpers et al., 2020)			x							x						x								x					x		x			3
(Leite et al., 2013)					x					x	x								x				x		x			x		x				2
(Chaminade et al., 2018a)	x								x											x			x			x		x		x				4
(Doumanis & Smith, 2014)								x						x					x			x			x			x					x	1
(Spaulding et al., 2016)								x			x								x				x		x				x				x	2
(Rajavenkatanarayanan et al., 2018)		x						x			x						x						x		x			x			x			2
(Katada et al., 2020)					x			x			x									x		x			x			x			x			1
(Talukder & Haas, 2021)			x										x					x	x					x			x				x			3
(Elkins et al., 2012)				x				x			x										x	x				x		x			x			1
(Ishii et al., 2013)				x							x					x						x			x			x			x			1
(Hutt et al., 2017)								x			x								x			x			x			x					x	1
(Szafir & Mutlu, 2012)		x									x									x			x		x			x				x		2
(Blankendaal et al., 2015)			x		x					x	x										x	x			x			x					x	1
(Mills et al., 2017)		x												x					x			x			x			x					x	1
(Ajenaghughrure et al., 2019)		x										x					x							x				x			x			5
(Hwang et al., 2020)			x										x					x						x			x				x			3
(Gupta et al., 2020)		x			x							x					x							x				x			x			5
(Rauchbauer et al., 2020)	x								x											x			x			x		x		x				4
(Youssef et al., 2020)	x								x											x			x			x		x		x				4
(Zaki et al., 2019)								x					x					x						x			x				x			3
(Tolgay et al., 2019)		x										x						x						x				x		x				5
(Bhattacharya et al., 2019)			x										x					x						x			x				x			3
(Ciechanowski et al., 2019)		x									x						x					x				x			x	x				2
(Chaminade et al., 2018b)	x								x											x			x			x		x		x				4
(Large et al., 2018)			x											x						x				x				x			x			3
(Samani, 2018)		x								x								x						x				x					x	1
(Yuasa et al., 2017)	x								x											x		x			x			x					x	1
Sum:	**6**	**10**	**11**	**2**	**6**	**1**	**1**	**8**	**7**	**7**	**10**	**5**	**6**	**5**	**1**	**2**	**5**	**10**	**6**	**10**	**4**	**13**	**11**	**13**	**16**	**7**	**6**	**28**	**3**	**9**	**16**	**1**	**10**	

Table 2. Concept Matrix, non-observed categories are excluded for space reasons.

When considering the development of the measured signal over time, neural signal und trust/decision making are of particular interest (see Figure 1). Both are not investigated before 2016. Neural signal is measured in one publication in 2017, three in 2018, one in 2019 and two in 2020. Trust/decision making is investigated in one publication in 2017, three in 2019 and one in 2020. Apparently, both are of increased interested in recent years. All other measured signals do not show a clear trend over time.

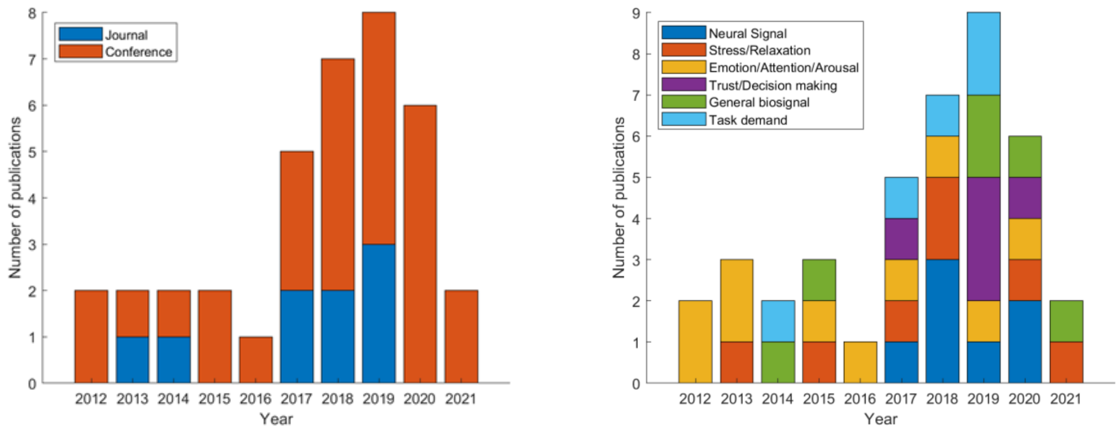

Figure 1: Distribution of the number of publications over the different outlet types (left) and the measurement of interest over time (right).

4.3 Results of Cluster Analysis

The cluster analysis resulted in the identification of five clusters. Table 3 shows the distributions of the observed dimensions over the clusters.

Cluster 1 termed 'CAs as virtual characters' is defined by its employment of predominantly fully and virtually embodied, and voice-based CAs. The majority (30%) of those studies use ECG, but there is no clear method preference. All but EMG are observed as employed neuroscience methods. This cluster has the highest proportion of 'other' employed neuroscience methods, ranging from modelling attention from eye tracking data, detection of deception from voice and eye tracking data (Elkins et al., 2012), engagement and attention from voice and video, and relaxation from breathing tracking. The measured signal also does not show a clear preference, with stress/relaxation and emotion/attention/arousal presenting the majority, followed by task demand. For instance, Yuasa et al. (2017) investigate the brain activity during the interaction of the participant with virtual characters in a conversational setting. Focus of this investigation was the evaluation of different verbal and non-verbal cues by the virtual avatars to engage the user in a 3-way conversation.

Cluster 2 is similar to cluster 1 regarding the type of CA employed. It is consisting of research regarding fully and physically embodied CAs, also known as robots. However, the second defining characteristics is the measurement of emotion/attention/arousal. EEG is the preferred method employed in this cluster, followed by uncategorized neuroscience methods consisting of emotion detection from video recordings. The examined context shows no clear direction with both individual task support and education representing the majority. An Example is the study of Rajavenkatanarayanan et al. (2018). In the study, EEG is used to assess the emotional state and task engagement of a user and used this information to adjust the behavior of the CA in real time.

In **Cluster 3** the defining features are the health context, ECG as a method, and a text-based CA without embodiment. The majority of the publication of this cluster measurements have been classified as measuring general biosignal. This cluster is exemplified by text based chatbots either providing medical diagnostic through the collected biosignals (Bhattacharya et al., 2019) or providing an awareness of the user regarding his current medical state and advice to maintain a healthy lifestyle (Hwang et al., 2020).

Cluster ID	1	2	3	4	5
Number of studies	**13**	**6**	**8**	**6**	**4**
Exemplary publication	(Elkins et al., 2012; Yuasa et al., 2017)	(Rajavenkatanarayanan et al., 2018)	(Bhattacharya et al., 2019; Hwang et al., 2020)	(Chaminade et al., 2018a)	(Ajenaghughrure et al., 2019)
Method					
fMRI	7.69%	0%	0%	83.3%	%0
EEG	15.4%	66.7%	0%	0%	100%
ECG	30.8%	0%	75%	0%	25%
Pupil dilation	15.4%	0%	0%	0%	0%
GSR	15.4%	16.7%	0%	16.7%	50%
Hormones	7.69%	0%	0%	0%	0%
EMG	0%	0%	12.5%	0%	0%
Other	38.5%	33.3%	12.5%	0%	0%
Measurement					
Neural signal	7.7%	16.7%	0%	83.3%	0%
Stress/Relaxation	30.8%	16.7%	25%	0%	0%
Emotion/Attention/Arousal	38.5%	83.3%	0%	0%	0%
Trust/Decision making	7.7%	0%	0%	0%	100%
General biosignal	0%	0%	62.5%	16.7%	0%
Task demand	23.1%	0%	12.5%	0%	25%
Context					
Professional task support	7.7%	0%	0%	0%	0%
Customer interface	7.7%	0%	12.5%	0%	0%
Individual task support	0%	33.3%	0%	0%	75%
Health	23.1%	0%	75%	0%	25%
Education	23.1%	33.3%	12.5%	0%	0%
Generic	15.4%	16.7%	12.5%	100%	0%
Other	23.1%	16.7%	0%	0%	0%
Embodiment					
Virtual	84.6%	16.7%	12.5%	0%	0%
Physical	7.7%	83.3%	0%	83.3%	0%
None	7.7%	0%	87.5%	16.7%	100%
Fully embodied	76.9%	83.3%	12.5%	0%	0%
Partially embodied	7.7%	16.7%	0%	83.3%	0%
CA Type					
Text	0%	0%	75%	0%	0%
Voice	100%	66.7%	12.5%	100%	100%
Both	0%	33.3%	12.5%	0%	0%
Design					
Human identity	7.7%	3.3%	0%	83.3%	25%
Verbal communication	30.7%	16.7%	87.5%	16.7%	75%
Non-verbal communication	0%	16.7%	0%	0%	0%
Combination	61.5%	33.3%	0%	0%	0%
Note that multiple selection was possible in some dimensions.					
Note the percentage reported is the share of articles of said cluster exhibiting the relevant characteristic.					

Table 3. Size and characteristics of the identified clusters

Cluster 4 presents neuroscientific research regarding interaction between humans and CAs. The method of choice is fMRI, with only one outlier (Chaminade et al., 2015). All publications in this cluster engage the user in a generic voiced based conversation with the CA. With some aspect of human identity as the most often addressed design. For example, Chaminade et al. (2018a) recorded the brain activity utilizing fMRI during an interaction between either a human experimenter, or a human experimenter posing as a CA.

Finally, **Cluster 5** is defined by the measurement of trust and decision making in CAs utilizing EEG. With two studies supplementing EEG with GSR measurements. The employed CAs are all voiced based without embodiment, mainly with task support as context, only the study of Tolgay et al. (2019) was conducted within a health context. Additional to trust and decision making, Gupta et al. (2019) is also measuring task load. An especially noteworthy publication from this cluster is Ajenaghughrure et al. (2019), who provide a way to measure trust from EEG measurements.

5 Discussion

The aim of this study is to examine the current status-quo of the application of neuroscience methods for the investigation CA and user interactions. Neuroscience methods provide a complement to the current approach of interview and questionnaire based research by going beyond self-reported measures and enabling the examination of bio-physical responses (Dimoka et al., 2011; Mast & Zaltman, 2005; Riedl et al., 2014; Riedl & Léger, 2016). Overall, our results indicate an increased interest in this topic after 2017. We see a rising number of publications investigating the neural signal present during CA interaction as well as trust and decision making when interacting with CAs. A systematic cluster analysis of the literature shows five clusters, concerning different areas of research. The first two clusters separate by the type of investigated CA embodiment, the third is employing CAs in a health context, the fourth describes neuroscientific research concerning the subject’s reaction to exposure to a CA, and the fifth cluster is investigating trust and decision making. Overall, the status-quo can be characterized by a slowly increasing interest in this style of investigation, focusing on investigation of fully embodied virtual CAs (cluster 1) and text-based CAs in a health context (cluster 3). Extending on these results, we would like to highlight the following implications for research and practice, flanked by a discussion of our study’s limitations.

5.1 Implications for research

Our study presents a comprehensive and descriptive overview of the literature regarding the investigation of CAs utilizing neuroscience methods. It provides a unique insight into the state of the research for interested scholars and allows to identified existing research gaps. In this section, we present a few of those open research questions and possible ways to move forward.

Regarding the applied methods, we see a dominance of EEG and ECG. With fMRI and GSR as a close second. Absent are fNIRS, TMS and tDCS. fNIRS presents a unique opportunity for NeuroIS research. fNIRS is combining portability and unobtrusiveness of EEG systems with the ease of interpretation of fMRI recordings (Krampe et al., 2018). However, it also is the newest of the missing neuroscientific methods, introduced in 1992 (Ferrari & Quaresima, 2012), which explains the low penetration of the field. For CA research, fNIRS could help to evaluate the brain activity during everyday interactions with CAs (e.g., Alexa and Siri) in a real-life setting. This is not possible with fMRI, since the necessary hardware (mainly, a multi ton magnetic coil and cryogenic cooling) requires a simplified and less naturalistic research paradigm (Shamay-Tsoory & Mendelsohn, 2019). EEG would allow to record in life like settings, but suffers from the source localization problem, complicating the interpretation of the recording (Hallez et al., 2007). TMS and tDCS both allow not to record, but influence the processing in a selected brain area presenting unique opportunities for research (Brunoni et al., 2012; Rossini & Rossi, 2007). For instance, TMS induces a selective current in the targeted brain area. Depending on the frequency and direction of said current, the neural processing can reversibly be facilitated, inhibited, and even completely disabled (Rossini & Rossi, 2007). As an example, this method has been utilized to investigate fairness behavior in economical transactions (Knoch et al., 2006). However, they require a suitable understanding of the brain mechanism involved in CA interactions, since it is of limited use, not to mention unethical, to randomly disable brain areas with TMS during a CA interaction, hoping for a chance find.

Regarding the examined context, we see a strong focus on the health and education context, but less for task support both at an individual and professional level. This is not comparable to the general CA research in the IS field. Diederich et al. (2022) showed customer interface as the most often investigated context, which is only examined in two publications in our literature sample. Therefore, there is a clear gap in the NeuroIS research of CAs in a business context. This gap is of relevance because CAs can be found in various service settings and many people have already interacted with one. Having this gap between practice (i.e., there is a strong interest for CAs for customer service (Hopkins & Silverman, 2016; Oracle, 2016)) and research (i.e., neuroscience methods are not/rarely applied to investigate CAs for customer service) could lead to negative consequences. Since the currently investigated contexts are not representative of the mainstream application of CAs, unintended and unwanted side effects will be missed. For example, recent examination of children interactions with voiced based commercial CAs, showed an increased parasocial bonding of the children with the CA, raising questions regarding their social development (Hoffman et al., 2021).

In conclusion, there is a strong need for interdisciplinary work and experimental research. The IS research community needs to find a way to interweave the needs of the IS community (i.e., design and examination of CAs mainly in a business context) with the needs of the neuroscience field. The current focus on health and education is probably driven by the adjacency of the fields. Researchers in the field of medicine and psychology are familiar with and have easier access to the necessary know-how and infrastructure. However, the IS community does not have a similar interface to neuroscience methods. Hence, we must find a way to frame our research questions to facilitate cooperation with neuroscientists. For example, decision making is an ongoing area of research in neuroscience (Rilling & Sanfey, 2010; Shiv et al., 2005). However, neuroscientific research does employ strongly controlled and, therefore, not life-like experimental designs, calling the generalization of the results into question (Shamay-Tsoory & Mendelsohn, 2019). The IS community has the opportunity to collaborate here, presenting life-like experimental designs (e.g., a CAs influence on the purchase **decision** for a product) to neuroscientists. The IS researcher would gain insight into the interaction with their artefacts and neuroscientist would benefit from more lifelike experiments.

5.2 Implications for policy

Overall, our results indicate that only a relatively small number of publications are investigating CAs with neuroscience methods. For comparison, Diederich et al. (2022) found 192 publications in the last 10 years by only analyzing the top IS journals and conference papers. Subsequently, we see a need for policy makers to shape future research on CA to the benefit of all. Primarily, we have to better understand how the human-like design of CA influences the decision-making of users, for instance during online shopping (Yen & Chiang, 2020). Similar to the fear of subliminal priming in the 1960s (Karremans et al., 2006), CAs pose a similar thread by tapping into humans social behavior to further commercial gains (order placement, was the second most common usage of CAs when examined in a business context by Bavaresco et al. (2020)). In this context, neuroscience methods provide a unique opportunity for understanding users' perception and behavior. Since the CA is perceived as a social actor by the user, the evaluation might be influenced by a social desirability bias (Fisher & Katz, 2000; Krumpal, 2013), or in other words, the user might answer in a way he/she thinks it is socially acceptable. Neuroscience methods allow to circumvent said bias by providing insight into the unbiased subconscious reactions of the user (e.g. stress, arousal), which has already provided insights into consumer decisions, spawning an entire subfield of NeuroIS termed neuromarketing (Bell et al., 2018; Hsu & Yoon, 2015; Plassmann et al., 2012).

5.3 Limitations

One limitation is the time-constraint of our research. We could only include articles in our literature sample that were known and accessible to us up to time of submission. Similarly, we searched in a wide variety of literature databases but, of course, could not include all databases available. Nonetheless, we are confident to have gathered a representative sample, despite missing some publications that were not part of our databases. Furthermore, cluster analysis and resulting clusters are never perfect, but allow the structuring of research (Nickerson et al., 2013; Remane et al., 2016). Therefore, we cannot be certain that we have found the ideal clusters, but given the rigor research process, the clusters have theoretical validity, nonetheless. However, its usefulness will become clearer as researchers begin to use the clusters as guidance for future research.

6 Conclusion

The goal of this investigation was the assessment of the status-quo of CA research employing neuroscience methods. We succeed in this goal by utilizing a structured literature review, followed by a time series and cluster analysis. We found an increased interest in the topic after 2017, with neural signal and trust/decision making as upcoming areas of interest. Via clustering algorithms, we found five different research clusters, highlighting that current research is mainly focused on health and education, with professional interactions, such as professional task support and customer interface, being underrepresented. This shows a disconnect and a possible research gap between CA research in general and CA research employing neuroscience methods. We are confident, that filling this gap will lead to new design implications for CAs. Against this background, we call upon the IS community to actively engage their neuroscience colleagues for cooperation to enable NeuroIS research into business orientated CA contexts. Furthermore, we call policy makers to consider the importance of such research because CA have found their way into many people private and work life. Not understanding how CA influence users on physiological and psychological level could lead to undesired side effects (e.g., influencing the social development of children by the formation of parasocial bounds) in the future and we, as a society, must engage with it now.

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