

**Towards Understanding Virtual Collaboration with Virtual Assistants in
Organizational Environments**

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Abbreviations

| | |
|------|-------------------------------------|
| AI | Artificial intelligence |
| CASA | Computers are social actors |
| CSCW | Computer supported cooperative work |
| IS | Information systems |
| VA | Virtual assistant |

Abstract (German)

Kollaboration ist ein entscheidendes Element für die Wertschöpfung von Organisationen. Der technologische Fortschritt überführt traditionellen Arbeitsumgebungen zunehmend in virtuelle Welten, in denen die Mitarbeiter¹ gemeinsam arbeiten. Aktuelle Forschung zu computer-supported cooperative work (CSCW, deutsch computerunterstützte Gruppenarbeit) befasst sich daher mit der Frage, wie Technologien die Kollaboration in virtuellen Umgebungen unterstützen können. Organisationen setzen vermehrt virtuelle Assistenten (VAs) ein, um Mitarbeiter bei der Ausführung arbeitsbezogener Aufgaben zu unterstützen, um dadurch Vorteile am Markt und gegenüber Wettbewerbern zu erzielen. Aufgrund ihrer Fähigkeit, menschenähnliche Interaktionen über natürliche Sprache zu imitieren und soziale Merkmale zu nutzen, sind VAs inhärent anthropomorph. Das CASA Paradigma (computers are social actors, deutsch Computer sind soziale Akteure) beschreibt, dass Menschen soziale Reaktionen zeigen, wenn mit Technologie interagiert wird. Bisherige Forschung deutet an, dass menschenähnliche Merkmale die Wahrnehmung von VAs als ebenbürtige Teammitglieder erhöht. Allerdings ist bisher wenig über ihren Einfluss auf virtuelle Kollaboration in Organisationen und das Auslösen von sozialen Reaktionen bei Menschen bekannt. In dieser Dissertation werden verschiedene theoretische Aspekte betrachtet, wenn VAs in virtueller Kollaboration eingesetzt werden. Unter anderem die Bildung einer Identität, die Erweiterung des individuellen Selbst, die Auswirkungen auf mentale Fähigkeiten und die Zuschreibung von Verantwortung. Die Ergebnisse zeigen Potenziale (z.B. die Entlastung von Mitarbeitern) und Herausforderungen (z.B. das Unvermögen, Probleme allein zu lösen) und verdeutlichen die verschwimmenden Grenzen zwischen menschlichen und menschenähnlichen Akteuren. Diese Arbeit erweitert vorhandene wissenschaftliche Erkenntnisse um eine neue Perspektive und Hilfestellung für ein tiefergehendes Verständnis der virtuellen Kollaboration mit VAs in organisatorischen Umgebungen.

¹ Im Folgenden wird das generische Maskulinum verwendet. Weibliche und anderweitige Geschlechteridentitäten sind damit ausdrücklich inkludiert, soweit es für das inhaltliche Verständnis erforderlich ist.

Abstract (English)

Collaboration is critical for enterprises to create value. Technological advancements have increasingly shifted traditional workspaces to virtual worlds in which employees collaborate. Recent research on computer-supported cooperative work (CSCW) has thus involved understanding how technologies, such as virtual assistants (VAs), are capable of supporting collaboration within virtual surroundings. Many enterprises have introduced VAs as work facilitators that assist employees in executing tasks to generate additional revenue and gain competitive advantage. Due to their ability to simulate human-like interactions via natural language and social cues, VAs are inherently anthropomorphic. The computers are social actors paradigm (CASA) explains that individuals exhibit social responses when interacting with technology. However, while extant research has indicated that human-like features allow VAs to be perceived as legitimate team members, less is known about VAs' influence on virtual collaboration within organizations or about the extent to which humans are engaged in social responses. This paper-based dissertation considers various theoretical aspects of VAs' application in virtual collaboration, such as the formation of an identity, extension of the individual self, impact on mental capacities, and attribution of responsibility. The results reveal potential (i.e., relieving individuals from certain burdens) and challenges (i.e., failing to solve problems individually) as well as highlight the blurring boundaries between human and human-like actors. This work extends the information systems (IS) literature by providing a novel perspective and guidance for gaining a deeper understanding towards understanding virtual collaboration with VAs in organizational environments.

1 Introduction

1.1 Research Context and Goals

Collaboration and teamwork are vital and pervasive elements that are necessary for enterprises to maximize revenue and gain competitive advantage (Alavi and Tiwana 2002; Boughzala et al. 2012). Working with team members inspires individuals to maximize their potential (Harkins and Petty 1982). However, technological advancements constantly reshape business models, internal processes, products, and services (Cetindamar Kozanoglu and Abedin 2020; Frick, Mirbabaie, et al. 2021; Nadeem et al. 2018; Vial 2019). This transforms enterprises' workplaces for exploiting relative leverages (Junglas et al. 2019; Meske and Junglas 2020).

According to research on computer-supported cooperative work (CSCW) “*collaborative activities and their coordination can be supported by means of computer systems*” (Carstensen and Schmidt 1999). The concept of CSCW was initially concerned with understanding how technologies are capable of supporting collaboration in physical teams (Ens et al. 2019). Since employees no longer work in one office but rather collaborate from different geographic locations and time zones, which might even be globally distributed (Andres and Shipps 2019; Berry 2011; Frick and Marx 2021; Hassell and Cotton 2017; Massey et al. 2003; Plotnick et al. 2016), research has shifted to focus on these virtual environments (Ens et al. 2019; Gutwin et al. 2008; Richter et al. 2018). Indeed, traditional environments are steadily shifting to virtual work spaces and computer-generated realities (Fromm et al. 2020; Litvinova et al. 2018), and individuals are increasingly assisted by certain technologies while collaborating in virtual teams (Changizi and Lanz 2019; Seeber, Bittner, et al. 2020; de Vreede and Briggs 2005). However, external forces, such as the COVID-19 pandemic (which coincided with the writing of this thesis), as well as cultural differences and short-term formations and existence of virtual teams, are challenging for organizations to, for example, establish a positive team atmosphere and identification (Bunker et al. 2008; Frick, Möllmann, et al. 2021; Frick and Marx 2021; Marks 2020; Waizenegger, McKenna, et al. 2020).

Organizations progressively rely on technology that complements the skills of employees collaborating in teams, for example, by assisting with certain tasks or solving complex problems (Seeber et al. 2019). Technology applied in virtual collaboration, especially enabled by artificial intelligence (AI), acts not only as a simple tool for virtual collaboration but also creates a unique and independent virtual environment (Maedche et al. 2019; Seeber, Waizenegger, et al. 2020). AI is part of a broad spectrum of technologies that

cover self-learning abilities (Batin et al. 2017; Coombs et al. 2020) which assist employees in many different areas, for example, in the decision-making processes on various strategic levels (Aversa et al. 2018; Pessach et al. 2020). AI turns traditional information technology into smart systems, such as virtual assistants (VAs) (Alter 2020; von Wolff et al. 2019) that “*mimic human-to-human communication using natural language processing, machine learning, and/or artificial intelligence*” (Schuetzler et al. 2018).

VAs are supposed to generate sustainable business value across a wide range of applications in organizations (Seeger et al. 2021). Nevertheless, they are mainly used as work facilitators that assist employees with work-related tasks and enhance customer satisfaction (Norman 2017; Quarteroni 2018; Verhagen et al. 2014). For example, VAs are employed as feasible support for answering customer service inquiries (Adam et al. 2020; Cui et al. 2017; Følstad et al. 2020; Nordheim et al. 2019). The application of VAs is growing steadily, and they are becoming one of the most preferred form of assistance within virtual collaboration (Maedche et al. 2019; Nuruzzaman and Hussain 2020). This growth in popularity has encouraged enterprises to invest heavily (Bughin et al. 2017). Information systems (IS) scholars comprehend the ongoing hype about these technologies, including their economic impacts (Adam et al. 2020; Selz 2020; Thiebes et al. 2020), which are likely to change the future of work (Coombs et al. 2020; Grønsund and Aanestad 2020; Mirbabaie, Brünker, et al. 2021) steadily turning these concepts into key elements for enterprises (Dwivedi et al. 2019). However, VAs are repeatedly introduced without awareness of the associated consequences, especially those regarding related attitudes, actions and social aspects of employees and teams (Coombs et al. 2020; Mirbabaie, Brünker, et al. 2021). Even though research on VAs in virtual collaboration is not a recent development (Demir et al. 2020; Panganiban et al. 2020; Seeber, Bittner, et al. 2020), scholars and practitioners still need to adjust their understanding on the different aspects of collaborative settings and examine whether knowledge from human teams is transferable to different technologies (Demir et al. 2020). The individual behavior towards VAs comparable to humans might alter extant perspectives on assistive technologies and raise similar implications known from human teams.

Human teams frequently fall short of their possibilities (Kozlowski and Ilgen 2007) and regularly face challenges in virtual collaboration, such as establishing a mutual and shared understanding of processes, goals, and information exchange (Kolfschoten and De Vreede 2009; Weick et al. 2005). Research has shown that VAs applied in virtual teams are capable overcoming collaborative issues and improving team performance (Seeber et al. 2018; Seeber, Bittner, et al. 2020; Waizenegger, Seeber, et al. 2020). For example, VAs are highly suitable for retrieving huge datasets from intricate infrastructures in real time (Dellermann, Ebel, et al. 2019). They are further capable of adapting to divergent

situations by continuously processing new information, and thus learn and develop over time (Alter 2020; Mitchell et al. 2018; von Wolff et al. 2019). Similar to humans, VAs can interpret and react to individual facial expressions and gestures, which enables the detection of group dynamics among users in multiparty collaborations by estimating the dominance of participants (Laumer et al. 2019; Nakano and Fukuhara 2012; Pfeuffer et al. 2019). VAs can also differentiate between and interpret individuals' emotions during team collaboration (McDuff and Czerwinski 2018), and they use different language styles to adapt to different users with varying roles, aiming to enhance self-disclosure of personal information (Gnewuch et al. 2020; Pfeuffer et al. 2019). VAs are further considered to be inherently anthropomorphic due to their capability to use social cues (Feine et al. 2019). In virtual collaboration, VAs might use verbal (i.e., acknowledgment and dialect), visual (i.e., eye and head movement), auditory (i.e., gender and tempo), or even invisible cues (i.e., response time and tactile touch). These social cues might cause individuals to feel that they are talking to another human (Hussain et al. 2019; Pfeuffer et al. 2019) and might trigger certain perceptions, such as dominance, even leading to interactional conflicts (Danilava et al. 2013; Gebhard et al. 2014).

The computers are social actors (CASA) paradigm demonstrates that individuals exhibit social responses when collaborating with technology (Nass et al. 1994; Nass and Moon 2000), especially when the technology possess human-like features (Feine et al. 2019; Gnewuch et al. 2018; Pfeuffer et al. 2019). According to the social response theory, these human-like features influence how individuals perceive a technology, including expectations towards their representation and behavior (Lankton et al. 2015; Nass and Moon 2000). Therefore, humans might respond to technologies with human-like attributes as they do to other humans. However, this might also imply that VAs are expected to behave the very same as humans. Anthropomorphism (i.e., transferring human characteristics to non-human entities) triggers social responses in individuals (Gnewuch et al. 2018; Pfeuffer et al. 2019) and might influence users' perceptions (Araujo 2018; Feine et al. 2019). These social responses might even lead to mindless behavior (i.e., applying certain expectations towards a technology without even thinking about it) (Nass et al. 1994; Nass and Moon 2000) and could thus substantially impact virtual teamwork. According to recent studies, social responses might raise certain potential and/or challenges, depending on a variety of factors (Bührke et al. 2021; Seeger et al. 2018; Tinwell and Sloan 2014). For instance, anthropomorphism might evoke positive perceptions toward offered services (Diederich, Janßen-Müller, et al. 2020; Gnewuch et al. 2018), but a high degree of human-likeness can also raise discomfort (Wiese and Weis 2020).

Interacting with VAs seems to engage individuals in similar behavior to that prompted by human interaction. However, it remains uncovered whether social responses appear when

individuals are assisted by VAs in virtual organizational environments. There is thus an urgent demand to conduct deeper research on VAs in virtual collaboration to reveal similarities and differences to human teams. The observable similarities between these two environments might imply comparable or even identical ramifications for employees, teams, and enterprises, such as improved organizational performance or an imbalanced distribution of responsibilities (Boughzala and De Vreede 2015). Potential differences could require rethinking existing theories, including determining distinctions between VAs and more traditional decision-support systems with simpler abilities (Alter 2020). Furthermore, interpretation pursuing a constructivist versus an interference hypothesis (Moreno et al. 2001) is fundamental to assess how VAs should be deployed in organizational surroundings. The associated consequences might significantly alter theoretical and practical perspectives regarding the purposes for which VAs are fruitful in virtual collaboration. Thus, a holistic approach to virtual collaboration and VAs as socio-technical arrangement is overdue. To examine the role of VAs in virtual collaboration in organizations, this thesis is guided by the following research questions:

RQ1: How do virtual assistants influence virtual collaboration in organizational environments?

RQ2: To what extent do virtual assistants in virtual collaboration engage human team members in social responses?

To answer the guiding questions and uncover observations regarding VAs in virtual collaboration, this thesis refers to theoretical foundations related to the CASA paradigm (Lankton et al. 2015; Nass et al. 1994; Nass and Moon 2000) and examines whether knowledge from human teams is transferable. Thereby, it investigates whether VAs in virtual collaboration cause similar effects as humans do. The effects could include providing the same level of assistance and relieving certain burdens, as well as lowering individuals' contribution and feelings of less responsibility for duties and outcomes. This paper-based dissertation therefore contributes to theory and practice by structuring the understanding of VAs in virtual collaboration in organizational environments. The results sharpen the perception of how virtual collaboration assisted by VAs differs from physical, human teams and under which circumstances humans exhibit similar or divergent social responses. This thesis therefore provides a novel IS perspective towards understanding virtual collaboration with VAs in organizational environments.

1.2 Thesis Structure and List of Publications

This doctoral thesis is a cumulative dissertation that follows the regulations governing doctoral proceedings at the Faculty of Engineering of the University of Duisburg-Essen. The present synopsis contains an overview and alignment of the results, which were published in journal articles as well as conference proceedings. This synopsis combines, analyzes, and discusses the findings of the individual papers in a wider perspective to answer the overarching research questions.

Section 2 outlines VAs and their application in corporate structures and explains the theoretical foundations which suit as the backdrop to this thesis. The third section summarizes the research strategy, including the varying research methods used in the papers. Section 4 demonstrates the results of the publications; the findings are not presented in detail for each paper, but rather their interdependencies are demonstrated. The fifth section discusses the findings and synthesizes them, serving to answer the research questions. Finally, section 6 depicts implications for theory and practice and concludes with limitations and recommendations for future research.

This thesis comprises multiple research papers published in various outlets (i.e., national, and international academic journals as well as conference proceedings). Table 1 provides an overview of the papers that are included in this thesis. It displays the title, the research colleagues with whom the article was published, the year of publication and the outlet as well as publication type. Furthermore, the table depicts the ranking of the respective outlet according to the German Academic Association for Business Research (VHB) and Journal Citation Reports (JCR) Impact Factors. Please note that the papers are sorted according to their date of publication.

| Paper | Publication ¹ | Type | VHB Ranking ² | Impact Factor ³ |
|-------|--|--------------------------|--------------------------|----------------------------|
| 1 | <p>Title: Der Einsatz von künstlicher Intelligenz zur Verbesserung des Incident Managements</p> <p>Authors: Frick, N.R.J., Brünker, F., Ross, B., & Stieglitz, S.</p> <p>Year: 2019</p> <p>Outlet: HMD Praxis der Wirtschaftsinformatik (HMD)</p> | Journal | D | N/A |
| 2 | <p>Title: Towards Successful Collaboration: Design Guidelines for AI-based Services enriching Information Systems in Organisations</p> <p>Authors: Frick, N.R.J., Brünker, F., Ross, B., & Stieglitz, S.</p> <p>Year: 2019</p> <p>Outlet: Australasian Conference on Information Systems (ACIS)</p> | Conference (short paper) | N/A | N/A |
| 3 | <p>Title: On the Ability of Virtual Agents to decrease Cognitive Load – An experimental study</p> <p>Authors: Brachten, F., Brünker, F., Frick, N.R.J., Ross, B. & Stieglitz, S.</p> <p>Year: 2020</p> <p>Outlet: Information Systems and e-Business Management (ISeB)</p> | Journal | C | 5.073 |
| 4 | <p>Title: Design requirements for AI-based services enriching legacy information systems in enterprises: A managerial perspective</p> <p>Authors: Frick, N.R.J., Brünker, F., Ross, B., & Stieglitz, S.</p> <p>Year: 2020</p> <p>Outlet: Australasian Conference on Information Systems (ACIS)</p> | Conference (full paper) | N/A | N/A |
| 5 | <p>Title: Understanding Collaboration with Virtual Assistants – The Role of Social Identity and Extended Self.</p> <p>Authors: Mirbabaie, M., Stieglitz, S., Brünker, F., Hofeditz, L., Ross, B., & Frick, N.R.J.</p> <p>Year: 2020</p> <p>Outlet: Business & Information Systems Engineering (BISE)</p> | Journal | B | 4.532 |

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|---|--|---------|-----|-------|
| 6 | Title: Hybrid Intelligence in Hospitals – Towards a Research Agenda for Collaboration Authors: Mirbabaie, M., Stieglitz, S., & Frick, N.R.J. Year: 2021 Outlet: Electronic Markets (ELMA) | Journal | B | 4.765 |
| 7 | Title: Comparison of disclosure/ concealment of medical information given to conversational agents or to physicians Authors: Frick, N.R.J. , Brünker, F., Ross, B., & Stieglitz, S. Year: 2021 Outlet: Health Informatics Journal (HIJ) | Journal | N/A | 2.681 |
| 8 | Title: The perceived surveillance of conversations through smart devices Authors: Frick, N.R.J. , Wilms, K.L., Brachten, F., Hetjens, T., Stieglitz, S., & Ross, B. Year: 2021 Outlet: Electronic Commerce Research and Applications (ECRA) | Journal | C | 6.014 |
| 9 | Title: Collaborating with Virtual Assistants in Organizations – Analyzing Social Loafing Tendencies and Responsibility Attribution Authors: Stieglitz, S., Mirbabaie, M., Frick, N.R.J. , & Rzycki, J. Year: 2021 Outlet: Information Systems Frontiers (ISF) | Journal | B | 6.191 |

¹ Sorted by publication year. The author Nicholas R. J. **Frick** changed his name to Nicholas R. J. **Möllmann** in August 2021.

² Ranking list released by the German Academic Association for Business Research (VHB), see <https://vhbonline.org/vhb4you/vhb-jourqual/vhb-jourqual-3/gesamtliste> (accessed 20th of June 2021).

³ 2020 impact factors by Clarivate Analytics, see <https://jcr.clarivate.com/>.

Table 1: List of publications in chronological order

2 Research Background

2.1 Virtual Assistants in Organizations

Studies on VAs and systems behaving alike, such as chatbots (Stieglitz et al. 2018) or AI-based chatbots (Adam et al. 2020), digital assistants or AI-based digital assistants (Maedche et al. 2019), intelligent personal assistants (de Barcelos Silva et al. 2020) and conversational agents (Diederich, Brendel, et al. 2020), have become increasingly prominent. Scholars have examined VAs from multiple perspectives (e.g., Luger and Sellen 2016; Saffarizadeh et al. 2017; Seeber et al. 2018) but have not been able to establish a consistent classification due to possible overlaps VAs' implementations, functionalities and/or capabilities. Gnewuch et al. (2017) used the primary mode of communication and the context as initial classifications. The authors further refined their classification in text- and speech-based inputs and general and domain-specific purposes. In contrast, Knotte et al. (2019) categorized VAs according to ten design characteristics, including assistance domain (general or specific), adaptivity (static or adaptive) and embodiment (none, virtual character, artificial voice, or virtual character with voice). Although some scholars' endeavors have been similar, a definite classification system has not been established. VAs might be customized by enterprises to cope with certain requirements (Chung et al. 2017), and systems could use different and multiple modules to convert human language for selective purposes (Gnewuch et al. 2017). Besides different terms and varying classifications, research is further lacking a consistent definition. Luger and Sellen (2016) defined VAs as *"IS that enable the interaction with users via natural language"*. Stieglitz et al. (2018) explained that systems *"can be addressed via voice or text and that can respond to the users input (i.e., assist) with sought-after information"*. This is comparable to the definition of Laumer et al. (2019) who described VA within healthcare as *"text-based and voice-based automated dialog systems that can interact with a human user via natural language and answer questions on specific topics"*. Hussain et al. (2019) underlined that *"the user thinks he is having dialogue with a human"*.

The growing prevalence of VAs for organizational purposes is due to constant advancements of AI and underlying machine learning algorithms (Berg 2015; Knijnenburg and Willemsen 2016). Moreover, processor speeds and storage capacity for data have increased while costs have dropped (Spohrer and Banavar 2015). Technology needed for building systems is now broadly accessible (Kersting 2018), enabling organizations to gather the growing amount of data in a shorter time (Nasirian et al. 2017). AI, as a ubiquitous concept, consists of multiple subfields and can be interpreted along (Russel and Norvig 2016; Wang and Siau 2018), for example, thinking humanly or rationally and acting humanly or rationally (Bellman 1987; Kurzweil 1990; Nilsson 1998; Winston

1992). Although no consistent definition for the term AI exists, it can be considered 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). AI is usually believed to be on par with human intelligence, but society is questioning how robot teammates reach this kind of intelligent behavior and to what extent the way people collaborate changes (Bednar and Welch 2020; Neuhofer et al. 2020). Research has also been concerned with the potential downsides of AI’s application in virtual collaboration in organizations, such as the related threats of employees and emerging resistance to AI-induced change processes (Aleksander 2017; Stieglitz et al. 2021). AI has a three-dimensional categorization (Batin et al. 2017). Narrow systems explain self-learning approaches outperforming humans in a specific task. Most implementations of AI in organizations, including VAs, fit to this category as they focus on a particular work-related issue. The other categories are general AI, which is comparable to human intelligence, and a hypothetical superintelligence, which potentially exceeds humans in all aspects. Both are still far from being within reach. The given definition of AI is admittedly very broad, and recent narrow systems are still far away from empathy-driven, creative robot teammates. Nonetheless, AI is capable of turning regular information technology or decision-support systems into VAs possessing the ability to adapt to deviating circumstances in which they behave reactively, proactively, and autonomously (Alter 2020; von Wolff et al. 2019). VAs in organizations seek to combine the complementary strengths of humans and AI (Kamar 2016). Humans are characterized by, for example, empathy, creativeness, innovativeness, and flexibility. VAs are favorable for, in example, identifying complex interdependencies in vast datasets (Dellermann, Ebel, et al. 2019). Humans provide VAs with knowledge, which is then used to enhance the VAs’ capabilities (human intelligence in the loop of AI/VA). Thus, VAs continuously learn and develop over time by processing human information as well as collecting additional data from digital sources (Mitchell et al. 2018). In turn, VAs supply humans with feedback to assist in the execution of certain tasks (AI/VA in the loop of human intelligence) (Dellermann, Ebel, et al. 2019; Dellermann, Lipusch, et al. 2019).

Despite the recent and numerous advancements of VAs in virtual collaboration, there are certain challenges and dangers heavily impacting the purposefulness in organizational environments. There are multiple stakeholders working in different hierarchical structures and branches that need to coexist with VAs (Finlayson and Raymont 2012; Schadewaldt et al. 2014; Seeber et al. 2018). VAs applied in virtual collaboration also enhance the transparency of working methods, roles and tasks which causes discomfort among users (Wünderlich and Paluch 2017). This feeling might be strengthened by a low level of trust in the VA and its level of competence (Seeber et al. 2018). Further issues are related to

security and privacy perceptions inherent to virtual collaboration. For example, perceived security as well as privacy impact individuals' willingness to disclose/conceal certain information (Abdelhamid et al. 2015; Dinev and Hart 2006; Kuckein et al. 2010). Lower security and privacy perceptions might cause employees to refuse to use VAs in virtual collaboration (Ba et al. 2003; Gefen et al. 2003) and even raise the feeling of being surveilled (Abdi et al. 2019; Siddike et al. 2018).

Nevertheless, VAs in organizational environments are beneficial on many levels across industries. They are used in, for example, customer support as practical and cost-effective means to answer repetitive inquiries and thus affect customer satisfaction positively (Adam et al. 2020; Cui et al. 2017; Følstad et al. 2020; Nordheim et al. 2019). VAs are also applied within human resource departments as human-like interviewers for job applications (Pickard and Roster 2020) or as virtual colleagues that enhance the onboarding processes of new hires by providing flawless guidance and answering personnel questions (Shamekhi et al. 2018). In principle, the application of VAs in enterprises aims to reduce employees' workload by assisting with repetitive tasks (McTear et al. 2016), and they have successfully been applied in real-world scenarios, including retail or finance (Okuda and Shoda 2018).

Recent research has demonstrated that application of VAs as virtual team members, resulting in a socio-technical arrangement with human colleagues, can enhance the overall effectiveness of the team (Seeber, Bittner, et al. 2020; Waizenegger, McKenna, et al. 2020). Since organizations sense numerous benefits, VAs are becoming more common in virtual teams (Maedche et al. 2019; Nuruzzaman and Hussain 2020; Stieglitz et al. 2018) and team dynamics have presumably undergo certain alterations. The human-like features (Feine et al. 2019; Maedche et al. 2019) indicate that VAs are perceived as social actors and that knowledge from human teams is transferable to virtual collaboration. However, the impact of VAs in collaborative organizational settings and whether previous theoretical findings regarding social responses still apply remains vague.

2.2 Virtual Assistants as Social Actors

Collaboration is understood as a social phenomenon in which individuals work together to reach a certain goal that is not achievable alone (Boughzala et al. 2012; Boughzala and De Vreede 2015). Extant research has formulated different definitions of collaboration. Briggs et al. (2003) explained collaboration as a *“joint effort toward a group goal”* while Koch and Gross (2006) further refined this definition to view collaboration as shared creation and/or discovery. Another definition of Boughzala and De Vreede (2015) summarized collaboration as *“a team's current maximum capability to collaborate (i.e., people) where team members effectively communicate (i.e., process), reach shared understanding*

(i.e., information), and adjust their tasks (i.e., management and process), behaviors (i.e., people), and means (i.e., technology and information) to produce high-quality outcomes". Although collaboration among employees in organizations aims to increase performance and outcomes (Banker et al. 2006; Jordan et al. 2002), teams are frequently confronted with certain challenges (Kozlowski and Ilgen 2007). These include, but are not limited to, challenges with communication, decisions, infrastructure, and responsibilities. For example, faulty communication hinders the seamless functioning of processes (Balogh et al. 2015; Salas et al. 1999); opaque responsibilities in teams raises the risk of incorrect decisions (Smith-Jentsch et al. 2001); complex infrastructures decelerate the execution of tasks (Meier et al. 2014); and decisions based on individual judgments contain more mistakes (Salas et al. 2005). However, integrating suitable technologies to assist with collaboration in teams can mitigate these issues (Gopal et al. 2018; Klinker et al. 2019).

Collaborative technologies have a long history in the IS discipline (Ens et al. 2019). Early research that emerged in the 1980s (Grudin 1994) was closely related to the term groupware (Carstensen and Schmidt 1999), which describes a software that supports group collaboration (Bannon and Schmidt 1989; Schmidt and Bannon 1992). CSCW was initially concerned with understanding and designing technologies to support collaboration in physical teams (Ens et al. 2019). Especially in organizations, in which individuals may have different goals and teams frequently lack in shared meanings and knowledge (Heath and Luff 1996; Kling 1991; Star and Ruhleder 1994), CSCW addressed approaches to solve emerging conflicts and thereby enhance collaboration and teamwork (Ackerman 2000; Malone and Crowston 1994; Schmidt and Simonee 1996). However, since traditional environments are constantly shifting to virtual work spaces (Fromm et al. 2020; Litvinova et al. 2018) in which individuals re-organize their work independently of time and place (Frick and Marx 2021), scholars have increasingly focused on virtual environments (Ens et al. 2019; Gutwin et al. 2008; Richter et al. 2018). Comparable to that on physical teams, CSCW research on virtual collaboration focuses on how technology enhances collaboration, team-building, and team-performance in virtual worlds (Wallace et al. 2017; Wiethof et al. 2021). Due to current technological advancements that ultimately replace the more traditional computing devices in virtual collaboration (i.e., regular IT or decision-support systems) (Wallace et al. 2017), scholars have progressively focused on systems that are capable of using features comparable to human behavior (Feine et al. 2019; Gnewuch et al. 2018; Pfeuffer et al. 2019). These yields individuals attributing human characteristics towards this kind of technologies.

The CASA paradigm suggests that individuals treat technology like real people (Nass et al. 1994; Nass and Moon 2000) and "*respond to computers in much the same way that*

they respond to other human beings” (Reeves and Nass 1996). Individuals automatically consider technology to be a social entity (Kim and Sundar 2012), as seen in anthropomorphism of that technology, or the “*assignment of human traits and characteristics to computers*” (Nass and Moon 2000). The social response theory emerged from the CASA paradigm and posits that individuals respond socially to systems when the systems show certain social cues (e.g., human-like features), such as voice, gender, or language style (Lee 2007; Nass et al. 1994, 1997). In these instances, humans apply mindless behavior that triggers social responses (i.e., scripts and expectations) (Nass and Moon 2000), even though they are aware that they are interacting with a machine (Araujo 2018; Reeves and Nass 1996). While earlier studies examined CASA as well as the social response theory in the context of computers and television (Araujo 2018), these concepts have also been adapted to websites (Kim and Sundar 2012), physical social robots (Edwards et al. 2016; Rosenthal-von der Pütten and Krämer 2015), and VAs (Bührke et al. 2021; Seeber et al. 2019). Current IS research endeavors are engaged in categorizing social cues and defining a taxonomy for VAs (Feine et al. 2019; Pfeuffer et al. 2019). Insights have also been garnered from experiments on how humans react to certain social cues when using VAs (Diederich, A. B. Brendel, et al. 2019; Diederich, Janßen-Müller, et al. 2020; Gnewuch et al. 2018) and scholars are designing anthropomorphic VAs (Diederich, Brendel, et al. 2020; Diederich, Lichtenberg, et al. 2019). However, the impact of VAs in virtual teams and humans’ social responses in virtual collaborative settings has yet to be studied (Diederich, A. Brendel, et al. 2019). The increasing capabilities of VAs blur the boundaries between human and human-like actors. Since VAs could possess human features that individuals mindlessly respond to, team dynamics and performance in virtual collaboration can be impacted. For example, human-like interaction might enhance decision-making and improve team atmosphere and cohesion (Bickmore et al. 2011; Seeber, Waizenegger, et al. 2020; Waizenegger, McKenna, et al. 2020). Nevertheless, the increasing human likeliness could also result in undesired negative effects, since VAs might be perceived as too human-like (Diederich, Brendel, et al. 2020; Seeger et al. 2018; Wiese and Weis 2020). Mindless behavior may lead to carelessness about certain tasks or duties, thereby facilitating laziness. Humans could also over-trust VAs and possess unrealistic perceptions of the systems’ autonomy and capabilities (Giger et al. 2019; Lombard and Xu 2021).

Not only are VAs perceived as colleagues with abilities on par with humans, but virtual collaboration teams are also likely to form some kind of shared identity that could improve individual as well as overall team performance (Lin 2015; Porck et al. 2019). The theory of social identity is described as “*a collection of individuals who perceive themselves to be members of the same social category, share some emotional involvement in this common definition of themselves, and achieve some degree of social consensus about*

the evaluation of their group and of their membership in it" (Tajfel and Turner 1986). Individuals' identities are therefore not only determined by their character traits that maintain their self-concepts, but also by their belonging to various social groups (Brown 2000). These groups can be formed via age, family, friends and, in organizational contexts, with colleagues and/or teammates (Bartels et al. 2019). Extant studies have prevalently focused on social identity in physical human collaboration and social behavior within teams (Kohler et al. 2011; Mueller et al. 2019; Pepple and Davies 2019). The social identity of team members can also be transferred to virtual work spaces (Guegan et al. 2017) and is considered as a facilitator for successful collaboration (Lin 2015; Vahtera et al. 2017). As explained by CASA (Nass and Moon 2000), and supported by existing research (e.g., Diederich, Brendel, Lichtenberg, et al. 2019; Diederich, Janßen-Müller, et al. 2020), individuals tend to treat VAs as human-like actors. Humans and VA are thus likely to form a virtual social group in terms of a social identity. A strong social identity of organizational teams consisting out of human workers and machines might solve overarching goals more efficiently (Lin 2015; Porck et al. 2019). Furthermore, team members might inspire each other to maximize the own individual potential and to work particularly hard (Harkins and Petty 1982). However, forming a social identity with VAs could also impact humans' self-beliefs. A weak social identity engenders the reduction of power, disengagement with processes and tasks, and a feeling of being constantly challenged (Craig et al. 2019; Jensen et al. 2009; Jussupow et al. 2018; Prester et al. 2019).

A unique effect that repeatedly occurs when collaborating in teams is described by the phenomenon of social loafing. Researchers have found that individuals in social teams might reduce efforts to reach a goal compared to their efforts when working alone (Jassawalla et al. 2009; Karau and Williams 1993; Latané et al. 1979). By engaging in social loafing, individuals work less for collective tasks than for individual tasks (Hardy and Latané 1988; Karau and Williams 1993). Loafing might occur when individuals think that their contribution seems to be unnecessary and/or the responsibility of the team is distributed among its members (Karau and Williams 1993; Latané et al. 1979). While social loafing can be a threat to a team's effectiveness, a clear explanation for this phenomenon is still missing. Studies have analyzed determinants of social loafing, including team sizes, task contribution efforts, and visibility (e.g., Jassawalla et al. 2009; Schippers 2014; Vaghefi and Lapointe 2012), and researchers have developed various theories to explain the phenomenon. According to the social impact theory, individuals feel deindividualized when team sizes increase and responsibility is distributed among multiple members; therefore, they distance themselves from their own performance (Latané et al. 1979). Based on the theory of social comparison, individuals compare their efforts, abilities, and skills with other team members and decrease their commitment when perceiving that others show laziness (Harkins and Szymanski 1989; Jackson and Williams 1985).

Within IS, scholars are primarily interested in validating whether the existing assumptions of social loafing are still valid for IT-related contexts and how negative outcomes of the phenomenon might be decreased (e.g., Dennis et al. 2005; Suleiman and Watson 2008). In organizational surroundings, a lack of motivation in teams represents a major issue since, for example, tasks may not be purposefully executed or team atmosphere is deteriorated (George 1992). Therefore, reducing individual tendencies to loaf is vital for maintaining the cohesiveness and performance of teams. VAs are increasingly perceived as legitimate and equal team members that are difficult to differentiate from humans (Cha et al. 2020; Feine et al. 2019; Hussain et al. 2019; Pfeuffer et al. 2019; Porra et al. 2020; Seeber et al. 2018). In virtual collaboration, therefore, VAs are likely to raise similar behavior as in human teams, including social loafing. VAs could, for example, take over humans' duties and responsibilities. However, social loafing of humans assisted by VAs generates certain disadvantages for enterprises and individuals, such as diminishing reputation or profitability of the organization and causing humans to feel less valued and more stressed as former roles are partly or even fully accomplished by a VA. Therefore, VAs could negatively impact teamwork in organizations. Although social loafing is initially perceived as unfavorable, attributing responsibility for certain duties to VAs might be beneficial, as the systems are explicitly developed for outperforming humans in repetitive tasks (Dellermann, Ebel, et al. 2019; Dellermann, Lipusch, et al. 2019). This reduction of effort in human-VA teams unleashes cognitive resources and conveys a feeling of satisfaction when individuals can focus on more meaningful duties; in turn, this reduces stress and the feeling of exploitation (Pace et al. 2019). Since social loafing is observable in human teams and VAs can be perceived as human-like actors, this phenomenon also likely occurs in virtual collaboration. Yet, this assumption holds true, and which consequences are associated with social loafing in virtual collaboration remains undetermined.

When solving problems, humans use their limited cognitive resources. The cognitive load theory explains how certain factors, such as mental resources or a task's difficulty, impact humans' ability to solve a problem (Sweller 1988). Altaf and Awan (2011) revealed that a high cognitive load prevents human employees from reaching their full potential, thereby creating disadvantages for organizations. The deployment of technologies reduces the cognitive load of humans and helps them focus on their tasks (Moreno et al. 2001; Schmuntzsch et al. 2012). For example, Mechling et al. (2010) identified that groups instructed by a digital assistant had better results compared to groups that did not receive instructions. Furthermore, Lohse et al. (2014) found that higher human-machine interaction enhances user performance while decreasing cognitive load, especially for difficult tasks. Still, no scientific evidence has been found to determine whether VAs in virtual collaboration reduce the cognitive load of human team members. In fact, since VAs might be yet another technology that humans are required to work with, they might

even enlarge cognitive load and interfere with the execution of work-related tasks. High amounts of interaction with VAs may even increase stress and failure rates, thereby decreasing work satisfaction and performance (Smith-Jentsch et al. 2001). However, reducing cognitive load in virtual collaboration assisted by VAs might be a feasible way to relieve employees and support their overall well-being and performance.

Despite the perception of VAs as human-equal team members, they still remain a technology. The increasing introduction of VAs as new workforce in organizations (Carter and Grover 2015; Tian and Belk 2005) might thus have an impact on individuals' identities. The individual self-concept is determined by rules and values that are developed in relation to others (Burke and Stets 2009; Stets and Burke 2000). The self is also extended by certain possessions, including digital technologies (Belk 1988, 2013; Tian and Belk 2005). For example, Carter (2012) revealed that humans extend their self-concepts by including the capabilities of certain technologies, which are thus considered as part of oneself, enhancing the own capabilities. Since VAs are increasingly deployed as team members in virtual collaboration, they might also be perceived as part of the self (e.g., capabilities, attributes, or associations are attributed to the own self-concept) (Belk 1988, 2013; Burke 2006; Carter and Grover 2015). However, experiencing a situation that contradicts the own identity might lead to a loss of self-esteem (Petriglieri 2011). In contrast to previous assumptions as proposed by the social response theory, the perception of VAs as collaborative technology might even contradict the perception of VAs as social actors, thus challenging findings from previous research. It thus remains obscure when VAs are perceived as human-like collaborator or acting as assistive technology. Nevertheless, a clear distinction is vital to understand how and when VAs rather perform as actors on par with humans or as technology. Depending on the individual's perception, different behavior and expectations could be attributed to VAs. For example, certain individuals could expect flawless conversations that are not limited to executing a certain task when VAs have human-like capabilities. These individuals might even get frustrated when the interactions do not comply with their expectations. VAs that are perceived as merely supportive are likely addressed differently and used for their intended purposes as work facilitators. In these instances, individuals might feel uneasy when VAs continue to develop and behave differently in similar situations.

The theories presented in this section serve as foundations and provide diverse perspectives on the influence of VAs in virtual collaboration within organizational environments. Considered separately and collectively, each theory aids in better understanding the impact of VAs in virtual surroundings. Various social phenomena and theories are highly relevant for understanding the design, development, and operation of information technology (Kling 2007). However, the theories considered in this dissertation are particularly

relevant for several reasons. Since VAs might be perceived as human-like actors while remaining a technology, individuals could behave equally and/or differently in virtual collaboration compared to how they would act in human-only teams (social response theory). The feeling of being part of a team and its cohesion is a vital part for employees to achieve high quality results (Kolfshoten and De Vreede 2009; Weick et al. 2005). Depending on how individuals perceive and react to VAs, resulting in a higher or lower social association to a team, heavily affects the accomplishment of mutual objectives (social identity theory). Individuals in teams perform well when they consider their contribution to be necessary and when their responsibilities are recognized by other collaborators (Karau and Williams 1993; Latané et al. 1979). Reducing individual effort and responsibility due to a VA's presence is likely to impact teamwork and values (social loafing). The application of VAs in organizations generally aims to reduce employees' workload by assisting with repetitive tasks (McTear et al. 2016). Thus, the influence of VAs on humans' mental capacities when solving a problem might raise certain implications for team performance and satisfaction (cognitive load). Furthermore, due to increasing interaction with VAs, individuals may extend their self by attributing capabilities of the VA to their self-concept (Belk 1988, 2013; Burke 2006; Carter and Grover 2015). When VAs are perceived as part of the self or when contradictions to an individual's identity are noticed, the self is impacted, as well as the team's capabilities and attributes. This alters the VA's perception as a social actor (extended self). In organizational surroundings, these aspects are particularly crucial for achieving the most effective application of VAs in virtual collaboration. However, certain aspects need to be considered when VAs are applied in virtual teams. Table 2 outlines exemplary potential and challenges of VAs in virtual collaboration according to the major theories considered in this dissertation.

| Theory | Potential | Challenges | Example References |
|------------------------|---|--|---|
| Social Response Theory | <ul style="list-style-type: none"> ▪ Increasing team dynamics and performance ▪ Enhancing decision-making, team atmosphere and cohesion | <ul style="list-style-type: none"> ▪ Creating feeling of strangeness ▪ Carelessness and facilitating laziness ▪ Over-trust and obtain unrealistic perceptions | (Bickmore et al. 2011; Diederich, Brendel, et al. 2020; Giger et al. 2019; Lombard and Xu 2021; Seeber, Waizenegger, et al. 2020; Seeger et al. 2018; Waizenegger, McKenna, et al. 2020; Wiese and Weis 2020) |
| Social Identity Theory | <ul style="list-style-type: none"> ▪ Solving goals more effectively and efficiently ▪ Team members inspire each other ▪ Maximizing individual potential and workload | <ul style="list-style-type: none"> ▪ Weakening self-beliefs and constantly feel challenged ▪ Reduction of power and disengagement with processes and tasks | (Craig et al. 2019; Harkins and Petty 1982; Jensen et al. 2009; Jussupow et al. 2018; Lin 2015; Porck et al. 2019; Prester et al. 2019) |

| | | | |
|----------------|--|--|--|
| Social Loafing | <ul style="list-style-type: none"> ▪ Unleashing cognitive resources ▪ Conveying a feeling of satisfaction ▪ Reducing stress and feeling of exploitation | <ul style="list-style-type: none"> ▪ Lower individual effort ▪ Feeling less values and more stressed ▪ Decreasing teamwork and cohesion ▪ Becoming dependent | (Dennis et al. 2005; Hardy and Latané 1988; Karau and Williams 1993; Pace et al. 2019; Suleiman and Watson 2008) |
| Cognitive Load | <ul style="list-style-type: none"> ▪ Focusing on more relevant duties ▪ Enhancing individual and team performance, receiving better outcomes | <ul style="list-style-type: none"> ▪ Interfering with work-related tasks ▪ Increasing stress and failure rates ▪ Decreasing work satisfaction and performance | (Lohse et al. 2014; Mechling et al. 2010; Moreno et al. 2001; Schmunzsch et al. 2012) |
| Extended Self | <ul style="list-style-type: none"> ▪ Improving self-esteem ▪ Enhancing own capabilities and attributes ▪ Raising joy of collaboration | <ul style="list-style-type: none"> ▪ Feeling of dependence ▪ Losing self-esteem ▪ Decreasing perception as social actor | (Belk 1988, 2013; Carter 2012; Carter and Grover 2015; Petriglieri 2011; Tian and Belk 2005) |

Table 2: Major theories considered in this dissertation

This chapter clarified the various perspectives and classifications that research on VAs in virtual collaboration has taken, and provided recent application areas in organizational surroundings. Furthermore, existing theories explaining how technologies in general, and VAs in particular, might be perceived as social actors were described, as well as the related consequences when being applied in virtual collaboration. The following chapter expounds the pursued research strategy and applied methods that were used to examine the theories serving as theoretical backdrop in this thesis, and how the results contribute to answering the guiding research questions.

3 Research Design

3.1 Research Strategy

The paper-based dissertation consist of two parts that aim to explore how VAs influence virtual collaboration in organizational environments and to determine the extent to which humans are engaged in social responses. The first research question examines potential and challenges for enterprises and employees while the second research questions explores how individuals socially respond to VAs when they are applied in virtual teams. Table 3 depicts how every publication contributes to answering the research questions.

| Paper | Title | RQ1 | RQ2 |
|-------|---|-----|-----|
| 1 | Der Einsatz von künstlicher Intelligenz zur Verbesserung des Incident Managements | X | |
| 2 | Towards Successful Collaboration: Design Guidelines for AI-based Services enriching Information Systems in Organisations | X | |
| 3 | Design requirements for AI-based services enriching legacy information systems in enterprises: A managerial perspective | X | |
| 4 | On the Ability of Virtual Agents to decrease Cognitive Load – An experimental study | X | X |
| 5 | Understanding Collaboration with Virtual Assistants – The Role of Social Identity and Extended Self. | X | X |
| 6 | Collaborating with Virtual Assistants in Organizations – Analyzing Social Loafing Tendencies and Responsibility Attribution | X | X |
| 7 | Hybrid Intelligence in Hospitals – Towards a Research Agenda for Collaboration | X | X |
| 8 | Comparison of disclosure/ concealment of medical information given to conversational agents or to physicians | | X |
| 9 | The perceived surveillance of conversations through smart devices | | X |

Table 3: Papers associated to the research questions

The publications included in this synopsis address issues related to VAs in virtual collaboration from two research fields: the organizational context and the healthcare context. Organizations are initially concerned with maximizing their revenue, achieving corporate success, and gaining competitive advantage. Healthcare is primarily interested in maintaining or improving the health of individuals and focuses on the well-being of patients. Nevertheless, both fields have certain overlaps. For example, hospitals can be considered as a type of organization since they strive to achieve economic stability, and organizations should be interested in the long-term well-being of existing and potential customers. What really distinguishes these two domains is the accessibility to the respective field for IS scholars. In contrast to organizations, IS research within the healthcare sector has been challenging for several reasons (Romanow et al. 2012). For example, a reliable evaluation

requires access to healthcare professionals whose time is usually limited while still struggling to understand and adopt new technologies. Furthermore, many ethical restrictions must be observed, and antiquated technological infrastructures hinder the integration of novel approaches (Frick, Möllmann, et al. 2021; Mirbabaie, Hofeditz, et al. 2021). Nevertheless, collaboration and teamwork are equally crucial and considered key factors in both healthcare and organizations for delivering high-quality outcomes (Boughzala et al. 2012; Mosadeghrad 2014). Thus, regardless of the overarching goal, both institutions pursue similar objectives by leveraging technological advancements, such as VAs. This dissertation therefore does not aim to identify their differences but rather tries to gain insights from both domains to determine whether observations on VAs in virtual collaboration are adaptive.

3.2 Applied Research Methods

Within this paper-based dissertation, multiple research methods were used to answer the research questions. Table 4 provides an overview of the conducted research approaches, including their data collection and analysis methods.

| Paper | Research Approach(es) | Data Collection Method(s) | Data Analysis Method(s) |
|-------|--|--|--|
| 1 | Quantitative (prescriptive) | Proof-of-concept implementation | Statistical analysis |
| 2 | Qualitative (prescriptive) | Interviews | Content analysis |
| 3 | Qualitative (prescriptive), quantitative (descriptive) | Interviews, online questionnaire | Content analysis, survey research |
| 4 | Quantitative (descriptive) | Laboratory experiment with prototype | Survey research and performance data |
| 5 | Quantitative (descriptive) | Laboratory experiment with prototype | Survey research and performance data |
| 6 | Quantitative (descriptive) | Online experiment with prototype | Survey research and performance/usage data |
| 7 | Qualitative (descriptive), qualitative (prescriptive) | Systematic literature review, interviews | Literature research, content analysis |
| 8 | Quantitative (descriptive) | Online questionnaire | Survey research |
| 9 | Quantitative (descriptive) | Online questionnaire | Survey research, statistical analysis |

Table 4: Overview of applied research methods

For adjusting the understanding on the different aspects of collaborative settings and gaining a deeper understanding on VAs in virtual collaboration, the outlined research approaches chosen in this thesis are meaningful for several reasons. Qualitative approaches, such as semi-structured expert interviews and literature reviews, are crucial for gaining novel and undiscovered insights. Quantitative approaches, such as laboratory experiments

and online questionnaires, aid in understanding actual perceptions and their related consequences.

Three of the papers (papers 2, 3, and 7) in this dissertation used qualitative procedures involving expert interviews. This method is considered an effective and concentrated research approach for gathering unique knowledge from proficient individuals that leads to profound contributions (Bogner et al. 2009; Kvale and Brinkmann 2009). Since VAs in virtual collaboration are increasing but are not yet widespread, descriptive (i.e., knowledge on current situations) as well as prescriptive (i.e., related consequences and future recommendations) insights are helpful for drawing a holistic picture. Meuser and Nagel (2009) suggest a semi-structured setting with an open interview technique as the most suitable approach for retrieving valuable information while providing participants with enough room to elaborate on individual beliefs. Prior to the interviews, a prefixed guideline with central questions acknowledging guiding concepts based on existing theories (descriptive) or related concepts (prescriptive) was developed (Bear and Knobe 2016; Bell 1989; Qu and Dumay 2011). To avoid unilateral and predictable results, the interviews were conducted with experts across industries and disciplines as well as those from different hierarchical structures and professions with varying obligations. Here, the term expert describes an individual with advanced knowledge in the investigated field of research (Meuser and Nagel 2009). The interviews were recorded and either transcribed or paraphrased depending on each research objective (Hansen and Kautz 2015). Paraphrasing, that is, reducing the volume of data by removing unnecessary words to form short and concise sentences (Schilling 2006), was the preferred method, as the experts' substantive statements were more interesting than their language habitus or physical gestures and facial expressions. The data were analyzed during an abstraction process (Mayring 2015). Short paragraphs or sentences were used as coding units (Gioia et al. 2013), such as simple phrases or in-vivo patterns (second order themes). The data were further classified using certain headings (first order theme), for instance, based on theoretical foundations or identified constructs, which suited as clusters where the data dealt with identical or similar issues (Glaser 2013).

One of the papers (paper 7) in this dissertation conducted a qualitative approach in the form of a systematic literature review. Precisely, it evaluated how the application of VAs in hospitals could enhance collaboration and team-building among clinicians to improve the quality of care process. Therefore, extant insights were examined to describe the current scientific situation, and existing findings were transferred from related research streams. This approach is beneficial for identifying and assembling emerging issues and prior knowledge (Webster and Watson 2002). It further enables scholars to recognize knowledge gaps, identify research areas that have received less attention, and emphasize

contribution to knowledge (Fink 2013; Webster and Watson 2002). The paper's procedure was built upon vom Brocke et al. (2015, 2009) and used bibliographic databases from the fields of computer science as starting point. A search query including certain expressions was constructed to identify relevant literature, and these expressions were further increased by using a backward and forward search. The results were then categorized using existing theoretical foundations and yielded in future research directions.

Most of the papers included in this dissertation conducted quantitative approaches (papers 1, 3-6, 8, 9). These methods are particularly valuable to validate derived hypotheses in real-world scenarios and/or with a larger population (Creswell and Creswell 2018). In one of the publications (paper 1), a proof-of-concept was implemented to provide a justification in practice based on a theoretical assumption (Kendig 2016). Furthermore, two laboratory experiments (papers 4, 5) as well as one online experiment (paper 6) were carried out. Such experiments allow for observations in a controlled environment with pre-defined conditions and enable researchers to adapt and replicate settings (Webster and Sell 2014). In all three cases, the participants had to solve a work-related task jointly and assisted by a VA. In the laboratory experiments, the subjects were randomly assigned into two groups; one group was assisted by the VA to reveal group differences. In contrast, paper 6 aimed to determine related effects in virtual collaboration supported by VAs and therefore did not need to analyze group differences.

In three of the publications (papers 3, 8, 9), online surveys were performed. This method has proven to be beneficial especially in terms of global reach and flexibility, as it enables scholars to attain a broad, diversified, and controlled sample (Evans and Mathur 2005). In paper 3, participants working in companies at the management level were surveyed to gain insights on a business perspective. Moreover, paper 8 addressed subjects who had already undergone an anamnesis with a doctor and compared the disclosure and concealment of medical information given to VAs or to physicians. Finally, in paper 9, participants that were already familiar with VAs were addressed to analyze aspects of security, privacy, and trust related to perceived surveillance. Since the impact of these factors is still less explored, a research model was developed and evaluated using partial least square structural equation modeling, a highly effective approach for testing reliability and validity as well as causal relationships within complex multistage models (Hair et al. 2019). Furthermore, this procedure provided robust approximations for final estimations, which are beneficial for investigating variations among diversified groups (Hair et al. 2011).

4 Research Results

This research examines the impact of VA in virtual collaboration and how individuals are engaged in social responses. Table 5 outlines a summary of the papers included in this dissertation, along with their contribution to the guiding research questions. A detailed clarification of the results can be retrieved from each respective paper.

| Paper | Summary | Contribution |
|-------|--|---|
| 1 | The development of a proof-of-concept using real-world data from a German company revealed that AI-based digital assistants can accelerate the incident management process. The prototype achieved an overall probability of 94% of correct categorizations outperforming manual endeavors. | <u>RQ1</u> : VAs in virtual collaboration represent a rapid and cost-effective for generating high quality outcomes superior to human efforts. VAs enable humans to focus on more relevant and cognitive challenging tasks but might also raise employees' fears and uncertainties. |
| 2/3 | Semi-structured expert interviews and a subsequent online survey with managers experienced with AI identified requirements that need to be considered to design an AI-based digital assistant enriching existing IT in organizations to generate business value. Acceptance and adoption, task support and service features, system characteristics and enhances user performance and training are considered relevant. | <u>RQ1</u> : VAs are sought to generate business value in the short term. Employees should accept VAs as quickly as possible for the rapid achievement of assistance with work-related tasks. Besides increasing the overall work performance, VAs are supposed to train users on certain duties thus overcome human limitations and enhance their abilities. |
| 4 | In a laboratory experiment with a pre-developed and validated VA, participants were divided into two groups and determined regarding their ability in solving a work-related task. Thereby, one group was assisted by a VA. The results exposed the capability of reducing perceived workload as well as the cognitive load of employees. | <u>RQ1</u> : Employees assisted by VAs perform better on a given task and show a lower perceived workload as well as cognitive load. VAs increase learning capabilities of individuals and enable to focus on more relevant tasks. The performance of executing a task when being assisted by a VA is superior compared to working alone. VAs aid in welcoming virtual collaboration in organizations. <u>RQ2</u> : VAs applied in virtual collaboration are accepted by individuals and perceived as appropriate team members. The quality of support when using VAs in virtual collaboration is perceived as equivalent to individuals. A differentiation from human assistance is not apparent. |
| 5 | Another laboratory setting with a pre-developed and validated VA separated participants into two groups for solving a task. One was assisted by the VA where the other was supported by another human. The findings recognized that individuals supported by VAs identify less with their (human) team after their interaction with a VA. And, individuals identifying with the VA as part of their self's are more likely to identify with (virtual) team members and vice versa. | <u>RQ1</u> : The increasing application of VAs in virtual collaboration raises employees' perception of not being part of human team. Individuals are less likely to collaborate with human team members once they had been interacting with a VA thus disengage themselves from their organizational goals. <u>RQ2</u> : There is no distinctiveness between humans and VAs as collaboration partners and identification with a team. The collaborative capabilities of VAs are perceived on par with humans. Individuals consider VAs as technology extending the own capabilities as well as social actor as an external attribution to an in-group. |

| | |
|--|---|
| <p>6</p> <p>In an online experiment with yet another a pre-developed and validated VA, participants were asked to solve a task while being assisted by the VA. The results revealed that social loafing behavior is observable when a VAs is being applied in virtual collaboration and that responsibility is attributed towards the VA.</p> | <p><u>RQ1:</u> Existing social loafing behavior and missing responsibility attribution in virtual collaboration, when a VA is present, yields in positive as well as negative consequences. For example, failing in identifying with the team, missing recognizing errors of VAs and decreases learning capabilities. However, it enables more efficient and effective results as well as reduced efforts do not need to be compensated by other humans.</p> <p><u>RQ2:</u> Individuals show laziness and slacking behavior which is particularly observable in human teams. When VAs are applied in virtual collaboration, humans avail the opportunity to loaf and show less effort compared to working alone. VAs are entrusted with tasks that are usually performed by individuals and responsibility is attributed to the VA.</p> |
| <p>7</p> <p>A systematic literature review enlightened by semi-structured expert interviews conceptualized the enhancement of collaboration and team-building in hospitals when introducing VAs. Four areas and research propositions were derived guiding future endeavors: Audience and interdependency, connectivity and embodiment, trust and transparency and security, privacy, and ethics. The paper further proposes a research model including collaborative challenges of clinicians and explains how VAs mitigate them while enhancing the overall team performance in hospitals.</p> | <p><u>RQ1:</u> VAs are capable of aiding in overcoming collaborative issues. In virtual collaboration, they retrieve information from multiple systems faster, derive decisions based on objective information, resolve opaque responsibilities, and reduce silo thinking.</p> <p><u>RQ2:</u> The increasing introduction of VAs in virtual teams leads to dependence and conveys a feeling of false security. Humans fail to take responsibility for tasks, do not question decisions and neglect to solve a problem in absence of VAs. In virtual collaboration, VAs make information more transparent causing discomfort for humans.</p> |
| <p>8</p> <p>An online survey analyzed the application of VAs within the anamnesis. Patients rather disclose medical information to a physician but there are no differences in the concealment of information from a VA. Patients' disclosure is generally insufficient regarding personal information that is perceived as negative or embarrassing. Security and privacy concerns are vital components for sharing personal information.</p> | <p><u>RQ2:</u> Humans rather share information with other humans, VAs raise a feeling of observance and controlling. Individuals fear being rejected due to certain information that do not correspond with social norms.</p> |
| <p>9</p> <p>Another online survey is concerned with individual factors contributing to the suspicion that conversations with smart devices using VAs are secretly recorded and used for advertisements purposes. The perceived surveillance of conversations is affected by, for example, security and privacy perceptions as well as trust and computer anxiety.</p> | <p><u>RQ2:</u> Privacy and security perceptions, trust in the VA and its vendor as well as computer anxiety impact the feeling of being monitored and recorded. In virtual collaboration, individuals may actively search for explanations and overthink how their VAs process data.</p> |

Table 5: Summary of papers and contribution to the research questions

Paper 1 hypothesizes that an AI-based digital assistant can optimize the categorization process of incoming user issues. The incident management aims to resolve problems (incidents) as quickly as possible to minimize disruption to business processes. The application might lead to rapid, cost-effective, and high-quality resolutions, thus creating long-term values for customers and improving the individual skills and performance of employees. To validate this assumption, a proof-of-concept was conducted; a prototype was developed and tested using real-world data from a German company with 43,000 existing incidents. The system was implemented in the programming language Python with a variety of open-source libraries, such as pandas (Python Data Analysis Library) (McKinney 2011) and keras (Chollet 2015). The prototype was an artificial neural network that used natural language processing to analyze existing text. To improve the quality of the results, a manual annotation was added to capture different spellings of certain terms (e.g., ERP, Erp, erp; IT, information technology). An overall probability of 94% of correct categorizations was achieved. The paper concludes that the probability would be likely to grow if a larger dataset were used, and the prototype outperforms humans in the categorization task. Thus, recent incident management can be further automated and accelerated. However, the paper also elaborates that integrating AI-based digital assistants in existing technical infrastructures generates various challenges, as employees must inevitably collaborate with intelligent systems. Furthermore, proper design of the intelligent systems is crucial for ensuring the specified purpose is fulfilled.

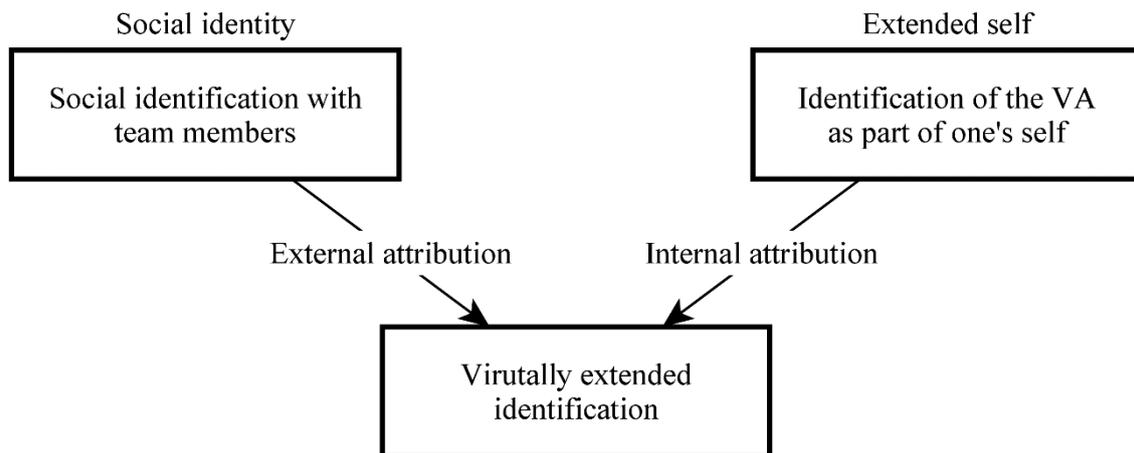
Papers 2 and 3 are concerned with requirements that need to be considered when designing AI-based digital assistants to create business value. Paper 3 is the extension of the research-in-progress paper 2. The papers argue that AI-based digital assistants are increasingly being used in enterprises, yet current literature mainly addresses technological aspects rather than providing guidance to implement appropriate systems (Duan et al. 2019; Mikalef et al. 2018). Therefore, general guidelines precisely formulating which factors must be observed when planning and developing systems are overdue. A mixed-method approach was chosen using a qualitative approach (expert interviews) to formulate design requirements followed by a quantitative approach (online survey) to validate the findings. The interviews were conducted with ten managers who had sufficient knowledge of AI and worked at a large German retail holding organization. The subsequent online survey was finished by 124 participants who met the major precondition that they worked in a company at the management level and had good experience with AI. The interviews yielded ten general requirements, but data analysis of the online survey indicated that managers considered only four of the ten requirements to be vital to generating business value. These four requirements were acceptance and adoption, task support and service features, system characteristics, and enhances user performance and training. The research concludes that executives are focused on design requirements that create

business value in the short term rather than in the long run. However, managers might not be exactly aware of the related potential and/or challenges inherent to the application of AI-based digital assistants.

Paper 4 focusses on the ambiguity regarding the reduction of employee workloads when assisted by a VA in the execution of work-related tasks. Research has found that learning outcomes are improved and that superior working results are achievable (Mechling et al. 2010; Schmunzsch et al. 2012). Nonetheless, the learning process is not enhanced in every situation, and the performance at work might even be decreased (Chandler and Sweller 1991; Schnotz and Rasch 2005). The paper argues that if VAs are becoming omnipresent in organizations, they might be beneficial for relieving employees and thus enhancing their overall well-being and performance. Still, reducing cognitive load with the help of VAs has not yet been sufficiently investigated. To examine this effect, the paper carried out a laboratory experiment in which 91 participants were divided into two groups to solve a work-related task. One group was supported by a VA while the other was not. The VA was developed using Google's cloud platform Dialogflow and, just like the task, validated within a pre-study. The experiment used a text-based task (critical path method) to organize a marketing objective for which the participants were given a time limit of ten minutes. The perceived workload and task performance were compared to assess differences between the groups. The findings indicated that participants collaborating with a VA performed better at the given task and had a lower cognitive load. Furthermore, cognitive load was negatively related to task performance. The paper concludes that VAs are an effective technology in virtual collaboration by reducing the cognitive load of knowledge workers. Moreover, VAs might aid in welcoming the digitization of the workplace and virtual collaboration in organizations. However, personal predispositions toward VAs need to be examined in detail.

Paper 5 attempts to understand the role of the social identity and extended self when VAs are applied in virtual teams. The paper argues that it remains indistinct whether VAs are just simple programs for assistance or really perceived as equal colleagues of a team (existing research stresses that the latter is the case but does not provide sufficient empirical evidence). To analyze how identification of VAs as virtual team members differs from that of humans, a laboratory experiment with 50 participants separated into two groups was conducted. The experimental group solved a work-related task in collaboration with a VA, while the control group virtually collaborated with another human. The VA and text-based task, which were also used in paper 6, served as prior validated instruments for this experiment. In the study, the interaction with the VA (experimental group) as well as with the other human (control group) was embedded in the chat platform Slack to ensure equal collaboration environments for all participants.

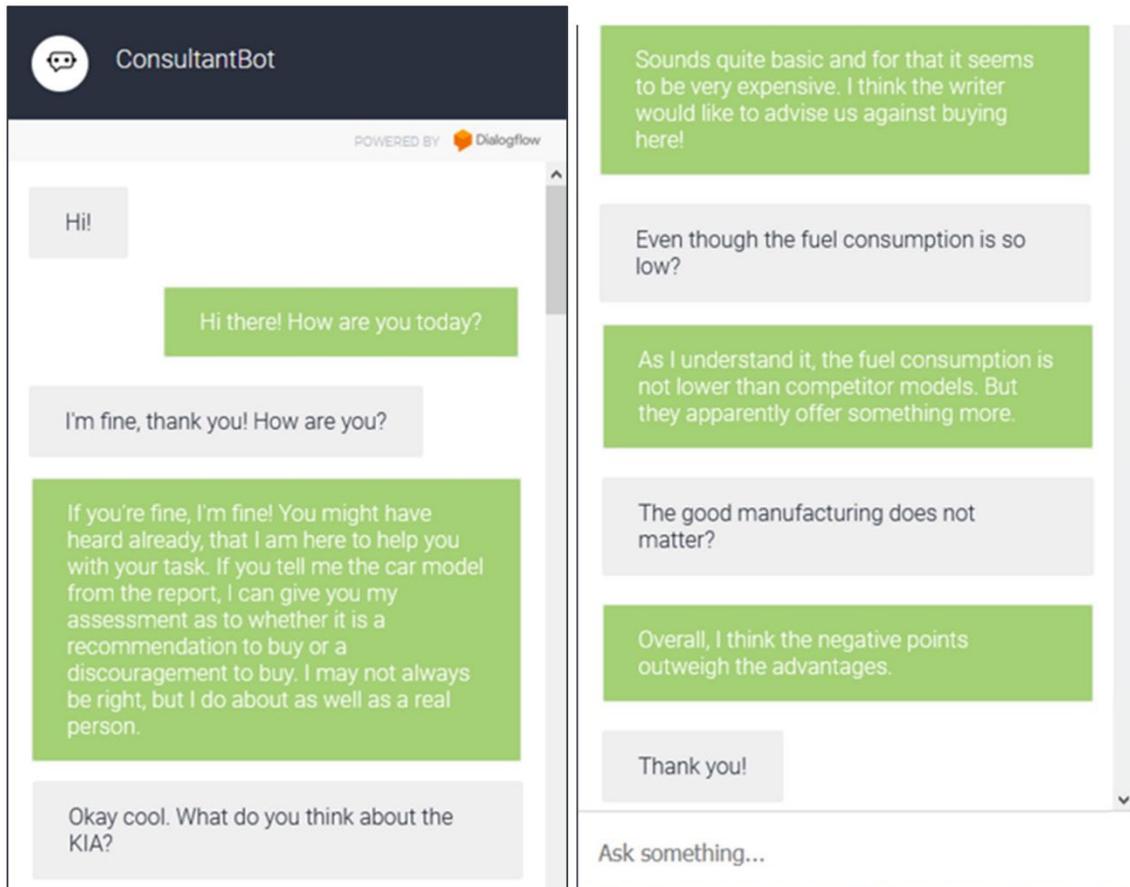
Figure 1: Symbolic formation of virtually extended identification



The results revealed that individuals assisted by VAs identified less with their (human) team after their interaction with a VA. Additionally, individuals who identified with the VA as part of their self-concept were more likely to identify with (virtual) team members, and vice versa. Thus, the paper derived the novel concept of virtually extended identification as formation of social identity and extended self in virtual collaboration (see Figure 1). This intertwining highlights that research studies should adjust their understanding of identification with VAs in various collaborative settings. The paper concludes that the concepts of social identity and extended self should be combined for full comprehension of human behavior in virtual collaboration supported by VAs. Furthermore, increased interaction with VAs might enforce employees' perception of not being part of a human team. Thus, certain measures to encourage continued identification with other human colleagues are advisable, as mixed teams are likely to achieve superior results.

Paper 6 analyzes whether VAs in virtual collaboration evoke social loafing in humans and how responsibility attribution differs when being assisted by a VA. Since VAs are attributed with human-like features and are likely to become commonplace in virtual work teams, findings from previous research on human teams and their associated consequences might be transferrable to virtual collaboration. The paper explains that social loafing in organizational teams generates enormous risks for enterprises (e.g., diminishing reputation or profitability) as well as for employees (e.g., feeling less valued and more stressed). Along with missing responsibility attribution when executing a task, the findings might decisively impact the effectiveness of human-VA teams and alter how VAs are implemented and applied in organizations, probably restricting their deployment to certain industries, departments, teams, or purposes. To make a first foray into the examination of social loafing tendencies and responsibility attribution in virtual collaboration facilitated by VAs, an online experiment with 102 participants was conducted in which the participants were assisted by a VA to solve a work-related task.

Figure 2: Exemplary interaction with the VA



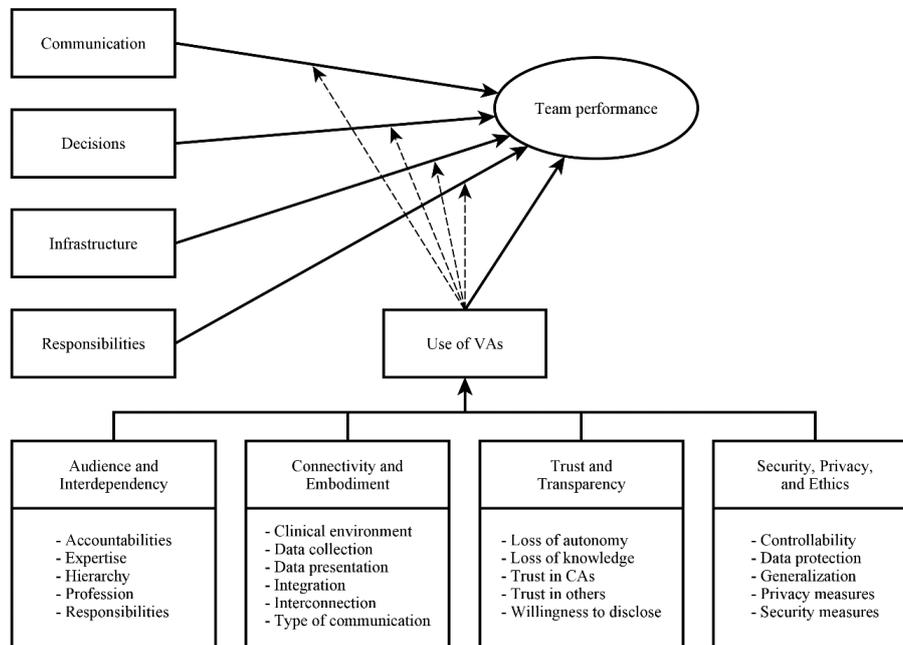
Another VA prototype was developed using Dialogflow (cf. Figure 2) and, along with two possible tasks for the subsequent experiment, validated within a pre-study. In the main questionnaire, the participants were asked to read car reviews and rate, assisted by the VA, whether they recommended buying the car. The paper identified a positive correlation between general social loafing tendencies and social loafing tendencies in virtual collaboration with the VA. Additionally, a positive correlation was found between social loafing tendencies in virtual collaboration with the VA and responsibility attribution to the VA. The paper argues that social loafing is not only limited to physical and virtual collaboration with other humans but is also detectable when interacting with VAs. Thus, the existing findings from human teams hold true in virtual collaboration; humans assisted by VAs in virtual collaboration might avail the opportunity to loaf and show less effort compared to working alone. Furthermore, missing responsibility attribution might, on the one hand, lead to humans' failing to identify with their team but, on the other hand, enable more efficient and effective results. Social loafing might thus yield negative consequences, such as failing to recognize the errors or mistakes of VAs, producing a deteriorating quality of work, and facing a reduced cognitive load, which decreases team performance. However, certain positive consequences exist as well, for example, a reduction in individual effort does not need to be compensated for by other human collaborators.

Moreover, a lower cognitive load along with social loafing showed that VAs relieve individuals. In an organizational context, the paper defines the concept of *smart loafing* as “*the reduction of effort in human-VA collaboration to maintain cognitive resources and enhance efficiency in work*”.

In contrast to enterprises, healthcare is characterized by traditional, physical teams. Paper 7 demonstrates that the quality of care in hospitals is influenced by diverse factors. Besides the expertise of medical professionals and their skillsets, interpersonal factors like effective communication and collaboration are crucial for providing accurate care. However, tasks are frequently performed in isolation, thus preventing a mutual understanding, and clinicians’ silo thinking hinders shared knowledge and collaboration across departments, encouraging competitive behavior. Nevertheless, goal-oriented collaboration and teamwork in hospitals is vital for coordinating multifaceted tasks, mitigating errors, and thus enhancing the quality of care process. Paper 9 argues that using VAs in virtual collaboration can improve care processes within hospitals and aid in overcoming collaborative issues frequently experienced by clinicians. Humans and VAs combine their complementary strengths, such as humans’ emotional intelligence and empathy paired with VAs’ rapid retrieval and interpretation of a vast amount of digital data. Paper 7 also argues that a conceptualization of when to introduce VAs to improve collaboration and team-building in hospitals is still lacking; thus, an associated research agenda is urgently needed to establish VAs for collaborative purposes successfully. To address this complex endeavor, a first foray in this largely unexplored research area was conducted. A systematic literature review was performed to transfer existing findings from related research streams to provide an overview of major challenges related to the introduction of VAs in hospitals. Additionally, semi-structured expert interviews were performed with physicians working in hospitals and computer scientists experienced with VAs to discover the consequences of the reviewed challenges. Based on the systematic literature review and further highlighted by the expert interviews, a research agenda with exemplary questions and research propositions to guide future research was derived. The paper found that the restricted existing definitions of VAs limited their actual functionalities. Thus, paper 7 proposed a new definition of VAs as follows: “*dialog systems simulating the behavior of humans via different modes of communication (e.g., written or spoken natural language, haptics, gestures, facial expressions, graphics), continuously learn and develop over time by analyzing and interpreting a given input combined with additional data sources for assisting with divergent tasks or execute them autonomously*”. The systematic literature review combined with the interviews yielded four areas in which the extant literature had dealt with identical or similar issues. *Audience and interdependency* propose more research on how VAs enhance collaboration in hospitals, focusing on different stakeholders with varying tasks, professions, and expertise. *Connectivity and embodiment* demand focus on the

interconnection of VAs and clinicians, departments, disciplines, and the existing infrastructure, as well as VAs' adaptation to diverse clinical environments. *Trust and transparency* request to validate how VAs assist in building clinicians' trust in other hospital employees and the technology itself while increasing the transparency between collaborators. *Security, privacy, and ethics* recommend addressing how VAs ensure secure data collection and information presentation while providing acceptable moral and ethical results. Finally, the paper proposes a research model, as depicted in Figure 3, that includes collaborative challenges and explains how VAs mitigate these challenges while enhancing team performance in hospitals. Paper 7 concludes that research should not only focus on the research agenda but should also take on deviant perspectives. For example, additional collaborative issues that hinder the quality of care or additional benefits VAs might achieve in hospitals should be identified.

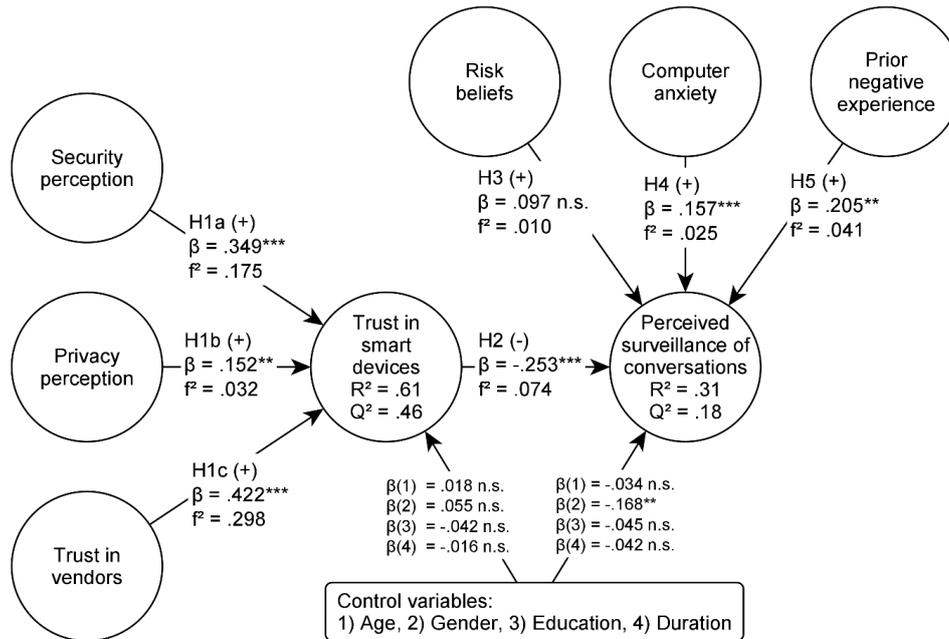
Figure 3: Research model for enhancing team performance in hospitals using VAs



In paper 8, the application of VAs within the anamnesis was analyzed to tackle that medical information is frequently withheld, incomplete, or incorrect and thus could potentially cause negative consequences for the patient. The paper argues that the fact that VAs are not real humans but are still able to conduct a conversation with patients could positively influence patients' response behavior and maximize their disclosure and minimize concealment of relevant medical information. VAs may ask patients further questions based on relevance and motivate them to answer the questions in detail, while physicians might not be able to spare time to do so. An online survey with 148 participants was conducted to verify this assumption. The subjects were randomly assigned into two groups, one of which was shown an example conversation with a VA, while the other was

not. The results showed that patients would rather disclose medical information to a physician, but no differences in concealment of information from a VA or from a physician was found. However, the results also clarified that patients' disclosure is insufficient to both, VAs and physicians, especially regarding personal information that is perceived as negative or embarrassing (i.e., illegal use of prescription drugs or excessive alcohol and tobacco consumption). The paper concludes that, currently, patients' attitudes toward concealing information from a VA does not differ compared that toward concealing information from a physician. Furthermore, privacy concerns as well as the security of the information might be vital components that were not considered.

Finally, paper 9 is concerned with users' suspicion that conversations with smart devices using VAs are secretly recorded by the device and that the topic of this conversation is used to personalize advertisements. The paper argues that personal data form the basis for advertising purposes and aimed to determine the effect on individuals when data are tracked, as well as the effects of where the data are stored, with whom they are shared, and how they are used. Even though scholars have not provided empirical evidence that conversations are secretly recorded, and companies such as Google and Facebook have denied capturing data without the consent of their users, the perception of surveillance remains persistent. Paper 9 introduces the term *perceived surveillance of conversations* to explain this phenomenon and analyzed a research model including individual factors (i.e., security and privacy perception, trust in vendors, trust in smart devices, risk beliefs, computer anxiety, and prior negative experience) that contribute to the understanding of data collection practices related to people's privacy concerns. Three predictors were found to be significant in affecting the perceived surveillance of conversations after evaluating an online survey of 277 participants. These are trust in smart devices (influenced by security and privacy perception as well as trust in vendors), computer anxiety, and prior negative experience (cf. Figure 4).

Figure 4: Surveillance effect model including constructs and hypotheses

The paper discusses that higher trust in smart devices lowers the perceived surveillance of conversations and that lower trust results in the feeling of being surveilled. Related to computer anxiety, individuals may actively search for explanations of their discomfort (i.e., being unknowingly surveilled), and previous negative experience might lead individuals to overthink how their data are processed. Individuals are therefore less likely to accept the coincidence that previously overlooked advertisements are only noticed after a certain conversation. Furthermore, people look for evidence that supports their existing beliefs and ignore potential counterevidence. The paper concludes that organizations need to counter the decreased willingness to use smart devices, especially regarding sharing private information.

5 Discussion

5.1 Virtual Assistants in Virtual Collaboration

The first research question of this thesis addresses how VAs influence virtual collaboration in organizations. The results of seven papers aimed to elucidate this aspect. In the following, the results of the publications are summarized, and potential and challenges of VAs in virtual collaboration are explained.

After jointly considering the results of the papers, VAs in virtual collaboration are clearly capable of shaping procedures to be more effective and efficient, saving the applying organization valuable resources (i.e., employees' time and costs), and increasing the over-

all team performance and quality. Nonetheless, some results were somewhat controversial. While paper 4 clearly showed that employees collaborating with VAs performed better on a given task (which is in line with Mechling et al. (2010) and Moreno et al. (2001)), paper 5 did not find any significant difference. This was interesting, as both papers used an identical task and text-based VA. However, in paper 4, the participants in the control group needed to solve the task alone, while in paper 5, the subjects were supported by another human collaborator. This indicates that the performance of virtual collaboration with a VA is superior to working alone. This conclusion is also supported by paper 1, which demonstrated that internal processes are enhanced when collaborating with a VA. Nevertheless, there seems to be no difference when humans are supported by a VA compared to when they are supported by another human. This finding certainly offers numerous possibilities for organizations since VAs might be more feasible and cost-effective for many tasks. Organizations might even cease hiring highly specialized individuals when VAs are equally suitable for certain tasks. Furthermore, VAs are able to create more benefits in the short term (papers 2, 3) than new hires that undergo intensive onboarding procedures. However, the current generation of VAs is narrowed down to one task (Batin et al. 2017). Several VAs are needed when organizations aim to assist employees in multiple processes. On the one hand, this would drive up costs for applying companies, on the other hand, employees might be overwhelmed by having to operate multiple VAs. Thus, the deployment of multiple VAs appears to be an inefficient approach. Organizations should instead identify valid use cases in which the application of VAs in virtual collaboration seems beneficial.

Paper 4 further revealed that VAs are able to reduce the perceived workload and cognitive load of employees. In this case, the interaction with the VA was intentionally kept very simple (e.g., text-based chat), and no additional effort was needed to learn how to use the VA. This is clearly the most favorable way as organizations aim to create business value via VAs that are adopted rapidly (papers 2, 3). Probably, a simpler interaction with VAs is helpful as individuals are not confronted with various stimuli; this enables them to focus on their actual work. From an organizational perspective, and along with the equal results achieved with human collaborators, this finding justifies why VAs tend to become the preferred team member when tasks need to be executed in a quicker and more cost-effective manner. From an employee perspective, this finding agrees with that of paper 5, which discovered that individuals are less likely to collaborate with human team members once they have been interacting with a VA. Employees might rather collaborate with VAs as they permit working independently of human colleagues. However, employees might thereby disengage themselves from their teams (papers 6, 7), resulting in disadvantages known from human teams (i.e., failing to establish a shared understanding of goals and diminishing cohesion (Kolfschoten and De Vreede 2009; Weick et al. 2005)).

Although VAs reduce the cognitive load of human collaborators, this could result in too little cognitive load. Paper 7 argues that employees might fail to solve a problem on their own in the absence of VAs. Initially, this is not necessarily a bad thing, since VAs are designed to assist humans to create more efficient processes (see also papers 1-3), and many issues cannot be solved without the help of technology. Nonetheless, the rising distribution of VAs might lead to dependent users and may convey a feeling of false security since it may be assumed that a VA always provides appropriate results (paper 7). Human collaborators might fail to take responsibility for their tasks or question decisions proposed by the VAs. VAs overcome human limitations and enhance their abilities (papers 2, 3), but individuals may forget certain information and even lose cognitive skills. VAs thus decrease learning capabilities rather than improving them (as suggested by paper 4). This (partial) human dependency on VAs was directly addressed in paper 6. As virtual collaboration with VAs in organizations becomes more commonplace, employees tend to show social loafing tendencies and missing responsibility attribution. The paper clarified that this effect is not limited to physical and virtual collaboration with other humans but is also observable during collaboration with VAs. The findings further indicated that the responsibility of solving tasks in virtual collaboration is likely to be attributed to VAs. Employees no longer identify themselves with a decision made by a VA, and they do not question or take responsibility for the decision. This results in possibly poor or incorrect choices (as argued in paper 7) and generates enormous risks for both enterprises (i.e., diminishing reputation or profitability) and individuals (i.e., feeling less valued and more stressed) (Chidambaram and Tung 2005; Grimes et al. 2021). Furthermore, this decisively impacts the way VAs are implemented and how they are applied in organizations, restricting their deployment to certain industries, departments, teams, and purposes. For example, VAs might need certain control mechanisms to prevent loafing behavior. However, a big difference exists between social loafing and responsibility attribution in virtual collaboration with VAs compared to that with humans. Reduced efforts do not need to be compensated by human team members, and lower cognitive load demonstrates the main purpose of VAs: relieving individuals and assisting in the execution of tasks.

Besides arguing that employees might achieve inferior results without a VA, paper 7 further addressed the advantages and disadvantages of organizational human-VA teams. VAs are generally capable of helping overcome collaborative issues. For example, they retrieve information from multiple systems quicker than humans would be capable of and identify complex interdependencies (Nasirian et al. 2017). They derive decisions based on objective information rather than (human's) subjective beliefs. Opaque team member responsibilities are resolved, as the VA is aware of collaborators' duties. Furthermore, silo thinking is reduced, and relevant information is distributed among the entire team.

However, employees do not only benefit from collaborating with VAs; more information implies increased transparency that might cause discomfort among human collaborators (Wünderlich and Paluch 2017). This transparency might not only include information that is needed in daily work but also increases the transparency of employees' roles, duties, and tasks. Thus, employees' errors are easier to detect, leading to a greater likelihood that they will be held responsible, and possibly leads to a feeling of being monitored. Individuals might even be less willing to disclose information to VAs, thereby worsening virtual collaboration. This is significant since organizations do not expect that information will be withheld during virtual collaboration. While paper 2 identified transparency as a vital component for the success of VAs in virtual collaboration, paper 3 revealed that managers do not consider it to be relevant for creating business value. Still, VAs aim to make information more transparent and accessible for every collaborator.

In three of the seven papers that aim to answer the first research question, a text-based VA was used to assist individuals with a narrow task. For these scenarios, this type of VA seems appropriate. However, different types of VAs (i.e., those using other embodiments) might be useful for other occasions. This possibility was addressed in paper 7, which explained that VAs should use the most suitable method of communication for the environment, emphasizing that text-based VAs simply cannot be used in some surroundings. Although research has provided various classifications for VAs (Gnewuch et al. 2017; Knotte et al. 2019), it has not provided guidelines on deploying different types of VAs (i.e., text-based or speech-based) for different purposes (i.e., assisting with a task or promoting collaboration) in varying areas or domains (i.e., IT sector or hospitals). This demand becomes visible when considering how organizations are looking for new human hires. A profile with certain characteristics and personality traits is defined for a potential candidate to meet (Karam et al. 2020). A similar approach is conducted in software development processes; requirements or use cases are defined to avoid differing levels of knowledge between client and contractor, thus ensuring a feasible implementation (Kasauli et al. 2021; Kautz 2010, 2011). If organizations aim to integrate VAs as long-term collaborators in virtual teams, they should follow predefined guidelines and contribute demanded skills as defined in advance (papers 2, 3).

| Potential | Challenges |
|--|--|
| <ul style="list-style-type: none"> ▪ Generating superior results, preserving organizational resources, feasible/cost effective alternative ▪ Shaping processes more effective and efficient, increasing team performance/quality/cohesion ▪ Enabling to focus on relevant tasks, increasing learning capabilities ▪ Relieving individuals, compensating reduced efforts ▪ Providing equal support, enabling to work independently ▪ Deriving objective decisions, avoiding subjective bias ▪ Distributing information, enhancing transparency, reducing silo thinking | <ul style="list-style-type: none"> ▪ Missing generalization, overwhelming individuals ▪ Increasing frustration, reducing trust ▪ Preventing individuals to solve problems alone, reducing skills and learning capabilities ▪ Enhancing dependency, missing responsibility, raising feeling of false security ▪ Reducing individual efforts, engaging in poor/wrong choices, diminishing reputation/profitability, raising feeling of less valued/more stressed ▪ Disengaging individuals from teams, reducing team cohesion ▪ Increasing discomfort, raising feeling of being monitored, concealing information |

Table 6: Potential and challenges of VAs in virtual collaboration

Organizations should consider certain factors when introducing VAs as virtual team members. Table 6 outlines exemplary potential and challenges, which show that VAs certainly influence virtual collaboration. Unlike existing technologies that assist employees with certain tasks, VAs have associated consequences since they possess human-like features and are likely to engage individuals in social responses due to their anthropomorphic capabilities (Feine et al. 2019; Hussain et al. 2019; Pfeuffer et al. 2019).

5.2 Virtual Assistants and Social Responses

While the first research question of this dissertation focuses on how VAs impact virtual collaboration, the second question analyzes the extent to which VAs engage humans in social responses. The findings from six papers are involved in answering this question.

Paper 4 revealed that humans in virtual collaboration with VAs are successfully assisted in the execution of work-related tasks (as highlighted by papers 7, 8). Specifically, individuals collaborating with VAs achieve better (i.e., higher scores) and quicker (i.e., less time) results compared to those achieved when working alone. Furthermore, VAs reduce the perceived workload of human collaborators. This initially indicates that VAs are accepted by individuals and are appropriate team members that provide guidance when tasks are collaboratively executed. Moreover, according to the results, it may not necessarily matter whether humans are supported by other humans or by VAs in virtual collaboration. Since the quality of VAs' support is equivalent to that of humans, a differentiation from human assistance might no longer be possible. This was confirmed by paper 5, which found no difference when humans were supported by another person compared to a VA; the results showed that the workload of solving a task in collaboration with a VA was neither higher nor lower. Moreover, no distinctiveness regarding the collaboration

partner (human or VA) as part of the individual's extended self was found. This was highlighted by the fact that no significant difference was found between collaborations with VAs or humans in terms of the degree of identification with the team. Therefore, as team members, VAs do not seem to differ from human colleagues, and they may act as social actors that engage humans in social responses (this was also indicated by earlier research by, for instance, Demir et al. (2020) and Edwards et al. (2019)). Paper 5 determined an intertwining of the social identity and extended self and defined a virtually extended identification in which individuals maintain as well as extend the self by comparing their current selves with a VA. This shows, on the one hand, that the collaborative capabilities of VAs are perceived as being on par with humans; thus, VAs are considered as social actors (Demir et al. 2020; Panganiban et al. 2020; Seeber et al. 2018). On the other hand, the findings illustrate that humans also consider VAs as technology that extends their own capabilities (Bajwa et al. 2007; Froberg and Schwabe 2006; Schwabe 2003; Vahtera et al. 2017). These results are certainly no contradiction as humans also apply mindless behavior that triggers social responses, even when interacting with a machine (Araujo 2018; Nass and Moon 2000; Reeves and Nass 1996).

While papers 4 and 5 provided evidence that VAs are perceived as virtual collaborators on par with human colleagues, paper 6 was concerned with the related consequences of social loafing and missing responsibility attribution (as stressed in paper 7). Both aspects repeatedly emerge in human teamwork and may be detrimental to organizations as well as their employees (Chidambaram and Tung 2005; Grimes et al. 2021). The results of paper 6 confirmed the assumption that VAs act as social actors and found that social loafing was observable in virtual collaboration with VAs. Individuals collaborating with VAs availed the opportunity to loaf and made less effort compared to those who worked alone. Furthermore, higher social loafing led to reduced cognitive load. This may be due to the fact that VAs are progressively perceived as authentic team members comparable to humans who are entrusted with certain tasks, which in turn, relieve individuals of their burdens. Such a conclusion agrees with recent research, which found that VAs possess special capabilities that make them more human-like and difficult to differentiate from humans (Cha et al. 2020; Feine et al. 2019; Hussain et al. 2019; Pfeuffer et al. 2019; Porra et al. 2020). Additionally, paper 6 recognized that when humans jointly solve a task with a VA, the responsibility is attributed to the VA. This corresponds to research of human teams (e.g., Jassawalla et al. 2009; Karau and Williams 1993; Latané et al. 1979), on which individuals feel less responsible for overall outcomes when the burden is distributed among multiple team members. The results of paper 6 also indicated that there seems to be no apparent deviation between human collaborators and VAs (this was confirmed by papers 4 and 5). The social impact theory, as well as the theory of social comparison, might serve as a valid explanation of this finding. Increased team sizes and distributed

responsibilities create deindividualization, distancing individuals from their own performance and decreasing their commitment (Harkins and Szymanski 1989; Jackson and Williams 1985; Latané et al. 1979). Furthermore, VAs seem to be perceived as equal team members; individuals appear to comprehend an increased team size when VAs are applied in virtual collaboration. Moreover, humans might compare their own abilities with the potentially superior skills of the VA, which could eventually lead to laziness. For example, these individuals might expect the VA to take over certain tasks and accomplish them without any human effort (this was also suggested by paper 7). When interpreting these findings in relation to the social identity theory, emergent social loafing and responsibility attribution to the VA might prevent team members from identifying with overall team outcomes and joint accomplishments. Thus, employees might not have the perception of belonging to their team and may slowly lose their association with their team. Vice versa, less identification with a virtual team could even evoke social loafing. These aspects might alter the findings related to the virtually extended identification (as derived in paper 5), as VAs have an external attribution as a social actor to an in-group (e.g., social identity theory). However, if social loafing prevents feelings of identification with team members, less or lost attribution to a group may then indicate that VAs are seen as extension of the self (e.g., extended self) and therefore are more likely to be perceived as collaborative technologies instead of social actors.

Although papers 4 and 6 were able to offer first insights that existing knowledge from human teams seems to be partly replicable in virtual collaboration (as also hypothesized by paper 7), this did seem not to be the case for every situation in which VAs were applied. Paper 8 found that individuals prefer to disclose medical information to physicians rather than to VAs, but that there are no differences in concealment of information between those disclosing to VAs and those disclosing to physicians. In this particular case, this could be explained by the fact that humans fear being rejected due to certain sensitive personal information that does not correspond with common social norms (Ho et al. 2018). However, transferring this to virtual collaboration in organizations, employees might not only perceive assistance but likely will gain the feeling of being observed and/or controlled (Abdi et al. 2019; Siddike et al. 2018). This feeling of surveillance was addressed by paper 7, which proposed more research on how VAs ensure secure data collection, information presentation, and storage of data while preventing unauthorized access. Paper 7 further argues (in line with paper 8) that violations might cause the concealment of relevant data, causing VAs to impact information sharing negatively. In line with paper 7, paper 8 argues that higher privacy and security perceptions of VAs mitigate the perceived surveillance that was, among other factors, investigated in paper 9. The results supported this assumption and indicated that trust in the vendor providing the VA, trust in the VA itself as well as computer anxiety impact the feeling of surveillance. These

factors are particularly relevant to and have been investigated in virtual collaboration with technology (e.g., Dinev et al. 2013; Kehr et al. 2015; Lee et al. 2020; Malhotra et al. 2004). However, they seem less relevant in human collaboration, which indicates that VAs are somewhat, under certain circumstances, still perceived as technology rather than as human-like teammates.

The results of this dissertation found that VAs in virtual collaboration are perceived by individuals not only as social actors but also as supporting technology. Moreover, even small modifications in the implementation, performance, or behavior of VAs may lead to different judgments. According to the findings of the individual papers, Table 7 summarizes which factors tend to indicate the extent to which VAs are perceived as social actors or as technologies.

| VA perceived as social actor | VA perceived as technology |
|--|---|
| <ul style="list-style-type: none"> ▪ The VA is accepted by individuals as appropriate team member assisting with work-related tasks. ▪ The quality of support is equivalent to humans, a differentiation from human assistance is not apparent (i.e., cognitive load theory and perceived performance). ▪ There is no distinctiveness between a human and a VA regarding the collaboration partner and identification with a team (i.e., social identity theory and extended self). ▪ Humans show laziness/slacking behavior known from human teams, the VA is entrusted with tasks usually performed by individuals (i.e., social loafing). | <ul style="list-style-type: none"> ▪ The VA is accepted by individuals as appropriate technology assisting with work-related tasks. ▪ The VA is considered as an extension of oneself, certain capabilities are attributed to the self (i.e., extended self). ▪ Attributing responsibility towards a VA leads to missing identification with joint accomplishments, humans lose their team association (i.e., social loafing and extended self). ▪ Humans rather share information with another human, the VA raises the feeling observance and controlling (i.e., disclosing and concealment). ▪ Privacy and security perceptions, trust in the VA and its vendor as well as computer anxiety impact the feeling of being monitored and recorded (i.e., perceived surveillance of conversations). |

Table 7: VAs perceived as social actors versus technologies

Based on the theoretical foundations examined in this thesis that are related to the CASA paradigm, individuals are not entirely engaged in social responses when collaborating with VAs, despite VAs' human-like features that make them inherently anthropomorphic (Feine et al. 2019).

6 Conclusion

VAs are increasingly difficult to differentiate from humans. As virtual team members, they influence (favorably and unfavorably) virtual collaboration in organizations, and depending on their functions and scope, they can engage humans in social responses. However, VAs are not always perceived as social actors but as technology.

In virtual collaboration, VAs might be perceived as human-like actors, which indicates that knowledge from human teams is transferable to virtual collaboration. The results of this thesis, along with findings from extant research on technologies and VAs as social actors (e.g., Bührke et al. 2021; Diederich, Janßen-Müller, et al. 2020; Lankton et al. 2015; Nass et al. 1996; Nass and Moon 2000; Seeber, Bittner, et al. 2020), show that social responses appear in human-VA teams even if only simple cues and VAs are used (e.g., text-based chat). Moreover, individuals seem to apply mindless behavior despite being aware of collaborating with VAs (Araujo 2018; Reeves and Nass 1996). Nonetheless, VAs are not perceived as human-like actors in every situation. This perception depends on their implementation and skills, as well as the application domain. In certain circumstances, VAs are perceived as technology rather than virtual colleagues (which is literally their initial characteristic). Therefore, VAs are not always attributed with human capabilities. Furthermore, individuals might assess a VA as a social actor and thus respond socially while simultaneously treating the VA as a form of technology for which the same requirements apply as for other collaborative technologies. The perception of VAs as technology and/or as social actors are not mutually exclusive but might even arise simultaneously.

This thesis was motivated by the argument that VAs possess human-like features that individuals mindlessly respond to and thus influence virtual collaboration in organizational environments. Without any doubt, VAs pose certain potential and challenges for organizations and their employees. For instance, they are able to reduce the cognitive load of employees, which enables individuals to focus on more relevant tasks but can also reduce certain mental abilities. Furthermore, lowering the individual's load of certain tasks relieves individuals from unwanted duties on the one hand but leads to decreased identification with team results on the other. The exemplary findings provide evidence that the boundaries between VAs as a collaborative tool and VAs as legitimate team members in virtual collaboration seem to blur, thus justifying the rationale behind examining whether previous concepts, such as social loafing, remain valid.

6.1 Theoretical Implications

The results of this thesis offer theoretical contributions by elucidating virtual collaboration in organizational environments with VAs. Researchers will be able to grasp better the phenomenon of VAs as teammates and its related impacts (potential and challenges) as well as how individuals are engaged in social responses.

This thesis investigates several theories related to the CASA paradigm and provides scientific evidence that humans can be engaged in social responses when collaborating with

VAs. Additionally, the findings reveal that knowledge from human teams can successfully be transferred to virtual collaboration with VAs. For example, no difference was found between social identity when collaborating with a human or a VA. Furthermore, reduced efforts and feeling less responsible were also observable in virtual collaboration with VAs. Thus, existing assumptions from theory and practice that VAs are perceived as legitimate team members in human-VA collaboration are likely to be recognized. However, the findings also demonstrate that VAs are not perceived as social actors in each virtual collaborative setting. Although VAs engage humans in social responses, they are perceived as technology in certain circumstances. For example, VAs that possess few functionalities or simpler interaction possibilities, as well as those that are narrowed down to a specific task or are clearly developed to shape processes in organizations to be more effective and efficient, are less likely to be perceived as human-like collaborators. Nevertheless, the results show that the concepts of VAs as social actors and VAs as collaborative technologies are not exclusive but should be combined, as the possibilities and challenges of both approaches are simultaneously applicable. Furthermore, novel theoretical approaches are fundamental for exploiting emerging correlations and challenges. Thus, the unilateral examination of VAs as social actors or as collaborative technologies seems less advisable, particularly because existing theories seem to interfere with each other when investigating virtual collaboration with VAs (i.e., social identity theory, extended self, and virtually extended identification).

Researchers understand that VAs may benefit virtual teams, but further deep dives on the related consequences of VAs in virtual collaboration are promising for the IS discipline. This work discusses areas that are somewhat contradictory and may not have been adequately covered by extant studies. Future investigations are required to refine the concept of virtual collaboration with VAs and to elucidate additional light on related benefits and drawbacks when applied as social actors.

6.2 Practical Implications

Organizations and their management understand why VAs are useful in virtual teams. However, enterprises also comprehend the conditions under which VAs are beneficial or under which they pose dangers for virtual teamwork. The development of VAs should thus follow predefined guidelines and demanded skills while focusing on sustainable benefits rather than short-term impacts.

Virtual collaboration with VAs has, under certain circumstances, a positive impact on team performance and improves the employees' learning outcomes. Additionally, there seems to be no difference in task performance when comparing VAs and humans as virtual collaborators. This creates benefits for applying enterprises, as VAs tend to be the

more feasible and cost-effective method for many work-related tasks. Nevertheless, VAs are not capable of abstracting and generalizing but are rather able to execute narrow tasks. Organizations should also create mechanisms to prevent undesirable behavior, as employees may depend on VAs when they are used as pervasive collaborators. They should also be aware that the growing prevalence of human-VA teams may have disadvantages for teamwork, as employees might gain the perception of being monitored and feel threatened, thus questioning their abilities and value.

Therefore, organizations should appreciate that VAs can be used as both social actors and technologies, simultaneously or exclusively. Depending on the purpose of the applying enterprise, VAs in different forms should be implemented. For example, simple text-based VAs seem fitting for tackling repetitive tasks for which less cognitive skills are required, while more sophisticated VAs might involve human collaborators in social interactions to strengthen the motivation of each individual in virtual teams. Organizations might want to use both projections.

6.3 Limitations and Future Research

This thesis is not without limitations; each of the papers included in this work bear their own restraints. In the following, the most important ones in relation to the guiding research questions are mentioned.

This dissertation strives to answer how VAs influence virtual collaboration and whether humans are engaged in social responses. Although this work was motivated by the fact that VAs have become increasingly prominent in virtual organizational teams (Maedche et al. 2019; Nuruzzaman and Hussain 2020; Stieglitz et al. 2018), the results are limited to specific theoretical foundations that were chosen conscientiously (e.g., Belk 1988; Harkins and Petty 1982; Karau and Williams 1993; Moreno et al. 2001; Nass et al. 1994; Nass and Moon 2000). The results thus represent valuable first insights based on well-established and sensible approaches for gaining a deeper understanding of VAs in virtual collaboration and further portray a suitable foundation for future investigations.

The theoretical contributions used in this dissertation emerged from the CASA paradigm, but knowledge from human teams was further adapted since individuals respond socially to VAs that are inherently anthropomorphic (Feine et al. 2019). The results indicate that VAs in virtual collaboration indeed engage humans in social responses. However, whether humans really react mindlessly because they feel reminded of another human or if they actually learn new behavior due to the increased prevalence and interaction with VAs in virtual teams remains unclear (Araujo 2018; Kim and Sundar 2012; Lombard and

Xu 2021). Scholars might therefore be interested in addressing whether this novel behavior exists, how it is learned and expressed, and to what extent it differs from existing social reactions. Learned behavior might lead to deviating results in the context of social responses. Moreover, there is no distinction between VAs' perception as social actors or as collaborative technologies. The findings of this thesis demonstrate that both aspects are not exclusive; VAs might be perceived in both roles, even simultaneously. However, under which condition VAs assume which role still needs to be examined, especially since organizations are interested in exploiting both prospects.

The insights of this cumulative dissertation are mainly based on online surveys and laboratory experiments. Thus, validation of VAs in real-world scenarios should be performed. Based on tangible use cases and tasks in which VAs seem beneficial, design principles need to be formulated to describe the function and development of a product (Dellermann, Lipusch, et al. 2019; Strohmman et al. 2018). These principles act as a blueprint for developing suitable artifacts when applying VAs in virtual collaboration (Baskerville and Pries-Heje 2010; Hevner and Chatterjee 2010). Although these aspects were partly addressed by validating a prototype using real-world data (paper 1) and deriving the requirements for developing systems (papers 2, 3), the results seem rather broad. Researchers are also highly advised to not only limit their investigations on interpersonal interactions between a VA and one individual (as usually addressed by extant studies) but rather to examine the impact on entire teams and their collaboration. Furthermore, future endeavors must not be limited to easily accessible surroundings in which virtual collaboration is persistent. More traditional environments, such as healthcare and hospitals, promise appealing result (e.g., Mirbabaie, Frick, and Matt 2021; Wessel et al. 2019). Access to healthcare professionals is seriously challenging for IS scholars, and this environment is not their habituated research setting. However, this should not serve as justification for excluding or ignoring such a promising research domain.

Drawing conclusions to the guiding research questions on how VAs impact virtual collaboration and to what extent humans are engaged in social responses, it can be noted that there are manifold potential as well as challenges. The increasing application of VAs in virtual collaboration is steadily blurring the boundaries between human and human-like actors. This work shows that existing findings as well as knowledge from human teams is somewhat transferable to virtual collaboration with VAs, nevertheless, scholars are highly encouraged to validate whether previous concepts remain valid or need to be rethought. This paper-based dissertation suits as significant foundation for future examination and extends current IS knowledge by providing a novel perspective.

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Appendix

Publications

Paper 1: Der Einsatz von künstlicher Intelligenz zur Verbesserung des Incident Managements

| | |
|-------------------------------|---|
| Type (Ranking, Impact Factor) | Journal article (D, N/A) |
| Rights and permissions | Closed access |
| Authors | Frick, N.R.J. , Brünker, F., Ross, B., & Stieglitz, S. |
| Year | 2019 |
| Outlet | HMD Praxis der Wirtschaftsinformatik (HMD) |
| Permalink/DOI | https://doi.org/10.1365/s40702-019-00505-w |
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Paper 2: Towards Successful Collaboration: Design Guidelines for AI-based Services enriching Information Systems in Organisations

| | |
|-------------------------------|--|
| Type (Ranking, Impact Factor) | Conference article (N/A, N/A) |
| Rights and permissions | Open access |
| Authors | Frick, N.R.J. , Brünker, F., Ross, B., & Stieglitz, S. |
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Towards Successful Collaboration: Design Guidelines for AI-based Services enriching Information Systems in Organisations

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Abstract

Information systems (IS) are widely used in organisations to improve business performance. The steady progression in improving technologies like artificial intelligence (AI) and the need of securing future success of organisations lead to new requirements for IS. This research in progress firstly introduces the term AI-based services (AIBS) describing AI as a component enriching IS aiming at collaborating with employees and assisting in the execution of work-related tasks. The study derives requirements from ten expert interviews to successful design AIBS following Design Science Research (DSR). For a successful deployment of AIBS in organisations the D&M IS Success Model will be considered to validated requirements within three major dimensions of quality: Information Quality, System Quality, and Service Quality. Amongst others, preliminary findings propose that AIBS must be preferably authentic. Further discussion and research on AIBS is forced, thus, providing first insights on the deployment of AIBS in organisations.

Keywords Information Systems, Artificial Intelligence, AI-based services, Collaboration, Design Guidelines

1 Introduction

Information systems (IS) have been used for years in large parts of organisations. “An information system can be seen as a system comprising human beings and/or machines which use and/or produce information” (Aram and Neumann 2015). When implemented in organisations, IS speed up business processes and thus save the adopting organisations a great amount of time (Neumann et al. 2014) and thereby money. In addition, benefits can be enhanced through the deployment of Artificial Intelligence (AI). There is no consensus on a precise definition, but AI is used for diverse objectives such as solving domain-independent problems, learning from the environment or interacting with other systems and humans (Dellermann et al. 2019). When used as components enriching IS in organisations, we relate to the expression AI-based services (AIBS), with the main objective of collaborating with employees and assisting in the execution of work-related tasks. AIBS assist employees in answering frequently asked questions by customers (Tsaih and Hsu 2018) which leads to a more effective and efficient way to handle inquiries and thus generates cost savings. AIBS are used for predicting desirable product preferences of customers (Nguyen and Sidorova 2018). Based on already existing information about customers, suitable related or new products can be offered. A targeted approach is possible, which is no longer determined by a subjective impression. AIBS are already used in the context of IT Service Management. Employed in the context of incident management, it massively accelerates the categorisation process (Frick et al. 2019), leading to time savings for employees.

Though AIBS generates numerous benefits for various areas in organisations focused on the collaboration between users and IS, no proper formulated guidelines for designing AIBS enriching IS in organisations can be found in the scientific literature. Securing the success in this fast-moving era, it is necessary to provide general guidelines precisely formulating which factors must be observed when planning and developing AIBS. To close this research gap, we propose suitable recommendations following the general guidelines for conducting Design Science Research (DSR). As contribution, results can be used by researchers as well as organisations and developers to design and implement AIBS. The development of our guidelines is based on qualitative research using ten face-to-face expert interviews as well as the review of existing literature. Theory-guided research recommends interpretation on two levels: results of one’s own survey and conclusions of existing theories (Kohlbacher 2005). The measurement of IS effectiveness is a relevant component for both research and organisations. In this context, the DeLone & McLean IS Success Model (D&M IS Success Model) can be considered to measure the success of applied IS in organisations (DeLone and McLean 2003). To ascertain the success of AIBS in IS, the developed guidelines will be assigned to the proposed categories of the model and validated if the propositions fit the success metrics. In this context, three major dimensions of IS quality are considered: (1) Information Quality, (2) System Quality, and (3) Service Quality. To formalise the overall goal of this paper, we derived the following research question:

RQ: What are the requirements that need to be considered to design AI-based services enriching information systems in organisations?

The paper is structured as follows. First, we provide a theoretical overview on AI and AIBS as well as IS success in organisations. Second, we present the research design and the preliminary results including derived propositions. Last, we outline the next steps of our research process.

2 Theoretical Background

2.1 Artificial Intelligence and AI-based services

We define AIBS as components enriching information systems which use intelligent behaviour to assist people in fulfilling tasks. Recently, interest in AI has renewed as building systems has become more practical (Knijnenburg and Willemsen 2016) especially due to remarkable improvements in machine learning algorithms (Goodfellow et al. 2016). There is no generally accepted definition of the term AI since researchers from different disciplines have varying opinions and perceptions. As an omnipresent concept (Maedche et al. 2019), AI consists of multiple subfields which can be subdivided into various dimensions like thinking humanly, thinking rationally, acting humanly or acting rationally (Russel and Norvig 2016). AI can be used in various domains, most notably combining non-specialised and task-specialised intelligence as well as interacting with users and other (information) systems (Dellermann et al. 2019). The deployment of AI has become increasingly relevant for organisations to gain competitive advantages and maximise the market share. The growing amount of data and the possibility of gathering information in a short time (Nasirian et al. 2017), leads to the possibility of generating benefits which are highly relevant. Organisations exploiting the opportunities of AI will gain an advantage over competitors (Brynjolfsson and McAfee 2017). The development of new, enhanced services based on AI,

generating benefits and simultaneously impacting collaboration within organisations (Seeber et al. 2018), enjoys an increasing attention. Oxford Dictionary (2019) defines service as the action of helping or doing work for someone. Adding AI capabilities to the services performed by information systems in organisations leads to the above definition of AIBS. The aim of using AIBS is for them to assist users in the execution of work-related tasks or even fulfil them entirely (Norman 2017). They are already applied in many organisations, and their impact has been validated. However, it has not yet been examined, how AIBS have to be properly designed to enrich IS in order to assist users, changing the nature of organisations (Seeber et al. 2018). Effectively integrating AIBS and its capabilities for collaboration, organisations find themselves at an ever-greater competitive advantage (Brynjolfsson and McAfee 2017).

2.2 Information Systems Success in Organisations

Organisations aim to improve business performance with IS. To this end, IS improve the effectiveness and efficiency of each organisation (Hevner et al. 2004) as well as facilitating collaboration by acting as communication and coordination systems (Aram and Neumann 2015). Thus, IS have three essential functions within an organisation: (1) Support the company's business operations, (2) Supporting managerial decision making, and (3) Support the achievement of strategic competitive advantages (Susanto and Meiryani 2019). Therefore, IS in organisations can be considered as business information systems (Aram and Neumann 2015). In this context, IS are composed of several information technologies (Orlikowski and Iacono 2001) which are applied to transmit, process or store information (Piccoli 2008). Considering the need for the ongoing improvement of IS to fulfil all business requirements, emphasises the impact of information technologies on business operations (Bjerknes et al. 1991).

In order to track the success of IS in organisations, it is necessary to conceptualise the quality of an IS within an organisation (DeLone and McLean 1992). To this end, the scholars developed the D&M IS Success Model "driven by a process understanding of information systems and their impacts" (DeLone and McLean 2002). Based on past research contributions, the D&M IS Success Model was updated. It describes three major dimensions of quality which each affect subsequent use and user satisfaction (DeLone and McLean 2003). Each quality dimension consists of various measurements. "Information quality" measures the overall content quality whereas "system quality" conceptualises the desired characteristics of an IS. Moreover, "service quality" explains the overall support delivered by the service provider. The dimension "use" measures the actual behaviour of a user whereas "user satisfaction" shows the opinion of the users about the applied IS. The dimension "net benefits" groups all impact measures, e.g. industry impacts, work group impacts, inter-organisational impacts or consumer impacts into one single category (DeLone and McLean 2003). To ensure that the developed design guidelines for AIBS follow the overall improvements of IS, results are assigned to the six dimensions of the D&M IS Success Model and it is validated whether they suit the success metrics.

3 Research Design

Despite the omnipresence of AIBS, there are still no clearly formulated guidelines for AIBS. To close this research gap, we produce design guidelines that can be used by researchers as well as organisations and developers to design and implement specific AIBS enriching IS in organisations focussing on the collaboration with employees. DSR advocates the construction of socio-technical artifacts (Gregor and Hevner 2013) to address relevant organisational problems (Hevner et al. 2004). Artifacts can be more specific (limited and less mature knowledge) and more abstract (complete and mature knowledge). Level 1 contains instantiations like software products or processes. Level 2 includes, for example, constructs and design principles. Level 3 describes design theories like mid-range and grand theory. The developed design guidelines, which contribute knowledge for operational principles or architecture, represent level 2. Following the DSR Methodology Process (Peppers et al. 2007), in this work in progress, we present the results of the first phase: identifying the problem. The development is based on qualitative research using ten face-to-face expert interviews as well as existing research results. Therefore, we reviewed relevant literature regarding topics of AI and adjoining subjects always concerning the enrichment of IS. Results are compared with the six dimensions of the D&M IS Success Model and validated if the developed requirements within the guidelines fit the various success metrics.

3.1 Expert Interviews

The method of the expert interviews has been established and grown in popularity as a valid method to obtain knowledge (Bogner et al. 2009). Especially in the exploratory phase of research, it is an efficient and concentrated method to collect relevant data (Bogner et al. 2009). The term expert describes

someone who has an advantage of knowledge in the investigated field of research (Meuser and Nagel 2009). In this study, experts are individuals who have a special knowledge on their job, the company's structure, internal processes and, most important, where AIBS can be applied in IS to improve business performance. All interviews were conducted in face-to-face sessions and took place at the workplaces of the experts. This facilitates providing assistance to the interviewee and ensuring familiar conditions. The interviews took between 35 and 65 minutes. After conducting the interviews, they were transcribed and anonymised. Respecting data privacy protection, all audio recordings were deleted afterwards. The material will completely be coded in MAXQDA version 18.

3.1.1 Selection Process

Initially, eligibility criteria were first defined to select suitable companies. These companies should use a variety of internal IS to fulfil the daily work. It should be ensured that IS are already enriched by AIBS or future adoptions of AIBS are planned. Based on these factors, a large German retail holding organisation was selected which owns equity interests in further companies. Here, we chose companies focussing on various areas within the holding organisation: agricultural trade (C1), animal husbandry advisory (C2), consulting energy products (C3), animal feed advisory (C4), construction services (C5), wholesale e-commerce (C6) and agricultural machinery distribution (C7). To gain a holistic picture, we conducted ten interviews with experts working in management level with a minimum of three years of experience, because when the expert has a long tenure in a key position, "opportunities for expanding the researcher's access to the field may well also be unearthed in the interview" (Bogner et al. 2009). We acquired two project managers (E1/C2 [male, 28 years old, tenure of 8 years], E2/C1 [f, 25, 8]), three managing directors (E3/C3 [m, 35, 10], E7/C6 [m, 40, 21], E8/C1 [m, 43, 19]), three heads of divisions (E4/C4 [f, 40, 9], E9/C3 [f, 30, 4], E10/C5 [m, 43, 18]), and finally two managers (E5/C7 [m, 57, 5], E6/C7 [m, 47, 15]). Participants were 39 years old on average, with three female and seven male experts.

3.1.2 Semi-structured interviews

Semi-structured interviews are a flexible, accessible and intelligible as well as the most effective and efficient way to get relevant information from participants (Qu and Dumay 2011). The method should ensure that all relevant aspects were captured to generate comparable responses and ascertain that the following coding process is simplified. In preparation, interviews involve creating "questioning guided by identified themes in a consistent and systematic manner" (Qu and Dumay 2011). Therefore, a prefixed guide with central questions was developed, considering literature from the method of expert interviews and prior experiences of the researchers. The guide was divided into 9 parts: (1) Introduction of the interviewer and brief summary of the purpose of the research, as the participants had already received relevant information when they were recruited. (2) Self-introduction of the interviewee, including career development, current responsibilities in the company as well as demographic data. (3) Definition of AIBS and prior experience, followed by the authors' explanation of AIBS to ensure the same level of knowledge among all participants. (4) Areas in which AIBS are applied in organisations and which IS are enriched focusing on collaboration with employees. (5) Adoption and acceptance of AIBS and which problems might arise when enriching IS and collaborating with AIBS. (6) Advantages, disadvantages and dangers when collaborating with AIBS in IS. (7) How AIBS need to be developed in order to collaborate with them on a daily basis in IS. (8) Responsibility for an implementation and what an introduction looks like. (9) Conclusion of the interview: Possibility for the interviewee to ask further inquiries followed by a debriefing.

3.1.3 Coding

We used qualitative content analysis to evaluate the interviews as the most broad and exact way to analyse qualitatively collected material (Mayring 2015). This method orders the data according to certain empirically and theoretically reasonable points. The data is analysed using codes, which represent words or short phrases for attributes of language-based or visual data (Saldaña 2009) aiming at reducing the intricacy of vocabulary in the field and in the data by identifying one or multiple core categories (Flick 2013), finally leading to design guidelines. A initial list of general codes is created and collected within a codebook and maintained by one researcher as editor who is responsible for updating, revising and maintaining the list of codes within the group during the research process (Guest and MacQueen 2008). The coding is divided into two cycles: The first cycle takes place during the initial coding of the data. The second cycle focuses on pattern coding for categorisation of coded data. Following the codes-to-theory model (Saldaña 2009), we are currently in the first cycle carrying out initial coding. For interpreting what respondents mean, researchers need to have extensive knowledge in the subject matter (Campbell et al. 2013). Therefore, the authors have a strong background on collaboration systems, AI and AIBS as well as their utilisation in organisations. The coding is

collaboratively done by two researchers. On the one hand, the effort for the coding process is distributed, on the other hand, different perspectives on the qualitative data are ensured.

4 Preliminary Results

4.1 Authenticity and Trust Perception

The first results show that the collaboration with an AIBS must preferably be authentic, since the method of communication differs between the individual colleagues. Besides, since AIBS are assisting users in their daily work, for example by generating recommendations, decisions or even fulfilling tasks autonomously, trust in such systems has to be as high as possible. One expert stated that *“[understanding the outcome is] very important! On the one hand, users can understand how the system came up with the decision, on the other hand, the users’ level of knowledge is adjusted”* (E1)¹. Authenticity and trust are interdependent and are critical for users to establish trust (Wunderlich and Paluch 2017). To positively affect authenticity and trust perception as well as use intention, the decision-making process has to be as transparent as possible (Wunderlich et al. 2013). As *system quality* of the D&M IS Success Model measures desired characteristics, authenticity and trust perception can be assigned to this dimension. We provide the following proposition as an approach to respond to our research question:

P1: The collaboration with an AIBS enriching IS in organisations must be as authentic as possible to gain trust in such technologies.

4.2 Safety, Security and Privacy Factors

A frequently mentioned topic in the interviews was the experts’ concerns about safety, security and privacy factors. Talking about safety and security factors, the experts were less cautious. In the opinion of the experts, it was much more important to clarify which (personal) data is processed, where, how and by whom. One expert outlined *“so there will be a lot of scepticism, because everyone is afraid that personal data will be published. So everyone has quite a bit of respect”* (E7). Within the D&M IS Success Model, *information quality* captures content issues of which safety, security and privacy factors are essential components. Being in control of personal data, its use and disclosure is mandatory (Cavoukian 2008). The interviewees indicated that adequate communication had to take place before the introduction of AIBS and that the legal basis had to be clarified in advance. We thus propose:

P2: Data processed by AIBS enriching IS in organisations must be legally clarified and expounded to users.

4.3 Enhanced Performance

Another prevalently mentioned point was the requirement that users should learn through the utilisation of AIBS. Experts underlined their statement by picturing situations in which users can better prepare for upcoming appointments and pay attention to matters they have previously disregarded. As one expert explained, *“I could well imagine [to learn from a system], so you get a well-grounded result”* (E10). Since enhanced performance has a positive effect on employees and organisations, this attribute can be viewed as part of the concept of *net benefits* in the D&M IS Success Model. Norman (1994) already pointed out that technology is an instrument to enhance people’s performances. Siddike et al. (2018) add that the interaction helps to boost performance at work. From this we derive following proposal:

P3: Content presented by AIBS enriching IS in organisations must be presented appropriately to positively affect users’ performances in their work.

5 Next Steps of Research Process

In this research-in-progress paper, we presented the first phase of the DSR Methodology Process by identifying the problem and presented further research by giving insight on defining objectives of the solution. The analysis of the expert interviews is still at the beginning, yet this study encourages further discussion and research on AIBS. We are currently in the first cycle of the codes-to-theory model, conducting initial coding following the previously created codebook. In the next step, the analysis of the qualitative text data, including tests on reliability and validity, will be finalised. Based on the interviews, design guidelines are conducted representing level 2 artifacts of DSR contribution types. Findings will

¹ Excerpts from the German interviews have been translated into English for the reader’s convenience.

be compared and supported with existing research. Results will be linked with the six dimensions of the D&M IS Success Model to validate if the developed requirements within the guidelines fit in the various success metrics or whether there are new aspects that have not yet been considered. Propositions are assigned to the measures of the model. We will emphasise how the derived proposition supports the design of AIBS focussing on collaboration, in contrast with IS in general. However, further points must be considered when planning and developing AIBS enriching IS aiming at collaborating with employees, such as technical aspects, ethics and politics, user characteristics as well as requirements potentially exposed by the interviews. Overall, IS and organisations benefit when adapting AIBS. However, it has not yet been examined how AIBS must be designed to assist people fulfilling tasks. As a contribution, we aim at closing this research gap. Preliminary results already provide aspects considered when conducting AIBS in IS but do not provide a holistic picture. Research here offers promising results. The final guidelines will contain relevant requirements that need to be considered to design AIBS enriching IS in organisations with the main objective of collaborating with employees and assisting in the execution of work-related tasks.

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Paper 3: Design requirements for AI-based services enriching legacy information systems in enterprises: A managerial perspective

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Design Requirements for AI-based Services Enriching Legacy Information Systems in Enterprises: A Managerial Perspective

Completed research paper

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Abstract

Information systems (IS) have been introduced in enterprises for decades to generate business value. Historically systems that are deeply integrated into business processes and not replaced remain vital assets, and thus become legacy IS (LISs). To secure the future success, enterprises invest in innovative technologies such as artificial intelligence-based services (AIBSs), enriching LISs and assisting employees in the execution of work-related tasks. This study develops design requirements from a managerial perspective by following a mixed-method approach. First, we conducted ten interviews to formulate requirements to design AIBSs. Second, we evaluated their business value using an online survey (N = 101). The results indicate that executives consider design requirements as relevant that create strategic advancements in the short term. With the help of our findings, researchers can better understand where further in-depth studies are needed to refine the requirements. Practitioners can learn how AIBSs generate business value when enriching LISs.

Keywords Artificial intelligence, AI-based services, legacy information systems, design requirements, enterprises

1 Introduction

Information systems (IS) have been used for decades to generate business value by gaining advantages over competitors in almost every part of organisational environments. Systems are used by individuals to process and produce data (Aram and Neumann 2015), to speed up business processes (Neumann et al. 2014), regulate the informational, material, and human resources as well as enhance efficiency, effectiveness and productivity (Xu and Topi 2017). Large parts of systems have been instituted over years in enterprises and thus can be described as legacy information systems (LISs). They are considered to be the “backbone of an organisation’s information flow and the main vehicle for consolidating business information” (Bisbal et al. 1999). Ensuring the ongoing operation is therefore mandatory for organisations as LISs are strongly linked to the strategic business goals (Robertson 1997). However, enterprises still need to be able to exploit novel and innovative trends to secure their future success. The continuous development of technology paired with the lack of time to replace LISs (Hasselbring 2000) requires the adaptation of existing applications. A currently popular group of technologies that enhance LISs in organisations is artificial intelligence (AI) (Frick et al. 2019a).

The term AI is used to describe a wide range of technologies with self-learning abilities which are possibly able to achieve superior performance compared to humans (Coombs et al. 2020). AI can have strong economic potential and generate strategic business advancements as it can take over repetitive tasks and relieves employees from unwanted duties (Siau and Wang 2018). When AI is used to enrich LISs in enterprises, we use the term AI-based services (AIBSs), which are “components enriching IS in organisations with the main objective of collaborating with employees and assisting in the execution of work-related tasks” (Frick et al. 2019a). AIBSs are applied in enterprises to support employees in the decision-making process (Brachten et al. 2020), accelerate internal support processes (Frick et al. 2019b) or facilitate strategic decisions on an organisational level (Aversa et al. 2018).

Despite the fact that AIBSs are increasingly being used in businesses (Dwivedi et al. 2019), there is an urgent demand to formulate requirements that should be considered when designing systems enhancing LISs. Most existing AIBSs adapted to business processes are considered to be narrowed down to a specified task (Batin et al. 2017), where the majority focuses on the short-term creation of added value while less attention is paid to design aspects. Research here needs to generate theoretical guidance to “create ideal AI systems for human decision makers” (Duan et al. 2019) in contrast with current literature that mainly targets technological aspects (Mikalef et al. 2018). Addressing the pressing need to do more research in this area, this study aims at proposing suitable recommendations and is thus guided by the following research question:

RQ1: What are the requirements that need to be considered to design AI-based services enriching legacy information systems in enterprises?

RQ2: To what extent do the identified design requirements for AI-based services enriching legacy information systems contribute to business value in enterprises?

This study makes a first foray into the examination of AIBSs from a business perspective following a mixed-method approach. We conducted semi-structured expert interviews with ten executives from multiple enterprises to derive design requirements. Preliminary results from these interviews were previously reported in a research-in-progress paper (Frick et al. 2019a). In this article, we additionally report on our quantitative evaluation of the findings using an online survey with $N = 101$ managers to verify which requirements create business value when enriching LISs.

Researchers and practitioners find the requirements helpful to consider important aspects before the actual introduction of AIBSs. From a theoretical perspective, this research gives an overview of design requirements when deploying AIBSs in enterprises and outlines an orientation for further in-depth research. From a practical point of view, practitioners can understand how AIBSs generate business value when enriching LISs. Hence, this article extends the IS literature by broadening our knowledge on how to design, implement and deploy AIBSs for enriching LISs. We believe this study is valuable to researchers and practitioners equally for understanding and overcoming difficulties when dealing with the introduction of AIBSs in enterprises.

2 Theoretical Background

Implementing IS in organisations aims to enhance business performance. IS ensure the effectiveness and efficiency of the organisation (Hevner et al. 2004) as well as supporting collaboration by fulfilling the role as a communication and coordination system (Aram and Neumann 2015). Within an

organisation, IS as support systems can be characterised by three central functions. First, supporting the company's business operations. Second, supporting managerial decision making. Third, supporting the achievement of strategic competitive advantages (Susanto and Meiryani 2019). Therefore, IS improving the organisation's business performance by ensuring these three functions can be considered as business IS (Aram and Neumann 2015) and is described as *"a collection of various information that has unity between one and the other aimed at business interests"* (Susanto and Meiryani 2019). IS in organisations consist of various information technologies (Orlikowski and Iacono 2001). These information technologies fulfil functions such as transmitting, processing, or storing information (Piccoli 2008). By doing this, IS in organisations help to process large amounts of information and to solve upcoming decision-making problems (Leavitt and Whisler 1958). Due to the generation of numerous benefits, organisations have been using IS to generate business value for decades. However, systems not coping with modern requirements or are not modifiable for business purposes (Robertson 1997) slowly turn into LISs but remain vital assets for organisations (Bianchi et al. 2003). The major problem with LISs is that they are deeply integrated into the running of a business (Robertson 1997) and that there is simply no rational reason for replacing them (Hasselbring 2000), thus organisations remain dependent (Robertson 1997). Nevertheless, enterprises are regularly required to invest in innovative technologies to generate or maintain advantages over competitors. Thereby, applications need to be adaptable to retain LISs as reasonably as possible (Bianchi et al. 2003) to enrich existing solutions and to assist employees in their daily work. Related to the dynamic development of new technologies, organisations need to consider ongoing improvements of LISs to ensure nascent business requirements, emphasizing the impact of information technologies on business operations (Bjerknes et al. 1991).

A concept which becomes increasingly relevant for the aligning organisational strategies is AI. There is no uniform definition, but AI can be considered 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). AI is believed to fundamentally change the future of business across industries, generating advantages over competitors and maximizing the market share (Benbya and Leidner 2018; Wang and Siau 2019). The potential benefits cannot be overlooked causing organisations to invest heavily (Schuetzler et al. 2018). When AI is applied as component enriching existing IS, it can be considered as AIBS (Frick et al. 2019a). They are typically implemented using machine learning algorithms (Kersting 2018) and are turning into a key element for enterprises (Dwivedi et al. 2019). In a recent study (Frick et al. 2019b) we demonstrated that AIBSs can be integrated into existing internal support workflows. The authors indicated that the categorisation and distribution of incoming customer inquiries are heavily accelerated. Another example (Pessach et al. 2020) evaluated the application of an AIBS to support human resource employees with the recruitment and placement of professionals. The results showed that insights might have been overlooked by internal recruiters who were using conventional methods. The examples illustrate that AIBSs promise great potential for organisations, including those which still rely on a multitude of LISs. Although AIBSs are becoming more ubiquitous within LISs, there are no properly validated requirements that need to be considered to design services enriching existing IS in enterprises.

3 Research Design

In order to examine which requirements need to be considered to design AIBSs enriching legacy IS in enterprises and likewise generate business value, we selected a mixed-method approach. This design strategy equips researchers with an effective technique in dealing with evolving situations and complex improvements while being able to achieve contributions for theory and practice (Venkatesh et al. 2013). Mixed-methods are capable of simultaneously addressing confirmatory and exploratory issues, provide greater insights compared to single methods and help to analyse divergent and/or complementary findings (Teddlie and Tashakkori 2003, 2009). The approach at hand is an exploratory sequential procedure combining qualitative and quantitative research to validate whether assumptions based on a small sample size can be generalized for a larger population (Creswell and Creswell 2018). We conduct qualitative research to identify core issues and obtain knowledge within a less explored domain (Kelle 2006), and use the subsequent quantitative phase to validate our findings with a larger population (Creswell and Creswell 2018).

3.1 Expert Interviews

Expert interviews established themselves and grown in popularity as an efficient and concentrated method to collect relevant data (Bogner et al. 2009). We chose this method to 1) give the interviewees

enough space to elaborate on issues, 2) provide selective assistance by the researchers and, 3) ensure capturing all relevant aspects to generate comparable responses to simplify the subsequent coding process. The term expert describes an individual with advanced knowledge in the investigated field of research (Meuser and Nagel 2009). In this study (see also Frick et al. 2019a), the experts are employees working at management level. Furthermore, experts needed to be familiar with AI and have knowledge of where AIBSs can be applied to improve business performance and further they needed to have a minimum of three years of experience to be well acquainted with the company and the sector. We also defined that the companies in which the experts worked should have applied AIBSs to enrich LISs and be planning future adoptions. In terms of sample size, we follow Creswell and Creswell (2018) who recommend using between three and ten individuals. Based on these factors, a large German retail holding organisation was selected which owns equity interests in further companies. Here, we chose companies focusing on various areas within the holding organisation: agricultural trade (C1), animal husbandry advisory (C2), energy product consulting (C3), animal feed advisory (C4), construction services (C5), wholesale e-commerce (C6) and agricultural machinery distribution (C7). We acquired two project managers (E1/C2 [male, 28 years old, tenure of 8 years], E2/C1 [f, 25, 8]), three managing directors (E3/C3 [m, 35, 10], E7/C6 [m, 40, 21], E8/C1 [m, 43, 19]), three heads of divisions (E4/C4 [f, 40, 9], E9/C3 [f, 30, 4], E10/C5 [m, 43, 18]), and finally two managers (E5/C7 [m, 57, 5], E6/C7 [m, 47, 15]). The interviews were conducted in person at the workplace of the interviewees. Participants were 39 years old on average, with three female and seven male experts and a mean tenure at the company of 11.7 years.

Conducting semi-structured expert interviews implies creating “*questioning guided by identified themes in a consistent and systematic manner*” (Qu and Dumay 2011). Therefore, a guideline with central questions on AI, AIBSs, LISs and business value was developed in advance, divided into the following 9 parts: 1) Introduction of the interviewer and brief summary of the purpose of the research, as the participants had already received relevant information when they were recruited. 2) Self-introduction of the interviewee, including career development, current responsibilities in the company as well as demographic data. 3) Definition of AIBSs and prior experience, followed by the authors’ explanation of AIBSs to ensure the same level of knowledge among all participants. 4) Areas in which AIBSs are applied in organisations and which (L)IS are enriched. 5) Adoption and acceptance of AIBSs and which barriers might arise when enriching (L)IS with AIBSs. 6) Advantages, disadvantages and dangers when using AIBSs in (L)IS. 7) How AIBSs need to be developed to use them daily in (L)IS. 8) Responsibility for an implementation and what an introduction looks like. 9) Conclusion of the interview: Possibility for the interviewee to ask further inquiries followed by a debriefing.

Interpreting what respondents mean in their answers to questions assumes that researchers have extensive knowledge in the subject matter (Campbell et al. 2013). Following this requirement, the authors have a strong background on IS, LIS, AI and AIBSs as well as its utilization in enterprises. We used content analysis as the most precise method to analyse qualitatively collected material (Mayring 2014). The research data was coded according to certain, empirically and theoretically reasonable points, enabling a structured description of the material (Mayring 2014). Codes represent words or short phrases for attributes of language-based or visual data (Saldaña 2009) aiming at reducing the intricacy of vocabulary and identifying core categories. The coding was collaboratively done by two researchers to distribute the effort of the coding process and to get different perspectives on the qualitative data. A list of general codes was created coding two interviews in front and collected inside a codebook. One of the researchers maintained the codebook as editor and was responsible for updating, revising and maintaining the list of codes during the research process (Guest and MacQueen 2008). Respecting the codes-to-theory model (Saldaña 2009), the analytic process is not linear but rather cyclical. It is divided into two cycles: an initial coding of the data, followed by pattern coding for the categorization of coded data. The first cycle was used to structure the data and assigning codes. In the second cycle, categories were created. In summary, we created 379 codes with 10 categories using MAXQDA (version 18). We finally validated the intercoder reliability using Krippendorff’s alpha, resulting in a value of .823 which is above the threshold of .800 (Hayes and Krippendorff 2007).

3.2 Online survey

To validate the design requirements, we conducted an online survey. As a precondition for participation in our study, participants had to speak English or German fluently, as the survey was designed in both languages. In addition, individuals had to work in a company within the management level to ensure an understanding of the business perspective. Various German organisations were approached directly by the researchers, plus, participants were recruited via Prolific, a platform designed to acquire subjects for surveys (Palan and Schitter 2018). The study started with a standardised briefing about anonymization and research purposes, followed by a detailed explanation

about AIBSs, why they are already introduced in organisations and what they are capable of. To verify each design requirement, we adopted and modified constructs from previously validated instruments to ensure the accuracy of the measurements. However, since the results provide new insights, we were not able to identify items for every design requirement, resulting in the development of own constructs. We used a combination of already existing as well as self-developed items which were validated as part of the evaluation. Besides items for the design requirements, we further measured the business value when using AIBSs to enrich LISs in enterprises. All items were measured on a 10-point numeric scale and questions starting with the phrase “how relevant are the following aspects/statements regarding AI-based services”. Example items are “the utilization of AI-based services is a good idea” or “the strategy regarding the utilization of AI-based services is congruent with the business strategy of organisations”. Participants had to answer 74 questions in total, excluding information about their demographic data. To ensure that the attendees were aware of the definition of AIBSs throughout the survey, they had to answer 2 questions with “yes” or “no” about the main intention as the last step: 1) “The main objective of AIBSs is to collaborate with employees and assist them in their daily tasks” and 2) “The purpose of this survey is to evaluate requirements to develop AIBSs”. The survey was designed using LimeSurvey and took about 15 minutes to complete, the analysis was conducted using jamovi (version 1.1.9.0).

4 Results

4.1 Requirements

The **Strategic Orientation** of an enterprise controls the actual use of AIBSs within an organisation. However, AIBSs must not be implemented in a sweeping way but rather specifically to enhance distinct functions. This may reduce costs and the need for resources of an organisation, which is a key aspect of common strategic orientations (Cao 2002; Johnson 2018). One expert explained “*The management and executive board have to support that. We have to achieve additional benefits for ourselves as well as for our customers*”¹ (E8). Furthermore, an activity within an organisation has a strategic value when it contributes to the organisational success (Barney 1991). Likewise, the deployment of services such as AIBSs needs to align along the strategic orientation of the organisation in order to fulfil the overarching organisational strategy and vice versa (Henderson and Venkatraman 1999). In this context, such services have to provide concrete advantages with respect to employees and customers of the organisation (Luse et al. 2013).

Process Organisation describes the actual process of coherent and individual operations. This step aims to support the existing IT processes in order to improve their velocity by reducing non automated work steps. One respondent emphasised “*This is a whole process, fast, effective and customer-friendly. The system thinks and acts in a processual way*” (E2). Organisations supporting new technology investments such as new business models and new business processes will get superior returns comparing to other competitors that do not invest (Susanto and Meiryani 2019). Therefore, the process organisation is integrally tied to the Strategic Organisation. Enriching LISs with AIBSs enables the organisation to digitize the individual processes and functions (Luse et al. 2013).

Before the actual and continual interaction with the system, the **Acceptance and Adoption** of AIBSs by users must be achieved. Experts point out that new technology in general has an acceptance problem in organisations. However, to interact with it at all, perceived usefulness and perceived ease are the major aspects that must be taken into account. One participant pointed out that “*AIBSs should not dictate how to act in specific situations, that would only create unnecessary barriers*” (E2). “*User acceptance and confidence are crucial for the development of any new technology*” (Taherdoost 2017). With the growing interest in AIBSs, organisations need to investigate the challenges referring to adoption (Alsheibani et al. 2018). Research has developed various models explaining individual technology adoption (Venkatesh et al. 2003) which have been continuously revised especially in an organisational context. However, adoption is not only an important issue for technology in general but also for AIBSs.

Authenticity, Trust and Transparency describes that the interaction with an AIBSs should preferably be perceived as authentic. In addition, trust in AIBSs and their transparency has to be as high as possible. One respondent stated “*[Understanding the outcome is] very important! On the one hand, users can understand how the system came up with the decision, on the other hand, the users’ level of knowledge is adjusted*” (E1). The decision-making process has to be as transparent as possible,

¹ Excerpts from the German interviews have been translated into English for the reader’s convenience.

given that transparency is identified as crucial for trust building (Wunderlich et al. 2013) and leading to an increase of authenticity as well as use intention. *“The perception of authenticity is critical for a user’s evaluation of the service as valuable and satisfactory and for establishing trust”* (Wunderlich and Paluch 2017). In addition, the interaction quality leads to trust and to usage intention (Nasirian et al. 2017).

A frequently mentioned topic in the interviews was the experts’ concerns about **Security, Privacy and Ethics** during the interaction process. In the opinion of the experts, it is most important to clarify which (personal) data is processed, where, how and by whom and that no ethically reprehensible decisions are made. One interviewee said *“so, there will be a lot of scepticism, because everyone is afraid that personal data will be published. So, everyone has quite a bit of respect”* (E7). Another underlined that *“[The artificial intelligence system] may ask for things that may not be relevant in the context. Also, sensitive topics, there is a lot of sensitive [personal] data which the user does not want to reveal”* (E9). Informational self-determination refers to *“the right or ability of individuals to exercise personal control over the collection, use and disclosure of their personal data by others”* (Cavoukian 2008). The interviewees indicated that adequate communication had to take place before the introduction of AIBSs and that the legal basis had to be clarified in advance. AIBSs are trained by developers and thus might contain considerable human bias (Rothenberger et al. 2019). Ethical concerns are a major challenge (Duan et al. 2019), thus AIBSs must be implemented with caution (Wang and Siau 2018).

An often mention requirement for AIBSs can be summarised as **Task Support and Service Features**. Experts point out that interaction with AIBSs has the main goal to support employees in their daily work in order to fulfil tasks more quickly and thus save time and therefore money, summarised as increased effectiveness and efficiency. AIBSs can particularly adopt repetitive tasks for which no cognitive abilities are needed. One expert specified AIBSs as *“An expedient”* and further *“A way that it makes my work easier and I can take care of what I enjoy”* (E3). Service Features can be seen as a comparison between what the employee feels should be offered and what is provided, in other words, the discrepancy between perceptions and expectations (Pitt et al. 1995). In this case, users should have the overall opinion that AIBSs increase the effectiveness and efficiency at work.

A major aspect when designing AIBSs are **System Characteristics**. This requirement essentially describes the technical characteristics of the system. Experts point out that AIBSs have to be user-friendly, reliable and extensible as well as provide a quick response. Combined, the ease of use and learnability of AIBSs must be guaranteed. One expert depicted *“It has to be simple and practicable and it has to deliver additional benefits right from the start”* and more *“It has to be easy to use”* (E6). Technology needs to be understandable and usable, delightful and enjoyable, with the goal to actually fulfil human needs (Norman 2013). In addition to paying attention on engineering, manufacturing and ergonomics, aesthetics of form and the quality of interaction must be taken into account (Norman 2004). The system acceptability must always be guaranteed in order to be utilised by users.

The requirement of **Implementation and Deployment** describes how systems are developed and how they are introduced within the organisation and to employees. The development of systems should not only be done by IT experts but integrate users who provide functional know-how. An introduction needs to involve affected employees to minimize the resistance against AIBSs. Furthermore, introduced systems should be reviewed regularly to ensure their functionality. One respondent explains that *“I need someone who is able to exploit the possibilities together with me in order to reach maximal benefits”* (E5). Barki and Hartwick (Barki and Hartwick 1989) describe participation as *“the behaviours and activities that users or their representatives perform in the system development process”* with the overall responsibility as a key dimension (Hartwick and Barki 1994). In the development of IS, it is considered an important factor for achieving system success and is commonly mentioned in research (Mann and Watson 1984).

Another significant point that has been mentioned are concerns about the **Connectivity and Collaboration** of AIBSs. On the one hand, enriching LIS with AIBSs means systems being interconnected and complementing each other and employees. On the other hand, through the collaboration with AIBSs, communication between departments and locations as well as between employees will be promoted. One attendee said that *“As an advantage I see the fact, that AIBSs can generally promote collaboration between centralised and decentralised units”* (E2). Systems can be designed to serve as knowledgeable collaborators of employees, helping to accomplish goals while ensuring to remain in control (Xu and Topi 2017), thus the collaboration is becoming a partner relationship (Oberquelle 1984; Oberquelle et al. 1983). AIBSs greatly enhance collaboration of people and resources in organisations (Tang and Sivaramakrishnan 2003). By using AIBSs, employees are

able to process all available and relevant data to mitigate unintentional bias in human decisions (Elson et al. 2018). In addition, systems can be joined into groups working together.

Another requirement for AIBSs is that users should learn through the interaction with such systems. Through the interaction with AIBSs users can, for example, prepare better for upcoming appointments and pay attention to matters they have previously disregarded. Therefore, **Enhanced User Performance and Service Training** means enhancing people's (cognitive) performances by learning from AIBSs as well as challenging employees' cognitive abilities. One interviewee clarified that *"It is also increasingly important that I as a user quickly have a value. I think this factor should not be underestimated"* (E7). Learning from AIBSs and thereby enhancing the performance of employees should have a positive effect on the organisation: the technology should be an instrument to enhance people's performance. Interaction with AIBSs helps to boost performance at work (Siddike et al. 2018) and helps to overcome human limitations and enhance human abilities (Rouse et al. 2009).

4.2 Validation

In total, 150 participants took part in the study, 124 of whom completed it. After excluding data sets with a short completion time (below 5 minutes) and answers with significant similarities as well as analysing the two validation questions as the last step of the survey, we resulted in N = 101 participants. In terms of gender, 48 (47,5%) were female, 53 (52,5%) were male with a minimum age of 22 and a maximum of 64 (M = 37, SD = 9.79). Regarding the level of education, 12 (11,9%) have an apprenticeship, 8 (7,9%) a secondary school degree, 15 (14,7%) a high school degree, 60 (59,5%) a university degree and final 6 participants have a PhD (6%). Participants live in a variety of different countries, with the majority in the United Kingdom (35/34,7%) and Germany (26/25,8%), working in full-time employment (75/74,3%), part-time employment (18/17,8%), self-employed (6/5,9%), mainly in companies of a size between 1 and 49 employees (21/20,8%), 5.000 and 9.999 employees (22/21,7%) and 1.000 and 4.999 employees (18/17,82%). In terms of industries, most participants work in IT (23/22,8%), consumer goods (12/11,9%) and energy (12/11,9%). 34 companies (33,7%) are using AI and 67 (66,3%) are not. For validating which design requirements are relevant for enriching LISs, we assessed the correlation coefficient of the constructs using the Pearson correlation (Zhou et al. 2016). We found significant correlations between design requirements and business value (cf. Table 1): 1) Acceptance and Adoption ($r = .324, p < .001$), 2) Task Support and Service Features ($r = .353, p < .001$), 3) System Characteristics ($r = .329, p < .001$) and finally 4) Enhanced User Performance and Training ($r = .477, p < .001$).

| Requirement | Pearson's r | p |
|--|-------------|--------|
| Strategic Orientation | .079 | .434 |
| Process Organisation | .146 | .145 |
| Acceptance and Adoption | .324*** | < .001 |
| Authenticity, Trust and Transparency | .172 | .086 |
| Security, Privacy and Ethics | .085 | .397 |
| Task Support and Service Features | .353*** | < .001 |
| System Characteristics | .329*** | < .001 |
| Implementation and Deployment | .156 | .120 |
| Connectivity and Collaboration | .154 | .125 |
| Enhanced User Performance and Training | .477*** | < .001 |

Table 1. Pearson's r between requirements and business value (*** significant at < 0.001 (2-tailed))

5 Discussion and Implications

IS used in organisations to improve business performance (Neumann et al. 2014), regulate resources and enhance efficiency, effectiveness and productivity (Xu and Topi 2017). However, the steady progression in improving technologies and the need of securing future success of organisations lead to new requirements especially for LISs, systems that have been used for decades but are not easy to replace (Hasselbring 2000) and remain vital assets for organisations (Bianchi et al. 2003). Thereby, the integration of AIBSs enriching LISs provides great potential for organisations. The goal of this

study was to identify design requirements from a business perspective that need to be considered to design AIBSs. Overall, managers assess 4 of 10 requirements as vital to generate business value (cf. Figure 1).

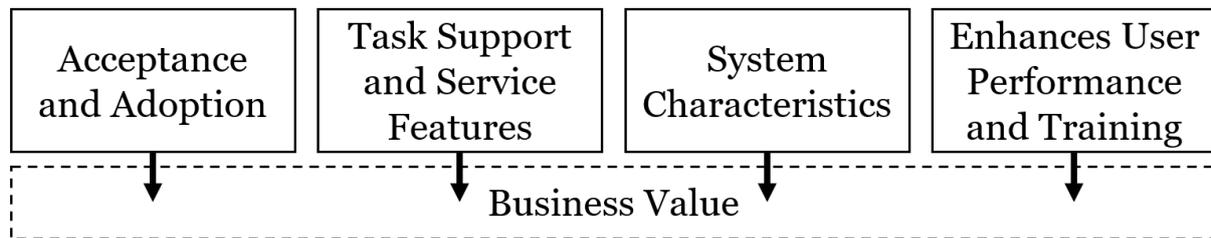


Figure 1. Significant requirements generating business value for AIBSs enriching LIS in enterprises

Acceptance and Adoption is considered significant. This goes in line with earlier research identifying acceptance as crucial for any technological advancement (Taherdoost 2017). We interpret this to mean that managers have a great interest in employees accepting AIBSs in order to really use them in the workplace. Furthermore, Task Support and Service Features assists employees in their daily work to perform tasks more efficiently, thus saving time and money. Our results show that managers consider this to be relevant for the future success of enterprises. We understand that the introduction of AIBSs enriching LISs must always create benefits for the applying organisation. The same might be valid for Enhanced User Performance and Training. Previous research explains that AIBSs can boost performance at work (Siddike et al. 2018) and enhance human capabilities (Rouse et al. 2009). We argue that manager might perceive AIBSs as a suitable method to educate employees and train them faster for a certain task. By improving the skills of employees, the organisational revenue might be increased. System Characteristics, as the last significant requirement, explains that the ease of use and learnability of AIBSs must be guaranteed. This was confirmed by previous research (Norman 2013). We thus state that managers sense quick values for enterprises when AIBSs are easier to use.

Surprisingly, according to the survey of managers, many of the requirements were not significantly related to business value. In case of Strategic Orientation and Process Organisation, we appreciate that LISs are probably not necessarily aligned with the overall business strategy but rather have an end of life. Therefore, AIBSs enhancing existing systems temporarily are less aligned with the strategy or new processes and are thus intended to create benefits in the short term. We interpret the missing correlation of Authenticity, Trust and Transparency that managers may not care whether employees understand the results of AIBSs. Even though the decision-making process needs to be transparent for trust building (Wünderlich et al. 2013) it is not necessarily essential if employees are forced to use a system. This might also apply for Security, Privacy and Ethics and further, doubtful decisions are not in the spotlight of the industry but profit maximisation. Regarding Implementation and Deployment, managers might simply not be interested in how services are developed but focus on the overall strategic outcome. Finally, Connectivity and Collaboration might miss any correlation as managers do not exactly know what AIBSs are capable of. This is also shown by our study as only 34 companies (33,7%) are using AI, thus the application in enterprises is not yet very widespread.

This research is not free of limitations. First, we derive design requirements from a limited group of ten experts. Although a number of experts was involved, they can each only cover their own perspective. In addition, interviews were conducted in just one holding organisation, although the experts represent very different departments. We describe results from an online survey which is based on a sample size of $N = 101$. Although the spread of AIBSs in organisations is increasing (Dwivedi et al. 2019), it was still difficult to acquire more participants from the management level who were already familiar with AI. Last, our design requirements do not cover personal user characteristics and innovativeness as major moderating effects on the intention to use such systems (Rzepka and Berger 2018).

The contribution of this paper is interesting for researchers and practitioners equally to design, implement and deploy AIBSs in enterprises to enrich LISs. From a theoretical point of view, this paper gives an overview of requirements to design AIBSs and provide insights for areas where future in-depth research is needed. IS researchers can better understand AIBSs' targeted characteristics which are fruitful to positively influence business value in enterprises. From a practical point of view, organisations appreciate the business value which can be generated by using our requirements. Enterprises following the recommendations are more likely to generate advantages over competitors. Practitioners further understand which design requirements are relevant for existing IS. Future

research should dive deeper into the design requirements as many of the requirements are rather broad. Therefore, studies need to conduct in-depth research working out the individual conditions for each requirement. In addition, IS scholars might also be interested in using the requirements to design an AIBS and evaluate a prototype in a real-world scenario possibly refining the design requirements.

6 Conclusion

Enterprises have been using IS for decades, however, many of those slowly became LISs. Nevertheless, organisations still need to adapt to ongoing technological advancements such as AIBSs. In this study, we have presented and discussed requirements for AIBSs from a managerial perspective. It became clear that executives consider design requirements as relevant that create business value in the short term. However, we argue that our requirements are still valid for AIBSs enriching IS in general. Admittedly, the picture painted by our research is far from clear as the requirements might have been formulated to broad. Researcher and practitioners need to watch future developments closely to understand how enterprises create and maintain business value using AIBSs.

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Paper 4: On the Ability of Virtual Agents to decrease Cognitive Load – An experimental study

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On the ability of virtual agents to decrease cognitive load: an experimental study

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Abstract

When attempting to solve a problem, humans call upon cognitive resources. These resources are limited, and the degree of their utilisation is described as cognitive load. While the number of parameters to be taken into account and to be processed by modern-day knowledge workers increases, their cognitive resources do not. Research shows that too high a load can increase stress and failure rates and decrease the work satisfaction and performance of employees. It is thus in the interest of organisations to reduce the cognitive load of their employees and keep it at a moderate level. One way to achieve this may be the application of virtual assistants (VAs), software programs, that can be addressed via voice or text commands and respond to the users' input. This study uses a laboratory experiment with $N=91$ participants comparing two groups in their ability to solve a task. One group was able to make use of a VA while the other could not. Besides task performance, the cognitive load of the participants was measured. Results show that (a) cognitive load is negatively related to task performance, (b) the group using the VA performed better at the task and (c) the group using the VA had a lower cognitive load. These findings show that VAs are a viable way to support employees and can increase their performance. It adds to the growing field of IS research on VAs by expanding the field for the concept of cognitive load.

Keywords Cognitive load · Virtual assistants · Chatbots · Conversational agents · Task performance · Perceived workload · NASA-TLX

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1 Introduction

The working memory plays an important role in learning and processing of information. As its capacity is limited so is the amount of information that can be processed at the same time. The amount of working memory used during this processing is called cognitive load (Sweller 1988). The concept of cognitive load originates in behavioural psychology and the realm of learning but has since been transferred to research on other disciplines, amongst others to Information Systems (IS) (e.g. Hu et al. 2017). Studies have also transferred the concept to the working context and could, for example, show that work-related well-being was decreased when the cognitive load was too high (Pace et al. 2019). Even more severely, findings also indicate that task performance of employees seem to suffer under too high a load (Altaf and Awan 2011). Taken together with the digitalisation that takes place in almost all industries and poses challenges to both employers and employees who need to adapt to new and complex processes (Matt et al. 2015) it is increasingly important to control the cognitive load experienced by employees in order to ensure their well-being and in turn the performance of the employer.

However, the digitalisation does not only pose challenges but also offers opportunities to reduce the workload, for example in the form of virtual assistants (VAs). These computer-based support systems are projected to be used by at least a quarter of digital workers within the next two years (Maedche et al. 2019). It follows that research has looked at the application of this technology in the working context from several angles, e.g. its potential for support in customer service (Cui et al. 2017) or internal communication (Stöckli et al. 2018). Furthermore, introducing VAs in organisations aims at reducing the workload of employees by assisting in the execution of work-related tasks (Norman 2017). Research on whether support through computer-based systems may be able to reduce the workload yields ambiguous results (Moreno et al. 2001). On the one hand, studies show that learning is promoted (e.g. Moreno et al. 2001; Schmuntzsch et al. 2012) and superior results are achievable (Mechling et al. 2010). On the other hand, the learning process is not always facilitated (Schnotz and Rasch 2005) and work performances can be impacted negatively (Chandler and Sweller 1991). However, to our knowledge, the potential of VAs to reduce cognitive load, or the question whether they even interfere when performing tasks, has not yet been addressed sufficiently. If these systems are actually to become widely-used within a few years and they furthermore hold the potential to reduce the workload, they could be a feasible way to relieve employees, thus supporting their well-being and performance, and they could therefore be of great value to enterprises. However, to make informed assumptions on this topic, more research is needed as it is currently inconclusive, which is why more clarification is necessary. The aim of this paper is thus to shed light on these aspects, especially on the ambiguity regarding the in- or decrease in cognitive load through technology and thus to answer the following questions:

RQ1 To what extent do virtual assistants influence the perceived workload during the solution of a task?

RQ2 How do participants supported by virtual assistants compare to those without support regarding their performance at a task?.

To address this shortcoming, we conducted an experiment with $N=91$ participants in two groups that had to solve a work-related task and where one group was supported by a VA. We then measured and compared the cognitive load of the participants in the two groups and their actual task performance. The paper presents the findings and aims to shed light on the potential of VAs to positively influence the cognitive load of their users. It first presents current literature on cognitive load and VAs before detailing the chosen methodological approach. Afterwards the results are described and discussed, followed by the conclusion as to what extent VAs are feasible to influence the cognitive load of employees.

2 Theoretical background

2.1 Cognitive load

Cognitive load theory explains how factors such as task difficulty and people's available mental resources influence their success in learning to solve problems effectively (Sweller 1988). It originates in educational psychology. An underlying assumption is that a learner has limited cognitive capacity that he or she can make use of when attempting to solve a problem. Effective learning takes place when the learner develops the ability to recognise that the task belongs to a category of problems, and knows which steps are normally required to solve such problems. This process is referred to as schema acquisition (Sweller 1988). It can only take place when enough cognitive capacity is available for categorising and systematising knowledge (germane cognitive load). If it is taken up by the task's inherent cognitive load demands (intrinsic load) and by additional cognitive load that is unnecessarily imposed, for example, by poor instructional design (extraneous cognitive load), then learning cannot take place (Paas et al. 2003). This implies that, counterintuitively, if all of one's cognitive capacity is devoted to achieving a specific goal set by the instructor, learning can actually suffer, and a goal-free approach might be better (Sweller 1988). The psychological resistance to stress or difficult situations, known as resilience (Neyer and Asendorpf 2017), might further impact the cognitive load in addition to task difficulty and people's available mental resources. The term resilience is defined as "*positive psychological capacity to rebound, to 'bounce back' from adversity, uncertainty, conflict, failure or even positive change, progress and increased responsibility*" (Luthans 2002). Resilience is related to satisfaction or commitment of employees at the workplace (Youssef and Luthans 2007) and changes when known behaviour and common

procedures vary. Cognitive load theory has obvious implications for instructional design. An overloaded or underloaded learner will acquire problem-solving skills less effectively. An appropriate instructional procedure should therefore encourage learners to use their cognitive resources in a way that furthers learning, while at the same time avoid demanding cognitive resources unnecessarily.

Cognitive load theory also has implications for management. In an organisational setting, the concept of learning how to solve a problem by attempting to solve it is commonplace, if not as a result of deliberate instructional design, then as a practical consequence of business demands. In an age of frequent technological and organisational change, Galy et al. (2012) argue, managing workload is an important part of ensuring employees' wellbeing and safety. Exorbitant cognitive load can have negative implications on business decisions: for example, managers under high cognitive load may face difficulties in evaluating job candidates appropriately (Nordstrom et al. 1996).

2.2 Virtual assistants in organisations

The deployment of virtual assistants in organisations seems reasonable for managing employees' workload, facilitating tasks and improving business decisions. Various synonyms for VAs exist which are used interchangeably (Luger and Sellen 2016). Terms that can be found in research and practice are, for example, *voice assistants* (Diao et al. 2014; Alepis and Patsakis 2017; Hoy 2018), *personal assistants* (Moorthy and Vu 2015; Sangyeal and Heetae 2018), *cognitive assistants* (Siddike and Kohda 2018; Siddike et al. 2018) or *conversational agents* (Saffarizadeh et al. 2017). Similar to the variety of words, there is no consensus on a precise definition. Researchers and practitioners explain VAs from different perspectives such as their primary mode of communication or their main purpose (Gnewuch et al. 2017) as well as by their tasks and system characteristics (Strohmann et al. 2018). The explicit classification of VAs in one of these categories is simply not possible due to overlaps. Text-based VAs might use speech-to-text modules to convert human language into text (Gnewuch et al. 2017). VAs might also be further developed and customised to adapt features to individual needs or specific tasks (Chung et al. 2017). However, VAs can generally be described as systems interacting with users by simulating the behaviour of human beings and using natural language (Luger and Sellen 2016; McTear et al. 2016; Diederich et al. 2019) to assist in the execution of work-related tasks or even have them fulfilled entirely (Norman 2017). In the current context, the definition used by Stieglitz et al. (2018) to define the term VA seems to fit best for our purpose: "software programs that can be addressed via voice or text and that can respond to the user's input (i.e. assist) with sought-after information" (p. 3).

Research has recently gained an interest in the interaction with VAs (Gnewuch et al. 2017) since building systems with the help of artificial intelligence and machine learning algorithms has become more practical to assist users in a wide variety of tasks (Knijnenburg and Willemsen 2016). VAs are particularly helpful in tackling repetitive tasks that require the fast retrieval and processing of digital data as well as the understanding of complex interdependencies (Dellermann et al.

2019). By tailoring systems to the users' needs, better assistance and added value can be generated (Maedche et al. 2016). Due to the fact that numerous benefits are generated, especially regarding competitive advantage, organisations are heavily investing in VAs (Schuetzler et al. 2018). Applied in organisations, for example in banking, insurance or retail, VAs aim at the prospect of generating additional revenue or cost savings (Quarteroni 2018) and positively influencing the customer's satisfaction (Verhagen et al. 2014). VAs can be used for the direct interaction with customers. When assisting while shopping online, VAs provide advice to find suitable products and thus reduce information overload (Benbasat and Wang 2005; Qiu and Benbasat 2009). Moreover, users are supported when having inquiries regarding the company's services (Quarteroni 2018). In addition, VAs also have the potential to enhance processes within organisations. Systems are utilised in human resource departments to facilitate the onboarding process of new employees by providing a question-and-answer assistant (Shamekhi et al. 2018). Further, VAs are applied in customer service (e.g. (e.g. Gnewuch et al. 2017; Hu et al. 2018) to reduce the workload of call centre agents. By supporting the handling of customer enquiries with VAs (McTear et al. 2016), a solution for users can be proposed immediately (Frick et al. 2019) as requests can be handled without additional overhead (Stieglitz et al. 2018).

2.3 Virtual assistants and cognitive load

Research has already taken several attempts to validate if the cognitive load can be reduced through the deployment of various technologies. Moreno et al. (2001) showed that students interacting with an animated pedagogical agent via natural language outperform students not using an agent when learning. Another study could show that VAs, embodied by an animated character, help to focus on relevant information and facilitate learning thus supporting users performing physical tasks (Schmuntzsch et al. 2012). However, a VA could also interfere with successful learning. Interacting with it requires the participant to exert cognitive resources. Cognitive load theory has long recognised that this additional, extraneous cognitive load may eliminate the benefit from the additional instruction (Tarmizi and Sweller 1988). Seemingly useful material can negatively impact performance if it is not essential to solving the task (Chandler and Sweller 1991). Schnotz and Rasch (2005) found that facilitating learning is not always beneficial as users are prevented from performing relevant cognitive processes on their own. Lohse et al. (2014) examined robot gestures and report that a higher human–robot interaction increases user performance and decreased cognitive load for difficult tasks but not for easy tasks. Regarding virtual agents, Moreno et al. (2001) make a similar argument, and refer to the constructivist hypothesis (that agents help learning) and the interference hypothesis (that they hinder it).

The application of VAs in organisations seems beneficial to facilitate internal processes and to gain competitive advantage in that it supports workers in better completing their tasks (Morana et al. 2017). As studies indicate that increased cognitive load at the workplace hinders employees from reaching their full potential

(Altaf and Awan 2011), it should be in the interest of organisations to keep this load at a moderate level. The utilisation of VAs aims at doing exactly that: reducing the cognitive load when enhancing humans in work-related tasks for further performance improvements. This might create significant benefits for the applying organisation itself and further for its customers. Studies have already shown that, under certain circumstances, cognitive load can be reduced through the use of technology, increasing the user performance. For example, Mechling et al. (2010) could show that groups instructed by a digital assistant showed better results than groups without that support. Likewise, cognitive load might be enlarged when dealing with additional instructions or different tasks. Until now there has not yet been any research giving evidence if VAs are able to reduce the cognitive load or if they even interfere when performing tasks. To test this, we conducted an experiment with two groups which had to solve a task and where the experimental group could use a virtual assistant to solve the task while the control group could not. In the following section we will describe the structure of the experiment, the task that was to be solved as well as the measures that were collected.

3 Method

3.1 Participants

The experiment was conducted at a German University between 28 May and 18 June 2019. The university's students were invited to participate on a voluntary basis. In this timespan, 91 people participated in the study. We then randomly assigned the participants into two groups, resulting in a well-balanced sample of 46 participants in the control group without a virtual assistant and 45 in the experimental group using a virtual assistant. Overall, 54.9% of the participants were female ($N=50$), and their age ranged from 18 to 31 ($M=22.01$, $SD=3.02$), indicating a rather young sample. Furthermore, 80% of the participants had passed their A-levels while 14% held a Bachelor's degree. Together with the young age and in accordance with the mode of acquisition of the sample this shows a typical undergraduate student sample.

3.2 Materials

3.2.1 NASA task load index (NASA-TLX)

Concepts related to cognitive load are frequently measured using self-report rating scales (Paas et al. 2003). This approach assumes that learners are able to report the amount of mental effort that they experienced while attempting to solve a task. It is worth noting that self-report rating scales do not typically distinguish between the three types of cognitive load (intrinsic, extraneous, germane) but rather measure the overall load experienced.

A commonly used scale to quantify the perceived workload of a participant is the NASA Task Load Index (Galy et al. 2012). The National Aeronautics and Space Administration (NASA) developed the NASA-TLX in order to measure the perceived workload of a task (Hart and Staveland 1988). This measurement was successfully used in several contexts such as in both laboratory and field studies (Rubio et al. 2004; Noyes and Bruneau 2007; Cao et al. 2009). The index itself contains six subjective subscales forming the NASA-TLX score: (1) Mental Demand, (2) Physical Demand, (3) Temporal Demand, (4) Performance, (5) Effort, and (6) Frustration. These clusters of variables were chosen to cover the “range of opinions and apply the same label to very different aspects of their experience” (Hart 2006, p. 904). Due to the subjective experience of conducting a specific task, the NASA-TLX was developed to consider the perception of a variety of activities such as simple laboratory task or flying an aircraft. While (1) describes how much mental and perceptual activity was required, (2) shows the perceived amount of required physical activity. Besides the perceived mental and physical efforts, the NASA-TLX also covers the perception of time pressure (3) during a task. Furthermore, the subscales (4) to (6) ask about the perception of the results of the given tasks. Therefore, (4) describes the personal performance perception – i. e. the perceived success reaching the given goals of the tasks and (5) asks to what extent the participants had to work to reach the achieved level of performance. As people sometimes feel frustrated when a given task is perceived as too difficult, subscale (6) asks the participants about the level of frustration during the task (Hart 2006). In our experiment, all subscales had high reliability (Cronbach’s $\alpha=0.89$).

3.2.2 Resilience scale (RS-11)

According to the appraisal theory, stress emerges when a task at hand exceeds one’s own resources and abilities (Smith et al. 2011). Following, an increasing level of stress might impact the participant’s task performance as well as the perception of the work and its outcome. In order to avoid undetected distortion towards the task performance, we consider the psychological resistance to stress or difficult situations, known as resilience (Neyer and Asendorpf 2017). We use the Resilience Scale (RS-11) as a short scale for assessing the resilience of a human (Schumacher et al. 2005). The RS-11 is a self-report scale containing eleven items which are divided into two sub-scales: (1) personal competence and (2) acceptance of the self and life. The subscales had a high reliability, all Cronbach’s $\alpha=0.90$.

3.2.3 Virtual assistant

In order to investigate the impact of a text-based VA on decreasing the cognitive load during task-solving, we made use of Google’s cloud platform *DialogFlow*.¹ This platform is widely used for developing natural and rich conversational experiences based on Google’s machine learning (Canonic and De Russis 2018).

¹ <https://dialogflow.com/>.

Furthermore, the implementation is based on four general concepts (Muñoz et al. 2018). First, *Agents* transform natural user language into actionable data when a user input matches one of the intents. Second, *Intents* represent a mapping between what the user says and what action is taken. Third, *Entities* represent concepts and serve as a tool for extracting parameter values from natural language inputs. Finally, *Contexts* are designed for passing on information from previous conversations or external sources. To reduce the degree of complexity caused by the interaction with the VA, we focused on establishing a disembodied VA with a messaging-based interface (Araujo 2018).

As VAs exhibit social and conversational dialogue (Hung et al. 2009), our VA is implemented to make a simple conversation at the beginning of the interaction. Participants can interact with the VA via a web-based interface, similar to contemporary instant messengers such as Telegram or WhatsApp, using a keyboard and a computer screen. This interaction could be a request for the participant's name and feelings. Furthermore, the applied VA is text-based to avoid additional influential factors which may evolve by voice interactions or embodied avatars. Figure 1 shows a translated example of a dialogue with the VA.

To support the participants during the task, the assistant simulates intelligence by selecting a prefabricated answer based on distinct keywords used in the participant's input. We defined 25 Intents to match the user input. The intents belonged into roughly 3 groups: Introduction, Tutorial and Task Support. The Intents in the Introduction Group mostly revolved around welcoming the users, asking for their well-being and readiness to start the task. The tutorial intents were designed to increase the users' familiarity with the VA and the capabilities of the VA. Most of the intents revolved around Task support where users could ask for help solving the task, for example by asking what certain parameters meant or how they were calculated. We also used the standard „sys.given-name“ entity provided by DialogFlow as an Entity. The VA's feedback includes a question-answering component (Morrissey and Kirakowski 2013; Lamontagne et al. 2014) that can be queried by the user to gain information, support and instruction about the specific task. In this context, the VA only provides helpful hints which support the participants solving the task. However, the VA does not deliver the actual solution to the current task.

3.2.4 Task performance and pre-study

Task performance was measured with a score ranging from 0 to 28 that captures how well participants did at a critical path method (CPM) task. A higher value represents a better performance in the execution of the task. The goal of this task was to use this method to plan a research project for the market research unit of a large organisation.

The task was determined in a pre-study to ensure that it is sophisticated and involves a potentially high perceived workload in the experiment. The sample of 10 participants (6 female, 4 male) consists of randomly selected students at the University. In this context, a good fitting task challenges the participants on decent level, and therefore causes an increased cognitive load score. A task which overwhelms

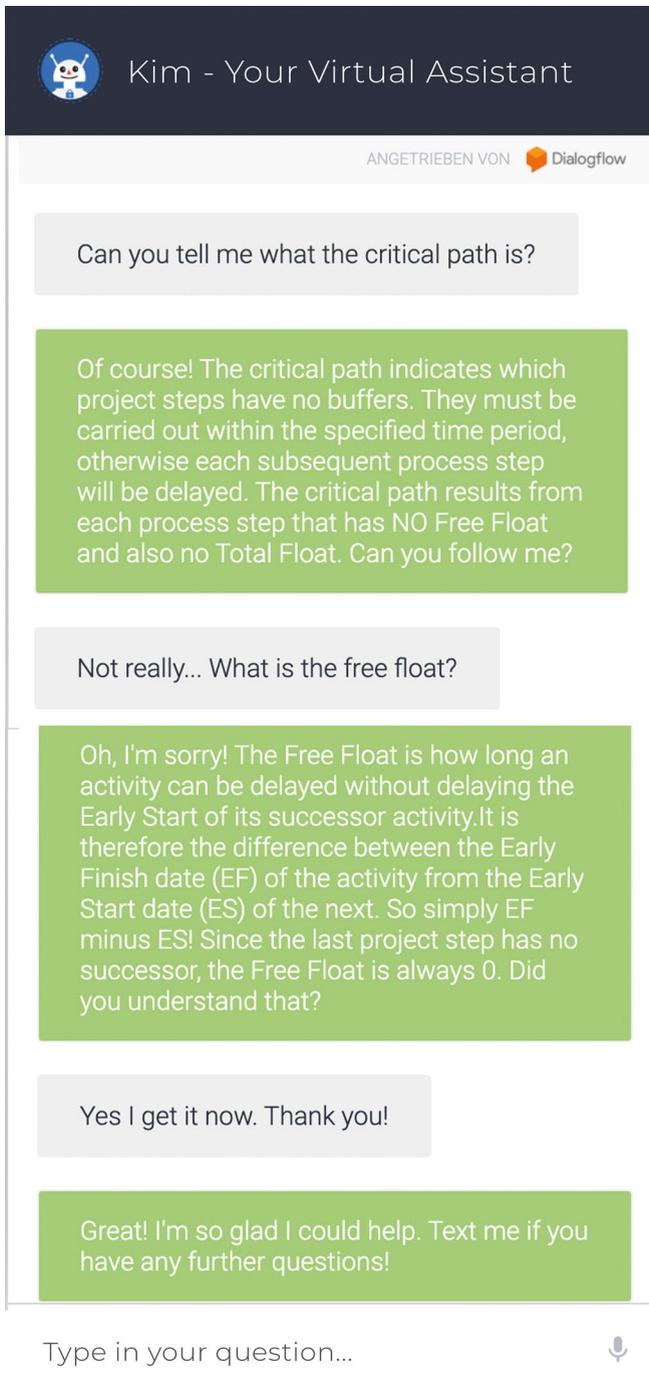


Fig. 1 Example of a dialogue with the Virtual Assistant

the participants may prevent sustained learning effects due to less available cognitive resources (Paas et al. 2003). To this end, a text-based task (TBT) and CPM were compared. On the one hand, the TBT required the participants to read three texts about medieval ages, a topic which does not rely on previous knowledge of the participants. On the other hand, the CPM was implemented with a scenario that puts the participants in a working context. In detail, the participants had to organise a marketing study using the CPM. The time limit for each of the tasks was 10 min.

Each task was given to five participants and the perceived workload was measured by the NASA-TLX. The age ranged from 22 to 31 ($M=25$). On average, participants given the CPM task engaged in higher NASA-TLX scores ($M=12.5$, $SD=3.85$) than the TBT group ($M=6.36$, $SD=4.06$). This difference of 6.13 was significant (95% CI [0.35, 11.91], $t(8)=2.44$, $p=0.040$). Furthermore, it represents a large-sized effect, $d=0.98$. Following, the CPM task has the potential to increase the cognitive load of the participants in a more effective way than the TBT does. Thus, due to its better potential to benefit from the use of a virtual assistant, the CPM was chosen for the main study.

3.3 Procedure

In order to investigate the influence of a VA on the perceived workload of a participant, the experiment used a between-subjects design. The independent variables were the resilience score (RS-11) and the usage of a VA (group variable) whereas the dependent variables were the perceived workload (NASA-TLX), the task-score as well as the time to finish the task. Analyses were conducted using the software SPSS Statistics (Version 25) and Jamovi (1.0.2.0).

The main study was conducted as a laboratory experiment at a German University in German language. A laboratory experiment was chosen to better control the surroundings, to ensure that the task performance was measured correctly and to ensure a steady and even experience with the virtual assistant. Furthermore, the investigators were present to assist the participants with questions should those arise. However, their assistance was not utilised by any of the subjects.

The participants were welcomed by the investigator and introduced to the study. They were then led to a computer to begin with the first questionnaire. First, the participants were presented with the RS-11 questionnaire to retrieve the resilience score.

Afterwards they were presented with an introduction to the CPM followed by an example. After reading through the briefing, participants were instructed to contact the investigator for the material needed. The goal was to use the CPM to plan a research project for the market research unit of a big organisation. Participants were given a list with unordered process steps (such as "literature research", "conducting the study" or "develop methodology"), the respective duration for each step as well as its dependencies on the other steps in the process. They were also handed an empty template for a CPM to fill out with the according parameters. Finally, the participants were informed of a virtual folder they were allowed to use which was

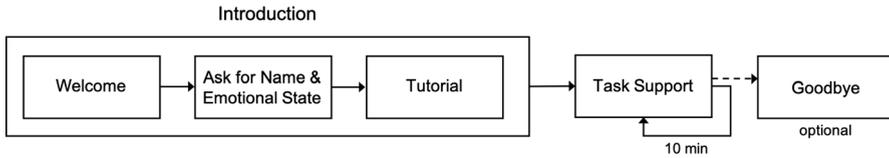


Fig. 2 Depiction of the interaction with the Virtual Assistant

located on the laboratory computer and included unordered text files explaining the CPM procedure and the calculation of the individual values.

Additionally, the participants in the experimental group were also presented with a sheet of paper which explained that they were allowed to use a text-based VA and that it was nested in a browser window in the computer. They were then explained how to use the VA properly such as using single sentences and that the VA did not have contextual knowledge. All subjects in the experimental group made use of the VA which provided the participants with the same information available in the folder to all groups but could be specifically asked for certain information, e.g. what certain parameters stood for or how they were calculated. Figure 2 depicts the steps a conversation with the VA consisted of. Except for the availability of the VA, the participants in the control and experimental group were presented the exact same task. Also, all participants had access to the same information for solving the task with the only difference that subjects in the control group could access the data via browsing through virtual folders on the computer whereas subjects in the experimental group could specifically access the information via dialogue with the VA.

Participants then had a time limit of 10 min to complete the task after which they had to stop solving the task even when they had not yet completed it. They were also instructed to give notice should they be finished before the time limit had run out. In the latter cases the investigator noted the time that was needed. After the participants either completed the task or the time ran out, they were re-referred to the computer to complete the remainder of the survey.

Following the task, the participants were presented with the NASA-TLX to assess their perceived workload immediately after solving the task. They were then asked whether they had already been familiar with the technique of CPM and the participants in the experimental condition were additionally asked whether they thought the support by VA was helpful.

Finally, all participants were asked for their gender, age, highest educational attainment and were debriefed, asked whether they had any further questions and then thanked for their time.²

² The concrete wording as well as the items can be taken from the supplementary material in the electronic version of this article.

4 Results

4.1 Descriptive statistics

Overall, 95% of the participants who used the virtual assistant found it helpful and on average had 14 interactions with the chatbot (where one interaction is defined as one user input followed by one chatbot reply), 94.3% of which were matched (i.e. the chatbot was able to match the input with intent). Participants scored between 0 and 28 points in the task, with $M=16.68$ ($SD=7.81$, $Med=17$) indicating that most of the participants achieved more than half of the 28 points possible. 14% reached the maximum score of 28 points. 70% of participants used the full 10 min to complete the task, 3.3% needed less than 5 min. Only 4 participants had already used CPM.

4.2 Relation between perceived workload and task performance

To check whether the perceived workload was connected to the performance of the participants, we conducted a bivariate correlation separate for each group (i.e. with assistant and without assistant). In both groups the NASA-TLX score showed a significant negative correlation with the performance score, indicating a better performance when the cognitive load was lower. The correlation $r(46)=-0.673$, $p<0.001$ in the control-group without an assistant was larger than in the experimental group with the assistant $r(45)=-0.462$, $p<0.001$. To assess whether this difference was meaningful, we calculated the z-scores, which showed that the correlation between NASA-TLX and task-score was not significantly different between the two groups ($Z=1.458$, $p=0.072$) which indicates that, regardless of the condition the participants were in, a higher cognitive load was connected to worse performance.

4.3 Resilience and perceived workload

A t-test was conducted to investigate possible differences between the groups in the participants' resilience. To test whether the resilience of the participants influenced their perceived workload, the correlation between the two variables was calculated for each of the groups. To assess whether the strength of a possible relationship differed between the groups, a z-test was used to determine if the two correlations differed significantly.

The t-test for a difference in mean resilience score between the group with the assistant ($M=130$, $SD=20.5$) and the group without the assistant ($M=128$, $SD=14.6$) does not indicate a significant difference, $t(89)=-0.52$, $p=0.602$, $d=-0.110$. In both groups, resilience and cognitive load correlated significantly with $r(46)=-0.354$ ($p=0.016$) in the control group and $r(45)=-0.380$ ($p=0.010$) in the experimental group. The correlation coefficients did not differ significantly between the groups ($Z=0.139$, $p=0.445$), indicating that the higher the participants' resilience, the lower the perceived workload – regardless of the group.

4.4 Performance of the groups

To assess whether performance differences between the groups with and without an assistant exist, we calculated an independent t-test with a 95% confidence interval and with the task-score as independent variable and the groups as factor (Table 1). As Levene's Test for Equality of Variances was not significant ($p=0.767$), equal variances were assumed. On average, participants who used an assistant performed better ($M=19.76$, $SD=7.36$) compared to participants in the group without an assistant ($M=13.67$, $SD=7.09$). This difference was significant $t(89) = -4.01$, $p < 0.001$ and represents a large-sized effect ($d=0.84$).

4.5 Difference between cognitive load of the groups

Next, to test whether participants using the assistant differed in their reported perceived workload, we conducted an independent t-test with a 95% confidence interval and with the NASA-TLX-score as independent variable and the groups as factor (Table 2). Levene's Test for Equality of Variances was not significant ($p=0.470$). The mean of the group without the assistant was significantly ($t(89)=3.55$, $p < 0.001$) higher ($M=10.28$, $SD=4.52$) than the mean of the group using an assistant ($M=7.17$, $SD=3.79$), indicating a higher perceived workload for the group without an assistant. The effect size was large ($d=0.75$).

4.6 Time needed by the groups

An independent t-test with the groups as factor and the time needed to complete the task was calculated to check whether one group on average took less time

Table 1 Comparison of Task score performance between the groups

| | Group | N | Mean | Median | SD | SE |
|------------------------|-------------------|----|------|--------|------|------|
| Task score performance | Without assistant | 46 | 13.7 | 14.0 | 7.36 | 1.09 |
| | With assistant | 45 | 19.8 | 20.0 | 7.09 | 1.06 |

Max. Score: 28

Table 2 Comparison of perceived workload between the groups

| | Group | N | Mean | Median | SD | SE |
|----------------|-------------------|----|------|--------|------|-------|
| NASA-TLX score | Without assistant | 46 | 10.3 | 11.3 | 4.52 | 0.666 |
| | With assistant | 45 | 7.17 | 6.83 | 3.79 | 0.565 |

Max. Score: 20

Table 3 Comparison of time needed for working on the task between the groups

| | Group | N | Mean | Median | SD | SE |
|----------|-------------------|----|------|--------|------|------|
| Time (s) | Without assistant | 46 | 586 | 600 | 58.0 | 8.56 |
| | With assistant | 45 | 518 | 578 | 107 | 16.0 |

Max. time: 600 s

Table 4 Comparison of personal performance perception between the groups

| | Group | N | Mean | Median | SD | SE |
|---------------------------------|-------------------|----|------|--------|------|-------|
| Personal performance perception | Without assistant | 46 | 10.1 | 8.50 | 6.86 | 1.01 |
| | With assistant | 45 | 7.00 | 5.00 | 5.70 | 0.849 |

Max. Score: 20

than the other (Table 3). As Levene's test for equality of variances was significant ($p < 0.001$), degrees of freedom were adjusted from 89 to 67. The control group without the VA needed significantly more time ($M = 586$ s, $SD = 107$) than the group with the assistant ($M = 518$ s, $SD = 107$), $t(67.35) = 3.74$, $p < 0.001$. $d = 0.79$ indicated a large effect size.

4.7 Difference in the personal performance perception of the groups

As subscale 4 of the NASA-TLX measured the perception of the participants own performance in completing the task it was used to assess whether this perception differed between the groups. A lower value on this scale indicates a better performance. An independent t-test with a 95% confidence interval was calculated. Levene's test for equality of variances was significant ($p = 0.045$), and the degrees of freedom were reduced accordingly (from 89 to 86.74). The groups differed significantly ($t(86.74) = 2.32$, $p = 0.023$) with the participants in the control group without the VA having a higher mean ($M = 10.1$, $SD = 6.86$) than the participants in the experimental condition ($M = 7.00$, $SD = 5.70$) indicating that the former believed they did a worse job at completing the given task than the group using a VA believed of themselves (Table 4). The effect size was moderate ($d = 0.486$).

5 Discussion

5.1 Key findings and implications

One question this paper aimed to answer was how VAs influence cognitive load during the solution of a task, as previous literature presented inconclusive findings on this matter (e.g. Lohse et al. 2014). The current findings support the notion that VAs are suitable to decrease said load, indicating that the application of VAs also has an impact on the perceived workload of its users in that it reduces this workload as

well. Prior findings were ambiguous, indicating that the application of technology supporting users may also hinder the users because of the additional effort needed to learn interacting with the supporting system (Tarmizi and Sweller 1988). In our study this was not the case, for which there are several possible explanations. VAs may be easy and intuitive to use. As the interaction with the VA applied in our study takes place in text form and natural language akin to a chat with a human, this concept may be familiar with participants, especially regarding the young age of the sample. Thus, there is no additional effort needed to first learn how to use the VA and it can solely help in supporting to reach the goal. Based on this assumption, one takeaway from the study is that a VA which is easy to use and whose usage is not connected to any extra effort is a good way to support people in fulfilling certain tasks. Then again, the VA used in the current study had a very special focus as did the participants while solving the task. It may be that specialised VAs are able to more easily help solve special goals while VAs with a broader skill set may be less effective. However, in practice it is not always feasible to provide several VAs for several tasks. On the one hand, that may drive up costs for an applying organisation; on the other hand, it may also be counterproductive in that it actually would require the users to always have to pick the right VA according to the task at hand but in turn increasing workload as additional mental resources are needed to make that decision. However, this was not the current studies' scope but needs more elaboration in future studies.

From a learning perspective, the result that the group with virtual assistant perceived a lower mental workload, performed better on the task and also perceived their performance as better means that more resources could be available for germane cognitive load, which fosters schema acquisition and thereby improves learning (Paas et al. 2003). However, this process is not automatic. Depending on the design of the materials, people who are exposed to too little cognitive load could also be less likely to learn permanently how to solve the problem. In other words, the availability of a VA might have helped them perform their tasks better but at the same time made the task too easy for them to be able to later recall how they solved it. This effect could be detrimental to their performance especially if they will not always have the assistant available. Future studies should examine retention, and employers who consider supporting their knowledge workers with VAs should keep this point in mind to avoid an undesirable over-reliance on technology.

The current study furthermore examined the influence VAs could have on task performance. Here, the findings show that the application of VAs had a positive influence on the performance while solving a task. This is in line with findings from previous literature e.g. from the learning domain which reported that students which received support by a system akin to a VA performed better than those who did not have the support (Moreno et al. 2001; Mechling et al. 2010). However, the current study demonstrated this aspect on a domain rather related to the working environment. This finding supports assumptions made by other researches (e.g. Morana et al. 2017) and shows the importance that these systems may have in improving organisational performance (through its employees) which may also lead to a higher satisfaction of the latter. Furthermore, it demonstrates, that VAs are not only beneficial for organisations when applied in contact with its customers (cf. Quarteroni

2018) but also for its own employees. However, as we discuss in the limitations and outlook section, the current study was conducted as a laboratory experiment which means that its external validity (i.e. in a practical context) has to be shown in future studies. Nevertheless, these findings lay the groundwork for further evaluation of VAs in the working context. Aspects such as the applicability over various industries and for various tasks could be examined. Also, the acceptance by the users and the applicability for different tasks or categories of tasks need to be explored.

Connected to the aspects discussed before, the current findings also show that a reduced perceived workload is beneficial in reaching a higher score on task solution. The findings thus show that it is desirable to reduce the workload in order to improve performance. In context of a working environment and regardless of the application of VAs, employers should in general strive to support knowledge workers in eliminating any distraction. Processes in the way to reach a certain goal could be examined regarding unnecessary or outsourceable steps which could then be reduced to a minimum. Especially steps connected to repetitive or overhead (i.e. bureaucratic) activities seem to hold potential to be reduced as especially the latter have been found to be negatively related to the perception of work-related well-being (Pace et al. 2019).

One important finding is also that the personal predisposition in the form of resilience plays a role in the amount of perceived workload the participants felt. The higher the resilience of the participants, the lower their perceived workload – regardless of whether they used a VA or not. This means that, besides external support, personal predispositions do also play a role in the amount of workload people report. This is an important aspect that should not be overlooked as it indicates that a person can get all the help in the world and still have a high workload which may impede the performance in solving a task. Furthermore, different people may need different amounts of support in solving a task or reaching a goal, which is important to consider when evaluating any performance-related finding in regard to perceived workload. While this aspect is not at the focus of the current paper, it shows that individual predispositions should be taken into account and considered when conducting research and interpreting results on perceived workload and in turn cognitive load.

5.2 Limitations and future research

As with all research, several limitations to the findings apply. Our findings are based on a sample consisting mostly of undergraduate students. Because of their youth and thereby assumed familiarity with communication technology, the experimental group using the VA may have had less trouble operating the VA than an average adult that may be not as affine to modern communication technology. Furthermore, our paper aimed to research cognitive load and task performance in a working context, for which one may argue that students are not as feasible as actual employees with working experience. However, as Kretzer and Maedche put it “students are suitable subjects, and students may also tend to be less biased than experienced professionals due to their general relative youth

and lack of work experience.” (2019, p. 1156). Still, future studies may take this aspect into account and aim to replicate the findings on different samples that may be older or have experience in a working environment.

Furthermore, the task chosen in the current context may not completely represent daily work processes as it is rather abstract. Still, with regard to the measurability of the performance outcome, the task chosen in the current paper is, in our eyes, a good compromise as it accomplishes two things: It simulates a task in a working environment (such as a process that needs to be planned in a short time span) and it ensures measurability and applicability in a laboratory research setting, which increases the validity of the results. Nevertheless, future studies may alter the task and, for example, conduct a case study in a real-world setting. Our research thus also adds to the emerging body of work considering the “Operator 4.0” – the worker who relies on increasing automation at the workplace for increased efficiency (Romero et al. 2020). As the technology becomes more capable and people become more familiar with it, this field of research is poised to grow.

Future studies may also deeper examine the relation of personal predispositions and the effect of a heightened perceived workload. In the current paper, resilience showed that it impacted the perceived workload of the participants. First, this connection could be further examined – is this true for other samples or for other tasks? As the resilience was correlated with the perceived workload – which in turn was based on the task to solve it would be interesting to see how this relation holds up if the task is changed, e.g. to be more complex or easier. Furthermore, different predispositions could also be taken into account like the involvement in a certain topic that is investigated with the task, the personality of participants or technological affinity and the likes. This would lead to better insights into what aspects play a role in increasing or decreasing perceived workload in individuals.

As the cognitive load theory originates in educational psychology it would also be interesting to conduct time-series analyses. These could show the effect learning has on the task performance. This way, the effectivity of VAs over time may be shown, e.g. to be even greater, as participants get used to working with such systems, possibly reducing cognitive load that is initially needed to adapt to the system. While the aspect of adapting to a VA didn’t seem to play a role in the current study, future studies that alter the task or the VA could help shed light on this aspect. This may be especially interesting to test how the interaction with a VA evolves over its lifespan and to evaluate its long-term value, for example for organisations.

Future studies should also examine whether our findings hold true for alternate VA approaches. For example, in the current study, the response the participants in the experimental group got was instant—i.e. there was no delay between sending a question to the VA and getting feedback (in part due to the realisation via Dialog-Flow). However, current research indicates that artificial delays in the response time by a VA may lead to a more satisfying experience for the users (Gnewuch et al. 2018). Here, it could be interesting to see how such modulations influence task performance or the perceived workload as in situations where a user is under pressure it may be more beneficial to deliver fast answers.

In summary, there is much research to be done on the effectiveness of virtual assistants. Our study has shown that they are a viable option that is worth exploring. If they can succeed in reducing knowledge workers' cognitive load in a variety of situations, then they might be able to help make the digitisation of the workplace something to be welcomed, and perhaps even enjoyed, by all.

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Appendix

Structure and content of questionnaire.

- Greeting of the participant
- Measurement of resilience (RS-11)
- Prompt to address the investigator regarding introduction to the task followed by the processing of the task
 - Measurement of task performance score
 - Measurement of time of processing the task
- Measurement of perceived work-load (NASA-TLX)
- Question whether CPM was known before the current study
- Question whether VA was helpful (only experimental group)
- Demographics
 - Gender
 - Age
 - Highest educational attainment
- Debriefing

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Understanding Collaboration with Virtual Assistants – The Role of Social Identity and the Extended Self

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Abstract Organizations introduce virtual assistants (VAs) to support employees with work-related tasks. VAs can increase the success of teamwork and thus become an integral part of the daily work life. However, the effect of VAs on virtual teams remains unclear. While social identity theory describes the identification of employees with team members and the continued existence of a group identity, the concept of the extended self refers to the incorporation of possessions into one's sense of self. This raises the question of which approach applies to VAs as teammates. The article extends the IS literature by examining the impact of VAs on individuals and teams and updates the knowledge on social identity and the extended self by deploying VAs in a collaborative setting. Using a laboratory experiment with $N = 50$, two groups were compared in solving a task, where one group was assisted by a VA, while the other was supported by a person.

Results highlight that employees who identify VAs as part of their extended self are more likely to identify with team members and vice versa. The two aspects are thus combined into the proposed construct of virtually extended identification explaining the relationships of collaboration with VAs. This study contributes to the understanding on the influence of the extended self and social identity on collaboration with VAs. Practitioners are able to assess how VAs improve collaboration and teamwork in mixed teams in organizations.

Keywords Virtual collaboration · Virtual assistants · Social identity theory · Extended self · Information systems · Organizations · Virtually extended identification

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1 Introduction

In virtual collaboration, teams are required to collaborate via technology (de Vreede and Briggs 2005; Changizi and Lanz 2019) which can result in a lack of a common social identity (Vahtera et al. 2017). With some technologies, such as virtual assistants (VAs), the role of technology is changing from a mere tool for virtual collaboration with other humans to its own virtual collaboration with VAs (Maedche et al. 2019; Seeber et al. 2020a). VAs are software programs that can be addressed via voice or text commands and respond to the users' input (Brachten et al. 2020). They are increasingly being used in organizations to optimize internal processes by assisting in the execution of work-related tasks (Norman 2017) to achieve, for example, increased customer satisfaction, thus creating substantial advantages over competitors (Benbya and Leidner 2018; Yan et al. 2018). Unlike physical robots, such as Nao or Pepper, which have a physical human representation

(Maniscalco et al. 2020), a physical interaction with VAs is not possible. However, VAs are used in virtual collaboration (Seeber et al. 2020a; Panganiban et al. 2020). It is predicted that they will be used by at least a quarter of employees working in virtual teams within the next two years (Maedche et al. 2019). To understand virtual collaboration between humans and machines such as VAs, knowledge from human-to-human collaboration research should be exploited (Demir et al. 2020).

Nowadays, many team members, such as those in global virtual project teams (Massey et al. 2003), are physically widely distributed and collaborate primarily virtually (Plotnick et al. 2016; Hassell and Cotton 2017; Andres and Shippis 2019). Virtual collaboration ranges from working together in virtual computer-generated worlds (Franceschi et al. 2009; Kohler et al. 2011) to collaboration using tools such as Google Drive (Van Ostrand et al. 2016). Successful virtual collaboration is influenced by aspects such as social presence (Franceschi et al. 2009) and social identity (Lin 2015; Vahtera et al. 2017). Identifying with team members at the workplace as a social group contributes significantly to improving the individual performance of each employee and encourages achieving an overarching goal more efficiently (Lin 2015; Porck et al. 2019). One's own identity can partially be depicted within the framework of a virtual collaboration, for example, by visualizing gender, age, and social class via embodiment through an avatar (Schultze 2010). The social identity of team members can also be transferred to virtual collaboration (Guegan et al. 2017). Social identity describes the identification with other (virtual) team members and the maintenance of one's own identity by comparing one's self-concept with other people's perceived values, norms, and characteristics (Brown 2000).

Research on the role of VAs as team members is not a recent development (Seeber et al. 2020a; Panganiban et al. 2020; Demir et al. 2020). However, it is still largely unexplored whether VAs are perceived as part of one's team or as a simple tool or object in virtual collaboration. The identification with an object as part of one's self has been called the "extended self" (Belk 1988; Tian and Belk 2005; Clayton et al. 2015) and has been transferred to the workplace and the digital world. People extend their identity by incorporating capabilities that fit to their self-concept, and thus, positively enhance their self.

In contrast, the theory of social identity focuses on the comparison with other humans in order to form and maintain one's identity (Tajfel and Turner 1986). This apparent contradiction raises the question of which approach applies to VAs as team members in virtual collaboration. Examining this is fundamental to understand how and with what purpose VAs should be deployed in organizations as collaborative partners. Deploying VAs

could help organizations to save valuable resources when they are used as tools to assist employees in work-related tasks or when they behave as team partner in order to increase team identity and therefore team efficiency. To examine the role of VAs in virtual collaboration in detail, our research is guided by the following research question:

How does identification with VAs vs. that with humans as virtual team members differ in virtual collaboration?

To answer the research question, we conducted a laboratory experiment with 50 participants. Those in the experimental group were asked to solve a typical work-related task in collaboration with a text-based VA, while the control group was assisted by another human via chat. We measured and compared the extended self and the social identity for both groups as well as the perceived workload. This paper contributes to research and practice by extending our understanding of the collaboration between employees and VAs in an organizational context to drive future research in this field of high relevance. Information systems (IS) researchers will find the insights helpful to understand what influence the extended self and social identity theory have on virtual collaboration with VAs assisting in work-related tasks. To guide future research, we introduce the concept of virtually extended identification as a combination of social identity and the extended self for virtual collaboration between VAs and employees.

2 Related Work: Virtual Assistants in Organizations

Collaboration technologies have a long history in IS research (Schwabe 2003; Frohberg and Schwabe 2006; Bajwa et al. 2007; You and Robert 2018). For VAs, as one of these technologies, the IS community uses a variety of definitions (e.g., Maedche et al. 2019; Seeber et al. 2020a; Diederich et al. 2020). Luger and Sellen (2016) define CAs as "*IS that enable the interaction with users via natural language.*" Stieglitz et al. (2018) state that VAs in enterprises "*can be addressed via voice or text and that can respond to the users input (i.e. assist) with sought-after information.*" VAs can generally be explained as software programs that can be addressed via different modes of communication (e.g., written or spoken natural language), assisting with tasks or executing them autonomously (Brachten et al. 2020). Related terms include but are not limited to chatbots (Stieglitz et al. 2018), conversational agents (Diederich et al. 2020), and digital assistants (Maedche et al. 2019). Research divides the concept of VAs into various categories, such as design characteristics or assistance domain (Knote et al. 2019). However,

systems are usually classified along two dimensions (Gnewuch et al. 2017) – their primary mode of communication (e.g., text-based or speech-based) (Lee et al. 2009) and their main purpose (narrow or broad task) (Nunamaker et al. 2011). A categorization into one of these classes is not always possible due to potential overlaps. For example, VAs can be augmented to cope with individual requirements (Chung et al. 2017), and text-based systems might convert human language into text to process information (Gnewuch et al. 2017).

VAs need to be differentiated from a number of related concepts. VAs can distinguish among and interpret the emotions of individuals within teams (McDuff and Czerwinski 2018) and use different language styles to adapt to varying users (Gnewuch et al. 2020). Thereby they might use social cues, including the dimensions of verbal (e.g., jokes, temporal expressions, or self-disclosure), visual (e.g., emoticons, facial expressions, or agent visualization), auditory (e.g., voice gender, grunt, and moan or laughing), and invisible (e.g., first turn, response time, or tactile touch; Feine et al. 2019). Thus, collaborating with VAs might not be restricted to certain commands, phrases, or keywords; rather, individuals can use their habitual language (McTear 2017; Feine et al. 2019). Although VAs theoretically have various verbal, visual, auditory and invisible characteristics that can impact social behavior in humans (Feine et al. 2019), in practice it is still hardly possible to simulate fully human behavior. VAs are usually capable of supporting a narrow task (Davenport 2018), but may not be able to provide appropriate answers in every context. They are therefore usually characterized by a certain selection of social cues, but cannot represent a fully human consciousness (Russel and Norvig 2016).

The ongoing improvements to artificial intelligence (AI) and machine learning (ML) algorithms as a prerequisite to developing collaborative systems had led to an increasing concentration on VAs as work facilitators (Berg et al. 2015; Spohrer and Banavar 2015; Luger and Sellen 2016; Knijnenburg and Willemsen 2016; Nasirian and Ahmadian 2017). The use of VAs in organizations is valuable for facilitating internal processes and supporting employees in better completing their tasks as well as generating additional revenue or cost savings (Quarteroni 2018). VAs are used for direct interaction with consumers, and they positively affect customer satisfaction (Verhagen et al. 2014). Question-and-answer assistants facilitate onboarding processes of new hires (Shamekhi et al. 2018). The workload of employees is reduced by supporting the resolution of customer incidents (McTear 2017) and the execution of work-related tasks (Brachten et al. 2020).

Current research demonstrates that VAs can improve virtual collaboration (Waizenegger et al. 2020; Seeber et al. 2020a). Organizational human teams frequently fall short

of their possibilities (Kozlowski and Ilgen 2007), thus the use of a VA as a legitimate virtual team member and socio-technical ensemble (Seeber et al. 2018) might foster decision making and improve team collaboration (Waizenegger et al. 2020; Seeber et al. 2020b). The integration of VAs as virtual colleagues is valuable to increase the effectiveness of virtual collaboration in teams (Goodbody 2005). With their unique characteristics (Maedche et al. 2019; Feine et al. 2019) and ongoing application in practice (Brachten et al. 2020), it can be assumed that an increasing degree of team dynamics from purely human virtual teams can be transferred to human–machine teams.

3 Theoretical Background

3.1 Social Identity

Social identity is a grounded concept that can influence the performance of virtual teams (Lin 2015). In social identity theory, Tajfel and Turner (1986) assume that human identity is not only composed of individually unique character traits and physical characteristics but also of belonging to certain social groups. This might include people of the same age group, family, friends, and even work colleagues (Bartels et al. 2019).

By comparing with other social groups, such as other departments or competing organizations, individuals try to draw a line to better understand who they themselves are (Tajfel and Turner 1986). People, such as employees, try to differentiate from others by means of positive characteristics that they attribute to themselves, which is known as intrinsically motivated positive distinctiveness (Haslam 2004). At the workplace, such characteristics can be team cohesion or quality of work.

In IS research, social identity theory at the workplace has been considered from perspectives including the psychological (Pepple and Davies 2019; Klimchak et al. 2019), the organizational (Dahling and Gutworth 2017; Mueller et al. 2019), and the societal viewpoints (Kenny and Briner 2013).

However, most previous studies have focused on examining social identity in human-to-human collaboration and the resulting social behavior (Kohler et al. 2011). With technologies such as VAs, which are capable of utilizing human social cues (Maedche et al. 2019), the role of technology is changing, and the boundaries between people and technology are blurring (Pickard et al. 2013). According to Young-Jae et al. (2020), people perceive it as increasingly difficult to describe the uniqueness of humans compared to machines and AI as the technology itself could be perceived as a social actor (Wang 2017; Edwards et al. 2019). This actor is less a technological environment

than a possible new individual that could be part of an in-group or out-group in the context of social identity formation.

Revealing insights about the relationship between people and AI will open up new opportunities for organizations and interesting insights for further research. However, social identity theory is not the only concept that could explain the role of AI in virtual collaboration. Another concept from psychology addressing the social relationship between humans and objects (e.g., technologies) could also help to better understand the virtual collaboration between humans and machines – the extended self (Belk 2013).

3.2 The Extended Self

People develop and maintain several identities according to the context of their current situation (Burke 2006). Thus, Burke and Stets (2009) argue that people play different roles. For example, people face specific actors and topics at the workplace according to the situation, such as a team meeting or an idea pitch. Likewise, people need to adapt to other situations at home, such as in the context of the education of one's children. Individuals have various roles prepared for the unique situations they face. Besides those roles, people maintain only one underlying self-concept connected to fundamental rules and values that they develop over time by categorizing in relation to others (Stets and Burke 2000; Burke and Stets 2009). Hence, identity is a well-discussed research area connected to various disciplines, such as psychology (Tajfel and Turner 1986), social psychology (Leary and Tangney 2011), sociology (Stets and Biga 2003), and economic psychology (Belk 1988). However, it is worth analyzing identity in relation to the increasing role of information technology as a new resource in our life and work (Tian and Belk 2005; Carter et al. 2015).

People extend their selves by considering particular possessions in order to supplement their self (Belk 1988, 2013). However, the concept of possessions is not limited to external objectives; it can also include other people or group possessions. Furthermore, under the perspective of upcoming technology, Belk (2013) argues that people can also consider digital possessions as potential extensions of the self. This might be achieved by, for example, dematerialization, sharing, or distributed memories. Particularly in the workplace of technology organizations, Tian and Belk (2005) argue that employees need to decide which part of the self fits the current situation of the work, and how. On one hand, this decision includes the process of negotiations between the “me” and the situation. On the other hand, this decision may stay hidden or might be retracted.

However, due to the integral role of information technology in everyday life and work, understanding information technology, for example, in the form of virtual collaboration and new social actors such as VAs, has become a relevant endeavor for IS research (Carter et al. 2015). In this regard, maintaining and extending the self are two central functions in the context of information technology and identity (Carter and Grover 2015). It is necessary to answer the question “Who am I in relation to this technology?” (Vignoles et al. 2011; Carter et al. 2015). This material perspective focuses on individual thinking and behavior (Dittmar 2011). Therefore, material identities are verified when people gain control and mastery of an object that they are interacting with.

Furthermore, people have a fundamental need to expand the self and seek self-enhancement. They can achieve this by supplementing social or physical resources, perspectives, and identities (Aron et al. 2003). One possible way for people to achieve this enhancement is by consolidating capacities yielded by (material) objects to which they have become emotionally attached (Belk 1988, 2013; Carter et al. 2015).

3.3 Derivation of Hypotheses

Social identity theory and the extended self describe two alternative pathways to maintain and form an individual's identity (Tajfel and Turner 1986; Belk 1988, 2013; Stets and Burke 2000). Social identity theory holds that identification with other (social) actors leads to a sense of belonging to the group (external attribution of an actor's values to the self; Tajfel and Turner 1986; Stets and Burke 2000). In comparison, the perspective of the extended self conceptualizes that a positive identification with an (virtual) object leads to an association of capabilities, characteristics, or meanings directly to the self (internal attribution of an actor's values to the self; Belk 1988, 2013; Tian and Belk 2005). Based on the considerations of the theoretical background, Table 1 contrasts how the extended self and social identity determine the perception of a VA as a team member.

Previous research has stated that VAs can change how we live and how we work (Wang and Siau 2018; Dias et al. 2019); thus, employees and organizations need to find out how to collaborate with VAs within their virtual teams (Seeber et al. 2018). People spend a large part of their lives at their workplaces, where they build and maintain complex social relationships (Ellemers 2004). Their work and team colleagues hence represent important social resources through which individuals build their social identity and develop in-group and out-group behaviors (Tajfel and Turner 1986). Thus, questions arise as to whether VAs are perceived as part of these social resources, and whether

Table 1 Social identity theory and the extended self in virtual collaboration with VAs

| Perception of VAs as virtual team members | Confirmation of self-concept | Contradiction of self-concept |
|---|--|---|
| Social identity theory | The VA is perceived as a social actor. Perceived values, rules, and standards also apply to the self. This leads to a sense of belonging to the group/person (Tajfel and Turner 1986; Stets and Burke 2000; Edwards et al. 2019) | The VA is perceived as a social actor. Perceived values, rules, and standards disaccord with the self. This leads to a dissociation from the group/person (Tajfel and Turner 1986; Stets and Burke 2000; Edwards et al. 2019) |
| Extended self | The VA is perceived as part of the self. Capabilities, attributes, or associations of the VA are attributed to the self (Belk 1988, 2013; Burke 2006; Carter and Grover 2015) | The VA is not perceived as part of the self to protect the self-concept. Capabilities, attributes, or associations of the VA are not attributed to the self (Belk 1988, 2013; Burke 2006; Carter and Grover 2015) |
| Similarities | Considering perceived aspect, such as values, rules, capabilities, and attributes of the VA that fit positively with the individual's self | Dissociation of perceived aspect, such as values, rules, capabilities, and attributes of the VA that do not fit with the individual's self |

they influence the identity of employees remains unanswered. As most VAs are designed as supportive tools (Lamontagne et al. 2014) and not as equivalent virtual team members, they still remain IS (Luger and Sellen 2016). Therefore, it can be assumed that collaborating with a VA as a chat partner or with a human chat partner impacts the identification with that chat partner. We therefore developed the following hypothesis:

H1: Virtually collaborating with a VA or a human chat partner impacts the identification with the chat partner.

VAs can increase collaboration within virtual teams (Bittner et al. 2019; Seeber et al. 2020a). However, when employees use VAs as supportive tools for solving work-related tasks, it is likely that they interact less with their virtual human team partners. Nevertheless, the time employees spend with their virtual team impacts the team identification (Massey et al. 2003). Therefore, we derived the following hypothesis:

H2: Identification with the human team is lower after collaborating with a VA than before.

Furthermore, Carter et al. (2012) have shown that young students extended their self-concepts by including the capabilities of their smartphones. According to Tian and Belk (2005) as well as Belk (2013), also digital tools or technology might be considered as part of one's extended self. This identification and enhancement might also be attained by using, and thus incorporating, the capabilities of a VA in a certain context, such as virtual collaboration at the workplace. It remains unclear whether a new technology such as a VA will be perceived as part of one's extended self. Thus, we derived the following hypothesis:

H3: Virtually collaborating with a VA or a human chat partner impacts the perception of the respective collaboration partner as part of one's extended self.

Research has shown that VAs are perceived as supportive technology (Brachten et al. 2020). However, it still needs to be researched what role such technology plays in self-identification at the workplace. Regarding social identity theory and extended self, two alternative pathways appear to maintain and form an individuals' identity (Tajfel and Turner 1986; Belk 1988). According to social identity theory, identification with other (social) actors leads to a sense of belonging to the group. Those social actors could be human team members or VAs (Edwards et al. 2019). However, perceiving VAs as social actors (Edwards et al. 2019) may contradict the perception of VAs as technology (Lamontagne et al. 2014; Carter et al. 2015). Therefore, it is possible that the approaches of social identity and the extended self interfere in virtual collaboration with VAs. Based on these assumptions, we derive that individuals' identification with the team contradicts their identification with technology as a part of their extended self. We, therefore, derive the following hypothesis:

H4: The individual's identification with the team negatively correlates with the individual's identification with technology as a part of their extended self.

4 Method

4.1 Participants

In this study, we conducted a laboratory experiment to examine how VAs in virtual teams are perceived when they assist individuals in performing tasks. The experiment was conducted in a lab at a German university between

November 12, 2019 and February 10, 2020. We invited people via email, social network sites, and direct contact. Participation was voluntary and could be terminated without providing any reasons. As prerequisites, participants had to be at least 18 years old and experienced in teamwork within an organization. In total, 50 people took part in our study. We randomly assigned the participants into two groups, resulting in a well-balanced sample of 25 participants for each condition. The groups were formed ensuring that the proportion of women and men was approximately equal by frequently checking the distribution of gender across groups. If the distribution of subjects was skewed, the smaller group was prioritized. However, due to extreme responding indicating a response bias, we excluded four participants from the total sample. This yielded a total of 46 participants (24 in the VA group). In the control group, the participants were asked to perform a task with the help of a human chat partner. In our experimental group, the participants were asked to solve the same task using a VA. In both cases, the collaboration with the counterpart was possible via the online chat platform Slack.¹ In both groups, a trained experimenter supervised the subjects to secure the subjects' attention during the course of the study. Overall, 84% of the participants were female (N = 39), and ages ranged from 18 to 63 (M = 23.1, SD = 7.54). Furthermore, 73% of the participants had passed the equivalent of their A-levels, while 15% held a bachelor's degree.

4.2 Materials

For our lab experiment, we used a set of questionnaires and modified scales to measure the constructs of interest. These were composed of questions on the extended self, social identity theory, demographic data, perceived workload, satisfaction, and the evaluation and perception of the VA. The analyses were calculated using the software tools Jamovi (1.0.8.0) and SPSS Statistics (Version 25). All data were presented and gathered via the LimeSurvey interface (Version 3.17.5).

4.2.1 Virtual Assistant

To examine how social identity is influenced and whether a VA expands one's own self, we developed a text-based system with the help of Google's cloud service DialogFlow.² By using underlying ML technologies, this platform provides easy access to the development of natural and rich conversational interfaces (Canonico and Russis 2018).

To keep the interaction with the VA as simple as possible, we developed a system using a text-based interface (Araujo 2018), which was integrated into the online chat platform Slack, one of the most widespread systems for simplified organizational communication. Participants were able to interact with the VA simply by using a keyboard and computer screen (cf. Fig. 1). We explicitly avoided using further influential factors, such as voice commands or embodied avatars, to keep the interaction straightforward. Moreover, embodiment does not necessarily affect social behavior (Schuetzler et al. 2018). The VA supported the participants in handling the task by providing answers based on distinct keywords to questions posed. The feedback included a question–answer component (Morrissey and Kirakowski 2013; Lamontagne et al. 2014), which could be queried to gain information, support, and instruction about the specific task. However, the VA is only able to support the user in solving the task by giving applicable hints but does not provide an actual solution for the task.

We deliberately chose aspects such as response time to be comparable between both groups to reduce potential influences on the performance and identification with the team member (Massey et al. 2003). Furthermore, the name of the VA (DialogFlow Bot) directly points to a VA as a collaboration partner. Therefore, the subjects should be aware that they were interacting with either a human or a VA. Although our VA had basic conversational skills and social cues such as 'Ask to start', 'Tips and advice', 'Excuse' or 'Greeting and farewell' (Feine et al. 2019) we did not aim to differ specific social cues between the VA and the human (Feine et al. 2019), because that was not our research focus.

We aimed to provide a medium level of social cues to ensure that the VA does not influence the results in one specific direction. Implementing more social cues may favor the perception of the VA as a social actor. In contrast, less social cues could increase the probability of perceiving the VA as a technical tool. With this, we ensured that potential differences in the perception of the team member are due to the team member's nature (VA or human). To summarize, the goal is not to deceive the subjects about the chat partner but to investigate the difference in perception of the VAs and humans based on the subject's awareness about the chat partner.

To ensure that the given task is realistic but manageable during the experiment, we conducted a pre-study to verify its suitability. This approach also served as verification of the operability of the VA to guarantee a seamless collaboration during the experiment. The test was performed with a sample of 10 students (6 female, 4 male) with ages ranging from 22 to 31 (M = 25), which were randomly selected at a university. We compared a text-based task

¹ <https://slack.com/>.

² <https://dialogflow.com/>.

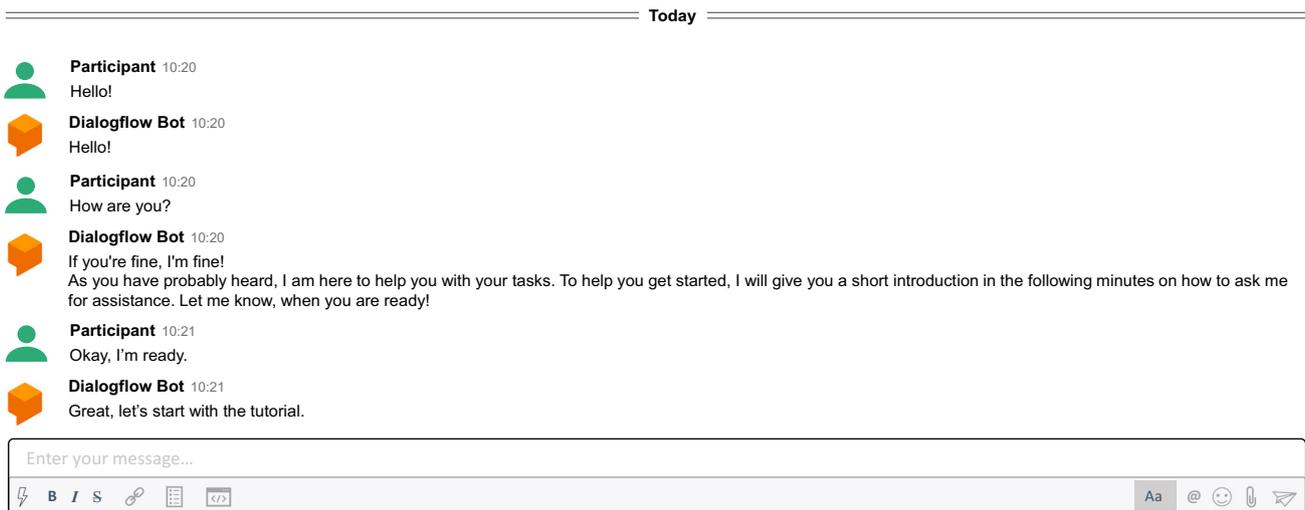


Fig. 1 Example of a chat interaction between a participant and the VA

(TBT) with the critical path method (CPM). The TBT required participants to read texts about topics that do not rely on previous knowledge. In contrast, the CPM sorts activities according to their dependencies and logical order for determining the overall duration. Both tasks are commonly performed in organizations. The time limit for the execution was 10 minutes. We measured the perceived workload using the NASA Task Load Index (NASA-TLX). On average, participants given the CPM task achieved higher NASA-TLX scores ($M = 12.5$, $SD = 3.85$) than the TBT group ($M = 6.36$, $SD = 4.06$). This difference of 6.13 was significant (95% CI [0.35, 11.91], $t(8) = 2.44$, $p = 0.040$). Furthermore, it represents a large effect, $d = 0.98$. We assess the CPM task to be more demanding of participants compared to the TBT. Hence, participants benefit more from a VA when being assisted with the CPM, justifying its choice for the experiment.

4.2.2 Social Identity

We used two different questionnaires to measure collective social identity as well as personal identification with the team. For identification with the team, we used the About-Me Questionnaire (Maras et al. 2018), in which the respondents were first asked to indicate how much they felt they belonged to the social group at their workplace. This questionnaire consists of four items, which are rated on a five-point Likert scale. One example item was “*I like being with my team.*” The subscale of the About-Me Questionnaire had a medium-to-high reliability for the first ($\alpha = 0.759$) and second ($\alpha = 0.732$) measurement time points. The About-Me Questionnaire was queried both before and after the interaction with the chat partner to determine a possible change of the specific social identity.

In addition to the two measurement time points, we asked whether in the interaction the VA or human chat partner was perceived as part of the social group at work. This took place after the chat interaction. For this purpose, we used a modified About-Me Questionnaire (Identification with the chat partner). An example item was “*I am similar to my virtual assistant.*” We decided to use the scale directed toward the chat partner to check for possible differences between the general social identity attitude and the social identity attitude toward the interaction scales. The subscale of the modified About-Me Questionnaire had a high reliability, $\alpha = 0.835$.

4.2.3 The Extended Self

To measure the extended self, we used the extended self scale by Sivadas and Machleit (1994). The scale is largely based on Belk’s (1988) view of the extended self. With the scale, Sivadas and Machleit (1994) aimed to assess the degree of incorporation of possessions into the extended self. The scale consists of six components scored on a seven-point Likert scale. The subscale of the general extended self scale (GES) had high reliability, $\alpha = 0.839$. We chose the scale as it was feasible to adopt for a VA as the considered object for the items. After the chat interaction with the VA or the human, the participants had to answer an adapted version of the extended self scale (AGES) related to the specific chat partner. The AGES measures to what extent the subjects perceiving the chat partner as part of one’s self. An example item was “*My virtual assistant is part of what I am.*” The subscales of the second measurement scored a high reliability, $\alpha = 0.886$.

4.2.4 NASA-TLX

To determine the perceived workload of the task, we used the NASA-TLX (Galy et al. 2012), a valid measurement developed by the National Aeronautics and Space Administration (NASA; Hart and Staveland 1988). Examining the perceived workload is important to check whether the new VA influences the performance due to the potential need for increased cognitive resources to interact with a new technology. This assessment tool has successfully been used in several research approaches and proven to be valuable for laboratory experiments (Rubio et al. 2004; Noyes and Bruneau 2007; Cao et al. 2009). The NASA-TLX includes the following six subjective subscales: (1) mental demand, (2) physical demand, (3) temporal demand, (4) performance, (5) effort, and (6) frustration (Hart 2006, p. 904). Mental demand explains how much cognitive activity is needed, and physical demand, in contrast, explains how much manual activity is needed. Temporal demand represents the perceived time pressure. Performance describes the perception of one's own personal accomplishment, effort is the opinion of how much work had to be done to reach a result, and frustration refers to the level of disappointment during the execution of a task. The subscale scored a high reliability, $\alpha = 0.808$.

4.2.5 Satisfaction

To analyze the perceived satisfaction of the chat interaction via the communication interface, we used the possession satisfaction index (PSI) by Scott and Lundstrom (1990). Measuring the perceived satisfaction may allow us to reveal potential influences that could be caused by the individual perception of the interaction. The PSI uses a seven-point semantic differential scale and contains of three two-pole items of (1) satisfied/dissatisfied, (2) pleased/displeased, and (3) favorable/unfavorable. Furthermore, the PSI scored a high reliability, $\alpha = 0.924$.

4.3 Procedure

We divided our experiment into one experimental group and one control group. Both groups were alternately tested and told that they should consider the situation as if they were at a workplace they are used to. In the experimental condition, we requested the participants to solve a task in collaboration with a VA. In the control condition, we replaced the collaboration partner with a human chat partner. The procedure of the experiment followed the structure described in the following. All major steps of our experiment are visualized in Fig. 2.

Fig. 2 Main steps of the conducted procedure

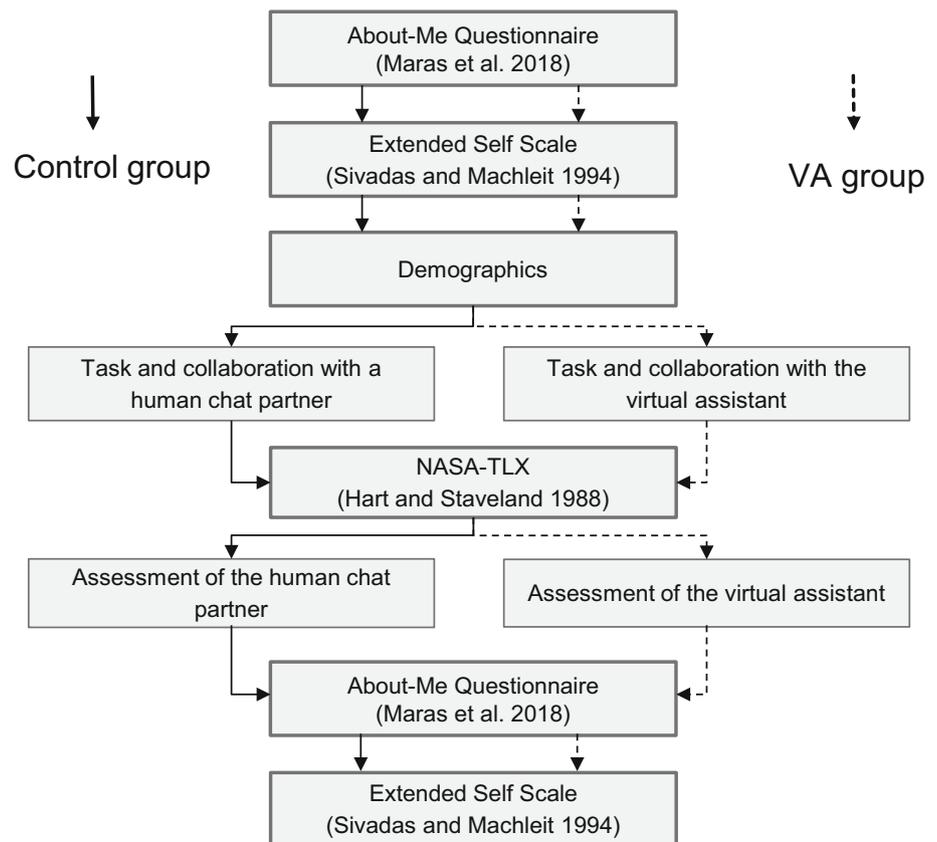


Table 2 Correlations in the VA group between perceived satisfaction and the single NASA-TLX items

| Items NASA-TLX | N | r | <i>p</i> |
|----------------|----|------|----------|
| Performance | 24 | .575 | .003 |
| Effort | 24 | .506 | .012 |
| Frustration | 24 | .534 | .007 |

Comparing the achieved score in the CPM task between the human group ($M = 15.2$, $SD = 6.13$) and the VA group ($M = 17.2$, $SD = 6.84$) revealed no significant difference, $p = .359$ and $d = .315$

First, we briefed the participants about the experiment. Furthermore, we asked them to read an introductory text and to start with the survey. We reminded the participants that they should imagine they are in a normal working situation and that they should relate the questions to the perception of their current team at work. Initially, we had administered general questionnaires on the extended self, social identity theory, and demographic data. In addition to demographic data such as age, gender, and educational level, we also collected information about the current professional activity and the industry in which the respondents are currently working.

After that, we asked both groups to solve a CPM. To compare performance between the groups, we awarded a point for each correct path and node. This yielded a maximum achievable score of 28. The goal was to plan a research project for a market research unit of a large company. Participants had to arrange an unordered list with various process steps (such as “develop study idea,” “literature research,” “conducting the study,” and “develop methodology”) to identify the minimal throughput time. They were to read an introductory text and an example to gain a rough understanding of the task, and we told them that they would have to solve a similar task shortly.

We informed the experimental group that they would have the support of a VA who is well versed with the CPM, whereas we told the control group that they would be contacting a human chat partner. The VA as well as the human chat partner could be contacted via a Slack chatroom. To familiarize them with the interaction, we instructed the participants to introduce themselves to the assistant (or human chat partner), whereby the assistant (or human chat partner) guided them through a tutorial dialog. After this familiarization phase, we provided the CPM task, which the participants had to solve within ten minutes. We advised them to contact the VA (or human chat partner) when any questions arose. We designed the task in such a way that the participants did not have all the necessary

information for the required solution in advance in order to initiate interactions with the VA. After ten minutes of processing time, the examiner received the solution. We then requested that the participants continue the survey. With the following questions, we aimed to evaluate the assistant and assess their skills during the task. Subsequently, we enquired the questionnaires on social identity theory and extended self a second time to determine a possible difference in perception. After completion of the last question, we provided a short written debriefing to the respondents to explain what had been examined in the study.

To counteract possible disruptive factors that can arise from interaction with a real human in the control group, the human chat partners followed a semi-structured guideline to ensure that the information provided was as similar as possible to that of the VA. The chat partners were controlled by one experimenter, who switched to the adjoining room for both conditions.

4.4 Influence of the Perceived Workload, Satisfaction, and Demographics on the Groups

To ensure that the results would not be unduly influenced by further variables such as the age, gender, or education of the participants or satisfaction with the chat interaction or the perceived workload, we conducted the following analyses. Determining demographical influences on the main constructs of the study revealed no significant correlation between age and gender and the extended self and social identity scales. However, we observed a small correlation between age and the About-Me Questionnaire (Identification with the team), $r(46) = 0.313$, $p = 0.034$. Additionally, checking for group differences between the various education levels did not show any significant differences toward the (modified) About-Me Questionnaire (Identification with the chat partner) as well as the GES (Perception of technology of one’s self) and the AGES (Perception of the chat partner as part of one’s self). The mean scores of both groups revealed a medium perceived workload. However, to check for a potential difference, we conducted a *t*-test for independent samples due to the non-significant Levene and Shapiro–Wilk tests. Overall, there was no significant difference between the VA group ($M = 10.7$, $SD = 3.16$) and the human chat partner group ($M = 11.2$, $SD = 3.65$), $p = 0.611$ and $d = -0.129$. Furthermore, the data did not show a difference between the VA chat partner group ($M = 2.88$, $SD = 1.56$) and the human chat partner group ($M = 3.11$, $SD = 1.89$) regarding the satisfaction score after the chat interaction, $p = 0.113$ and $d = -0.134$.

To check whether satisfaction with the interaction and perceived workload are related, a correlation was

Table 3 Validation of measurements

| | Composite Reliability | Cronbach's α | AVE | About-Me | Modified About-Me | GES |
|-------------------|-----------------------|---------------------|------|-------------|-------------------|------------------|
| About-Me | .780 | .759 | .477 | – | – | – |
| Modified About-Me | .843 | .835 | .576 | $r = -.003$ | – | – |
| GES | .840 | .839 | .471 | $r = .111$ | $r = .323^*$ | – |
| AGES | .891 | .886 | .577 | $r = .152$ | $r = .589^{***}$ | $r = .467^{***}$ |

Note: $*p < .05$, $**p < .01$, $***p < .001$

Table 4 Model coefficients towards social identification with the chat partner (modified About-Me scale)

| Predictor | Estimate | SE | t | p |
|-----------------|----------|--------|--------|-------|
| Group: human–VA | 0.0606 | 0.2384 | 0.254 | .801 |
| Age | –0.0147 | 0.0188 | 0.254 | .439 |
| Gender | 0.1421 | 0.3751 | 0.379 | .707 |
| Satisfaction | –0.1687 | 0.0774 | –2.180 | .035* |
| NASATLX | 0.0718 | 0.0414 | 1.734 | .091 |

Note: $*p < .05$

Table 5 Model coefficients towards identification with the chat partner as part of one's self (AGES)

| Predictor | Estimate | SE | t | p |
|-----------------|----------|--------|--------|------|
| Group: human–VA | 0.03410 | 0.3284 | 0.104 | .918 |
| Age | 0.00897 | 0.0259 | 0.346 | .732 |
| Gender | –0.37018 | 0.5166 | –0.717 | .478 |
| Satisfaction | –0.16296 | 0.1066 | –1.529 | .317 |
| NASATLX | 0.05785 | 0.0570 | 1.014 | .317 |

calculated between the two variables. To reveal insights about the two groups, we conducted correlations separately for each group. Satisfaction was positively correlated with perceived workload $r(24) = 0.662$, $p < 0.001$ in the VA group but not in the human group, $r(22) = 0.204$, $p = 0.363$. Table 2 presents further significant correlations in the VA group between perceived satisfaction and the single items of the NASA-TLX score.

5 Results

In this section, first, we check the observed major scales' (GES, AGES, About-Me, and Modified About-Me) reliability and validity measures (Cronbach and Meehl 1955; O'Leary-Kelly and Vokurka 1998; Peters 2018). Second,

we introduce the results regarding social identity theory and the extended self. Table 3 summarizes the values for composite reliability, average variance extracted (AVE), and construct validity. The comprehensive results are shown in the Appendix (available online via <http://link.springer.com>), including factor loadings as well as correlation coefficients for each item of the major scales. In summary, the described constructs explain on average more than 50% of the variance (Table 3). Regarding the validity measurements, construct validity shows that the modified About-Me Questionnaire might be linked to the AGES.

5.1 Social Identity

To check for potential group differences regarding the distinct social identity questionnaires, we conducted a one-way ANOVA. According to Levene's test for equality of variances, we cannot assume equality for the collective identity orientation scale ($F(1,44) = 6.294$, $p = 0.016$), thus we chose the more robust Welch's one-way ANOVA. For collective identity orientation, the VA group ($M = 2.18$, $SD = 0.364$) differs significantly from the human ($M = 2.82$, $SD = 0.711$) group, $F(1,30.7)$, $p < 0.001$.

To examine social identification with the specific chat partner (bot or human), a linear regression model was calculated that predicts the score on the modified About-Me Questionnaire based on the participant's group and the control variables age, gender, satisfaction, and perceived workload. According to Levene's test of equality of variances ($p = 0.484$) and the Shapiro–Wilk test of normality ($p = 0.713$), we assume equality of variances as well as normal distribution. Results of the multiple linear regression model indicated no significant effect overall, $F(5,49) = 1.44$, $p = 0.230$, $R^2 = -0.153$. The individual predictors were examined further and indicated that satisfaction ($t = -2.18$, $p = 0.035$) is a significant predictor in the model (Table 4).

H1 stated that virtual collaboration with a VA, compared to a human partner, affects social identity, that is, the

degree of identification with the chat partner. This is not supported by the findings.

To test within each group whether identification with the teams and colleagues differs before and after solving the task, we conducted a paired samples *t*-test for group differences with a 95% confidence interval and the two measurements of the About-Me Questionnaire as paired variables for each group. For the VA group, the Shapiro–Wilk test of normality was non-significant ($p = 0.173$), and no violation of normality was therefore assumed. On average in the VA group, the first measurement ($M = 3.58$, $SD = 0.810$) of the About-Me Questionnaire was slightly higher than the second measurement ($M = 3.34$, $SD = 0.638$). This difference was significant $t(23) = 3.15$, $p = 0.004$, with a medium-sized effect ($d = 0.64$). Therefore, the results support H2, indicating that people who collaborate with VAs indeed identify less with their human team after interaction with the VA than they did before. For the human group, the Shapiro–Wilk test of normality was also non-significant ($p = 0.056$), so no violation of normality was assumed. Thus, a paired samples *t*-test was conducted for the human group. The test showed no significant differences ($p = 0.773$, $d = -0.063$) between the first measurement of the About-Me Questionnaire ($M = 3.38$, $SD = 0.427$) and the second measurement ($M = 3.33$, $SD = 0.633$).

5.2 The Extended Self

To examine the role of the extended self in the context of social identity and virtual collaboration, we conducted group comparisons and correlations. We analyzed the score of the GES as well as the score of the AGES regarding the chat interaction used in the experiment.

To reveal potential influences of the groups and control variables on the identification with the chat partner (AGES) as part of one's self, we applied a linear regression model. Levene's test for equality of variances was not significant for the AGES ($p = 0.279$); thus, equality of variances was assumed. Results of the multiple linear regression model indicated no significant effect of the group (human or VA) or the control variables age, gender, satisfaction, and perceived workload on the identification with the chat-partner as part of one's self (AGES), $F(5,49) = 0.666$, $p = 0.652$, $R^2 = -0.0768$. The individual predictors were examined further, and none of them were significant (Table 5). These results do not support an impact of the groups, thus H3 is not supported by the findings.

Furthermore, we investigated the relationship between the two scales of the extended self and the perception of the chat partner (VA and human) as being part of one's social group at work. To this end, we conducted a bivariate correlation overall for both groups as well as separately for

each group. Overall, the GES score, $r(46) = 0.467$, $p = 0.001$, and AGES score, $r(46) = 0.589$, $p < 0.001$, showed significant positive correlations with the modified About-Me Questionnaire. Analyzing the relationship for the VA group revealed a significant positive correlation between the GES score and the modified About-Me Questionnaire, $r(24) = 0.486$, $p = 0.016$. Likewise, the AGES score correlates significantly, $r(24) = 0.641$, $p < 0.001$. The human chat partner group showed only a significantly positive correlation for the AGES score and the modified About-Me Questionnaire, $p = 0.009$, $r(22) = 0.540$. Therefore, the correlation between the GES score and the modified About-Me Questionnaire was not significant, $p = 0.336$, $r = 0.215$. To summarize, the results do not support a negative relationship between individuals' identification with the team and individuals' identification with technology as a part of their extended self (H4). However, the results revealed a positive relationship.

6 Discussion

6.1 Key Findings

In this study, we examined how a VA affects social identity and the extended self in virtual collaboration. First, we did not find a significant impact of virtual collaboration with a VA, compared to a human partner, on social identity, that is, on the degree of identification with the team (H1). In this context, VAs may do not differ as a team member compared to a human. This is consistent with the results of Edwards et al. (2019), who found that VAs could act as equal social actors.

However, a key finding of this paper is that people who collaborate with VAs identify less with their (human) team after their interaction with the VA than they did before (H2). This medium-sized effect indicates that working with VAs could influence the social identity of a person in the context of virtual collaboration. This may be explained by the fact that the person feels more independent and able to solve the task alone. Even if, according to Young-Jae et al. (2020), people increasingly face difficulties in expressing the uniqueness of humans compared to AI applications, VAs seem to reduce the social identification with team members. This may be explained by the feeling that people experience less connection to their team after interacting with the VA solely. However, this does not appear to be due to an emotional attachment to the VA as You and Robert (2018) found a connection between team identity and emotional attachment to VAs. Therefore, further questions arise for future IS research: How should we design a VA in order to strengthen the feeling of being connected to the team? How important is the role of

identification with one's own team for future work? What impact will VAs have on team collaboration? What implications will VAs have on the digital workplace?

There is no significant difference in the perceived workload of the task and the achieved score between the group supported by a VA and the group assisted by another human. The workload of solving the CPM assisted by the VA is therefore neither perceived as higher nor as lower. This result is contrary to Moreno et al. (2001) and Brachten et al. (2020), who were able to show that individuals supported by VAs outperform humans who did not use a VA. Furthermore, Mechling et al. (2010) demonstrated that groups advised by a VA reach better outcomes. However, a positive lesson that can be drawn from this is that the task-solving with the VA did not put any additional strain on the participants in solving the tasks. In this respect, the support by a VA seems to be similar to the support by another person.

The results do not suggest an influence of collaboration with a VA or a human chat partner on the perception of the respective collaboration partner as part of one's extended self (H3). According to identity research, the formation of identity and its extension is a dynamic process that adapts over time (Burke and Stets 2009; Carter et al. 2015). At the point of introducing a new technology, the participants did not perceive the VA and the human chat partner differently regarding the chat partner as a resource for maintaining or enhancing the self.

6.2 Implications for Theory: The New Concept of Virtually Extended Identification

As a key finding and in contradiction to H4, the study revealed that someone who identifies with their team members is also more likely to identify with the technology as a part of their extended self and vice versa. This highlights a possible connection between the theory of social identity and the concept of the extended self, as some literature hinted at. We found a positive correlation between the individual's identification with the team and the individual's identification with technology as a part of their extended self (H4 not supported). Particularly, for social identification with technology, such as VAs as team members (Seeber et al. 2020a), the underlying concept of the extended self could be considered to explain upcoming interactions. Considering individuals' mental processes in social groups, individuals divide other team members into either their in-group or out-group. They apply social rules and determine the value of their own group related to other groups (Tajfel and Turner 1986). This conceptualization does not sufficiently consider that technology, specifically, a VA, is capable of being a virtual team member. Working with a VA as a virtual team member might enrich one's

social group by perceiving the VA as a team member of the group (external perspective). Furthermore, a VA might support one's self-esteem by positively identifying with the VA's characteristics and capabilities, which might lead to enhancing one's human capabilities (internal perspective). Therefore, VAs may be externally attributed to one's in-group as a team member or be part of one's in-group by internally attributing the VA to one's self. However, past research does not differentiate the two pathways that we examined with H4.

People use newly introduced technology such as a VA and identify with the capabilities and characteristics of these supportive tools when they start to compare themselves with the VA. On one hand, people feel connected to this technology that might lead to improving their own capabilities with the aid of a VA. On the other hand, people then perceive the VA as a social team mate, according to Seeber et al. (2018). This can also be the other way around. Therefore, both concepts are necessary to understand how human behavior is influenced by newly introduced technology such as VAs. Furthermore, analyzing the construct validity has shown that the constructs of the extended self and social identity theory directed toward the VA are connected (Cronbach and Meehl 1955; O'Leary-Kelly and Vokurka 1998). We hence derive that for the context of virtual collaboration, the construct *identification with team (members)* of the social identity theory and the concept of the *extended self* are intertwined. Each may represent different facets of the same underlying construct. This becomes evident regarding the aspects of social comparison and positive distinctiveness of the social identity theory and the process of extending the self. People consider personal attributes, other people, groups (e.g., values of the group), or abstract ideas (e.g., morals of society) in regard to their self when forming the self. An extension of the self can take place by regarding these (social) aspects through control (e.g., a technology), knowledge (e.g., a person), or a feeling of belonging (Tajfel and Turner 1986; Belk 1988; Carter et al. 2015). Thus, people compare themselves with people and technology to determine and extend their own identity. This also happens with possessions, such as technology at the workplace (Tian and Belk 2005). By positively identifying with the VA, positive distinctiveness can be brought about, especially in the workplace.

Our findings suggest a positive connection between social identity theory and extended self (H4). We therefore propose combining these two aspects of identification into the overarching construct of *virtually extended identification* to understand the relationships evolving in virtual collaboration with VAs (see Fig. 3). Virtually extended identification describes the process of maintaining and extending the self by comparing the current self with a VA.

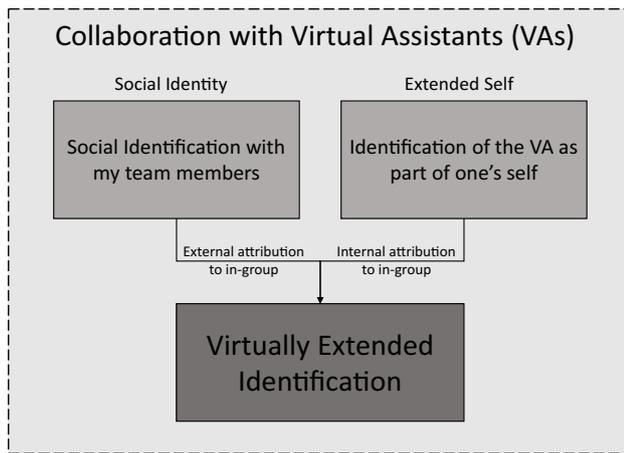


Fig. 3 Symbolic formation of social identity and the extended self in the context of virtual collaboration with technology such as VAs

On the one hand, the VA substitutes the role of a human collaborator, according to Seeber et al. (2018), Demir et al. (2020), and Panganiban et al. (2020). On the other hand, the VA is also considered as technology, according to Schwabe (2003), Bajwa et al. (2007), Froberg and Schwabe (2006), and Vahtera et al. (2017). Thus, the observed relationship between the extended self and the social identification with the VA reveals that a VA as a supportive conversational technology has a dual function. This means that people can assess a VA as a social actor as well as a form of technology at the same time. Therefore, virtually extended identification describes the degree to which a person's identity matches the perceived identity of the VA as a team member (social actor as an external attribution to the in-group) and the degree to which the capabilities of the VA are attributed to the person's self (internal attribution to the in-group by the identification of the VA's characteristics, values, and capabilities with the self). This dual function of the VA is also based on the results suggesting that VAs do not significantly differ compared to a human chat partner regarding influence on perceived workload, performance (H1 and H3 not supported). However, satisfaction might have an impact on the identification with the chat partner in the context of virtual collaboration as the findings imply. Thus, companies could save valuable resources by deploying VAs in virtual collaboration as a chat partner. VAs should be deployed as both supportive tools to assist work-related tasks and as members of virtual teams to increase social identity and positive distinctiveness. In this way, the positive aspects of both theories (Lin 2015; Vahtera et al. 2017) could be used to achieve an overarching goal more efficiently. The creation of a social presence through social cues (Feine et al. 2019) could further reinforce these aspects (Franceschi et al. 2009).

Thus, one of the most relevant findings of this study is that social identity and the extended self in virtual collaboration with VAs are not contradictory, as assumed in H4. VAs can be perceived simultaneously as team members and as tools. The boundaries between technology as a collaboration platform and tool and technology as a partner for virtual collaboration seem to blur. However, the question arises as to whether our findings can be generalized since we examined a specific VA in our experiment. In this respect, recent research is currently using many VAs, chatbots, and conversational agents that are purely text-based agents (Hofeditz et al. 2019, p. 201; Diederich et al. 2020; Brachten et al. 2020). We used the social cues that are effective according to current knowledge (Feine et al. 2019) and tried to keep the interference factors, such as the influence of a time limit on team performance (Massey et al. 2003), as low as possible. Our insight into the relationship between social identity theory and the extended self in the context of virtual collaboration with VAs leads to an advanced understanding of machines as teammates and can be explained by the existing IS literature (Schwabe 2003; Waizenegger et al. 2020; Seeber et al. 2020a, b).

6.3 Limitations and Further Research

This study examined the effects of a newly introduced technology. It may be possible that the perception of the VA changes over time by using the VA for a longer period. Further studies may use and compare these findings with studies where VAs are used over longer periods of time. The level of anthropomorphism of a VA and the use of different social cues might also influence the perception of a VA. This aspect should be considered in future research.

As we focused on understanding the perception of VAs in the context of social identity and extended self, we examined one cultural background which is Central European. Further studies may consider cross-cultural differences in regard to VA adoption. Moreover, further studies may aim for a larger sample size to show possible unrevealed effects. Furthermore, we strongly recommend testing the proposed construct of virtual identification in different collaborative scenarios to take the next steps in understanding identification in the context of virtual collaboration.

Moreover, not only text-based communication but also interaction via speech may have an influence on the perception of VAs (Edwards et al. 2019). Additionally, the collaboration platform used in which the VA was integrated could also have influenced the social identity (Hu et al. 2017). Furthermore, the virtual collaboration environment might also be an influencing factor on the perception of the VA. We suggest that future research consider

potential differences in virtual collaboration between distinct environments.

7 Conclusion

This study provides new insights regarding social identity theory as well as the concept of the extended self in the context of virtual collaboration. First, it was shown that people who work with VAs identify less with their (human) team after their interaction with a VA. Therefore, collaborative VAs may influence the social identity of a person. Second, this study highlights that someone who identifies the VA as part of their extended self is also more likely to identify with (virtual) team members and vice versa. The revealed intertwining emphasized that research needs to change its understanding of (social) identification in the context of virtual collaboration with VAs. Neither concept should be regarded in isolation.

This study contributes to social identity theory as well as the extended self by proposing a new construct to understand identification with team members and technology in a collaborative context. The study reveals that the relationship between social identification with (virtual) team members and expanding the self through technology such as VAs is not contradictory but rather that they complement each other. VAs are not only perceived as resources to maintain and extend one's identity but also as social actors. This implies that research should not separate these concepts but rather combine their specific aspects to understand human behavior in virtual collaboration. To this end, items of both constructs may be combined and evaluated to develop the new virtually extended identification construct. This concept may be better suited for understanding human behavior in the changing landscape of virtual collaboration.

This study also provides practical contributions. VAs are a collaborative tool with a low entry barrier. The findings suggest that the support of a VA is similar to that of a human. Thus, organizations could save valuable resources by using VAs to support employees in their tasks. Especially in the context of a newly introduced technology, one could expect the effort needed to learn the technology to lead to an increase in perceived workload, but no significant effect was observed. However, the results indicate that the collaboration with a VA might lower the identification with other team members. As a worst-case scenario, employees do not feel part of the human team in return. Thus, decision makers should take measures to encourage the continued identification with other colleagues when introducing such technology within the organization. However, people might identify VAs as resources for expanding their own capabilities, but at the same time VAs

might be seen as social actors during collaboration. Overall, VAs are a resource-saving tool that managers may use to support their human employees. In this context, the introduction of VAs should be accompanied by measures to support the continued social identification with other colleagues, such as social events or gatherings.

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Paper 6: Collaborating with Virtual Assistants in Organizations – Analyzing Social Loafing Tendencies and Responsibility Attribution

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Collaborating with Virtual Assistants in Organizations: Analyzing Social Loafing Tendencies and Responsibility Attribution

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Abstract

Organizations increasingly introduce collaborative technologies in form of virtual assistants (VAs) to save valuable resources, especially when employees are assisted with work-related tasks. However, the effect of VAs on virtual teams and collaboration remains uncertain, particularly whether employees show social loafing (SL) tendencies, i.e., applying less effort for collective tasks compared to working alone. While extant research indicates that VAs collaboratively working in teams exert greater results, less is known about SL in virtual collaboration and how responsibility attribution alters. An online experiment with $N = 102$ was conducted in which participants were assisted by a VA in solving a task. The results indicate SL tendencies in virtual collaboration with VAs and that participants tend to cede responsibility to the VA. This study makes a first foray and extends the information systems (IS) literature by analyzing SL and responsibility attribution thus updates our knowledge on virtual collaboration with VAs.

Keywords Virtual collaboration · Virtual assistants · Social loafing · Responsibility attribution · Organizations

1 Introduction

In today's business world, technological advancements constantly reshape organizational efforts for remaining competitive (Cetindamar Kozanoglu & Abedin, 2020; N. Frick & Marx, 2021; Soto Setzke et al., 2021), transforming digital workplaces in enterprises for exploiting relative advantages (Junglas et al., 2019; Majhi et al., 2021; Meske & Junglas, 2020). This also implies employees and teams increasingly collaborate with and via technology (Changizi & Lanz, 2019; de Vreede & Briggs, 2005). The collaboration with technologies enabled by artificial intelligence

(AI), such as virtual assistants (VAs), shifts from simply using a tool for virtual collaboration with other employees to shaping a novel and independent virtual environment to collaborate with VAs (Maedche et al., 2019; Mirbabaie et al., 2020; Seeber, Waizenegger, et al. 2020a). VAs are software dialog systems simulating the behavior of humans which can be addressed via voice- or text-based commands and respond to the users' input appropriately (Brachten et al., 2020; Mirbabaie et al., 2020, 2021b). The application possibilities in organizations are manifold but VAs are foremost used as work facilitators (Brachten et al., 2020; Luger & Sellen, 2016; Mirbabaie et al., 2020). VAs collaborate with employees to optimize internal processes (Norman, 2017), generate additional revenue or cost savings (Quarteroni, 2018), and increase customer satisfaction (Behera et al., 2021; Verhagen et al., 2014), thus aim to establish substantial advantages over market competitors (Benbya & Leidner, 2018; Yan et al., 2018). Even though VAs do not provide a physical interaction and human representation (Maniscalco et al., 2020), they are increasingly used in virtual collaboration (Panganiban et al., 2020; Seeber et al. 2020a) and their distribution in enterprises is likely to grow (Maedche et al., 2019).

Many teams in organizations collaborate in virtual teams, which might even be globally distributed (Andres & Shippis,

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2019; Hassell & Cotton, 2017; Massey et al., 2003; Plotnick et al., 2016). Virtual collaboration happens through using simple tools such as Microsoft Teams or Slack (N. R. J. Frick, et al., 2021a, 2021b, 2021c) and reaches to computer-generated virtual realities (Fromm et al., 2020; Litvinova et al., 2018). Existing research takes the standpoint that employees and VAs collaboratively working in virtual teams exert greater results (Seeber, et al., 2020b; Waizenegger et al., 2020). However, less research is concerned with potential downsides. As in virtual collaboration, working with members in physical teams should inspire individuals to maximize their potential and to work particularly hard (Harkins & Petty, 1982). Nevertheless, research on teamwork also identified social loafing (SL), i.e., individuals working less for collective tasks than for individual tasks (Hardy & Latané, 1988; Karau & Williams, 1993). Employees might apply less effort to achieve a goal in a team compared to when working alone as the individual contribution is perceived as unnecessary and/or responsibility attribution is distributed among team members (Jassawalla et al., 2009; Karau & Williams, 1993; Latané et al., 1979). In corporate contexts, a possible decrease in motivation is one of the biggest obstacles for teamwork (George, 1992); it is thus vital to minimize individual tendencies to loaf (Schipers, 2014) especially for maintaining cohesiveness of teams (Taylor et al., 1983).

SL has been observed multiple times in physical teams uncovering scientific evidence that individuals working in teams show less effort compared to working independently (Karau & Williams, 1993; Latané et al., 1979). However, individuals increasingly collaborate in virtual teams with VAs (Maedche et al., 2019; Mirbabaie et al., 2020; Seeber, et al., 2020a, 2020b, 2020c) thus scholars need to adjust their understanding on the different aspects of collaborative settings (Mirbabaie et al., 2020). To gain a deeper understanding on virtual collaboration with VAs, knowledge from human-to-human collaboration research needs to be exploited (Demir et al., 2020). As collaboration with VAs in organizations is likely to become commonplace, and VAs are increasingly perceived as human-like actors since they are being inherently anthropomorphic (Feine et al., 2019; Hussain et al., 2019; Pfeuffer et al., 2019; Porra et al., 2020), there is an urgent demand for the information systems (IS) discipline to conduct further research on virtual collaboration to reveal differences and similarities to human teams (Mirbabaie et al., 2021a). Associated consequences might significantly alter theoretical and practical viewpoints of how and for what purpose VAs are applied in virtual collaboration. Employees no longer identifying themselves with a decision made by a VA, not questioning or taking responsibility for it, which possibly means making poor or even wrong choices (Trocin et al., 2021). This generates enormous risks for both enterprises (i.e., diminishing reputation

or profitability) and individuals (i.e., feeling less valued and more stressed) (Chidambaram & Tung, 2005; Grimes et al., 2021). Missing responsibility attribution in human-VA teams decisively thus impacts the way VAs are implemented and how they are being applied in organizations, restricting their deployment to certain industries, departments, teams and purposes. Moreno et al. (2001) clarified that there is generally a contradiction on positive (constructivist hypothesis) and negative (interference hypothesis) outcomes when collaborating with VAs. On the one hand, VAs assist employees in virtual collaboration, freeing them from unwanted duties and allowing them to focus on their key responsibilities (Brachten et al., 2020). On the other hand, intensified collaboration with VAs might yield in employees becoming dependent and showing greater SL tendencies and missing responsibility attribution (Mirbabaie et al., 2021b). To examine the role of VAs in virtual collaboration and related consequences regarding SL and responsibility attribution, our research is guided by the following questions:

RQ1 To what extent do virtual assistants cause social loafing in virtual collaboration?

RQ2 How does responsibility attribution differ in virtual teams?

To answer these questions, we conducted an online experiment with 102 participants who were assisted in the execution of a work-related task by a text-based VA. We measured and compared general SL behavior and SL behavior in virtual collaboration with a VA as well as the attribution of responsibility. This study contributes to theory and practice by structuring our understanding of collaboration with VAs and related negative effects. Researchers will find the novel insights fruitful in understanding what consequences are related to virtual collaboration with VAs assisting in work-related tasks. Practitioners, such as managers and software developers, will be able to comprehend possible downsides for human-VA teams and which measures might be rewarding to cope and/or prevent negative outcomes. This article seeks to extend the IS literature by attempting to make a first foray into the examination SL tendencies and responsibility attribution in virtual collaboration with VAs to drive future research in this field of high relevance.

2 Related Work

Collaboration with technology was examined from multiple perspectives within the IS discipline (Bajwa et al., 2007; Bednar & Welch, 2020; Beer et al., 2005; Frohberg & Schwabe, 2006; Schwabe, 2003; You & Robert, 2018). Throughout decades of fundamental research, several terms

evolved for systems behaving alike. Popular terms that are related to VAs and found in theory and practice are chatbots (Stieglitz et al., 2018), digital assistants (Maedche et al., 2019) and conversational agents (Frick et al., 2021a, 2021b, 2021c). Scholars examined VAs from different perspectives (e.g., Luger & Sellen, 2016; Saffarizadeh et al. 2017; Seeber et al., 2018). Gnewuch et al. (2017) differentiated VAs in their primary mode of communication (how users interact with VAs) and their main purpose (whether a VA covers a narrow or broad task). Knotte et al. (2019) characterized VAs by their design characteristics, for instance, adaptivity (how VAs learn and adjust to changing environments) and assistance domain (in which area VAs provide assistance). While research is lacking a consistent classification of VAs due to possible overlaps in their capabilities (Mirbabaie et al., 2021b), multiple definitions emerged but somewhat limit the manifold functionalities of VAs. In this research we follow the interpretation of Mirbabaie et al. (2021b) who defined VAs as “dialog systems simulating the behavior of humans via different modes of communication (e.g., written or spoken natural language, haptics, gestures, facial expressions, graphics), continuously learn and develop over time by analyzing and interpreting a given input combined with additional data sources for assisting with divergent tasks or execute them autonomously” (p. 4). Figure 1 outlines two examples of VAs that were used in earlier studies (Brachten et al., 2020; Mirbabaie et al., 2020).

VAs have become increasingly relevant as work-facilitator in organizations in recent years due to constant technological enhancements (Berg, 2015; Spohrer & Banavar, 2015) turning regular information technology (IT) or decision support

systems into smart systems (Alter, 2020). The development of VAs is based on AI and underlying machine learning (ML) algorithms attempting to create intelligent systems augmenting the abilities of humans (McTear, 2017). However, there are certain distinctions of intelligent behavior (Mirbabaie et al., 2020). On the one hand, there are agents that respond to a certain input based on predefined rules (Russel & Norvig, 2016). On the other hand, there are adaptive systems that behave reactively, proactively and autonomously (von Wolff et al., 2019) while continuously learning and developing over time by processing different types of digital information (Mitchell et al., 2018). VAs aim to combine the complementary strengths of humans and AI (Kamar, 2016), for example, associating emotional intelligence of humans with the processing of huge amounts of data (Dellermann, et al., 2019a, 2019b). Thereby, VAs supply humans with feedback to assist in decision-making (e.g., AI in the loop of human intelligence), and humans supply VAs with feedback to optimize their capabilities (e.g., human intelligence in the loop of AI) (Dellermann, et al., 2019a, 2019b; Dellermann, et al., 2019a, 2019b; Mirbabaie et al., 2021b).

In virtual collaboration, VAs use multiple communication styles, such as written or spoken natural language, and are capable to interpret and react to gestures or facial expressions (Laumer et al., 2019; Nakano & Fukuhara, 2012). They adapt to users with varying roles by addressing them via different languages (Gnewuch et al., 2020; Pfeuffer et al., 2019), interpret emotions of individual team members (McDuff & Czerwinski, 2018) and foster disclosing of relevant information (Frick et al., 2021a, 2021b, 2021c). VAs

Fig. 1 Example interactions with VAs from earlier research (Brachten et al., 2020; Mirbabaie et al., 2020)

Kim - Your Virtual Assistant

ANGEBOTREFFEN VON Dialogflow

Can you tell me what the critical path is?

Of course! The critical path indicates which project steps have no buffers. They must be carried out within the specified time period, otherwise each subsequent process step will be delayed. The critical path results from each process step that has NO Free Float and also no Total Float. Can you follow me?

Not really... What is the free float?

Oh, I'm sorry! The Free Float is how long an activity can be delayed without delaying the Early Start of its successor activity. It is therefore the difference between the Early Finish date (EF) of the activity from the Early Start date (ES) of the next. So simply EF minus ES! Since the last project step has no successor, the Free Float is always 0. Did you understand that?

Yes I get it now. Thank you!

Great! I'm so glad I could help. Text me if you have any further questions!

Type in your question...

Today

Participant 10:20
Hello!

Dialogflow Bot 10:20
Hello!

Participant 10:20
How are you?

Dialogflow Bot 10:20
If you're fine, I'm fine!
As you have probably heard, I am here to help you with your tasks. To help you get started, I will give you a short introduction in the following minutes on how to ask me for assistance. Let me know, when you are ready!

Participant 10:21
Okay, I'm ready.

Dialogflow Bot 10:21
Great, let's start with the tutorial.

Enter your message...

B I S [Icons]

are further inherently anthropomorphic since they use verbal, visual, auditory, and invisible social cues, for instance jokes, facial expression, laughing and response time, which makes users feel like talking to another human (Feine et al., 2019; Hussain et al., 2019; Pfeuffer et al., 2019). Within the research stream of CASA (Computers Are Social Actors) it has been identified that individuals exhibit social reactions when collaborating with technology (Nass & Moon, 2000). As explained by the Social Response Theory, individuals subconsciously associate social rules towards technology that uses human-like traits or behavior (Nass & Moon, 2000; Reeves & Nass, 1996). Furthermore, individuals have certain expectations towards VAs that use human-like design characteristics which might not be in line with their actual capabilities or purpose (Luger & Sellen, 2016). Nevertheless, yet existing limited conversational skills of VAs remind individuals that they are still collaborating with a machine, raising feelings of strangeness possibly leading to a discontinued usage (Diederich et al., 2020). Furthermore, there are also certain challenges and dangers related to security and privacy heavily impacting trust in VAs (de Barcelos Silva et al., 2020; Lee et al., 2020). For example, the feeling of being surveilled or that data is misused or retrieved for dubious purposes decreases trust in the agent and hinders the distribution of information (Frick et al. 2021). Moreover, interacting with VAs increases the transparency of working methods, roles and tasks which causes discomfort (Wunderlich & Paluch, 2017) and yields in a feeling of being monitored, losing personal value and control as well individual knowledge (Mirbabaie et al., 2020).

The application of VAs in organizational surroundings is fruitful on many levels and is already implemented across industries. VAs are used internally and externally to optimize processes by assisting in the execution of work-related tasks (Norman, 2017), increase the overall customer satisfaction (Cui et al., 2017; Verhagen et al., 2014), establish substantial competitive advantage (Benbya & Leidner, 2018) and generate additional revenue or cost savings (Quarteroni, 2018). For example, VAs are used in form of a virtual colleague from the human resource department to enhance the onboarding processes of new hires by providing flawless guidance (Shamekhi et al., 2018). Furthermore, VAs are applied in customer service and assist in answering customer inquiries more quickly (Gnewuch et al., 2017; Hu et al., 2018). In principle, the application of VA in organizations aims to reduce the workload of employees by assisting with repetitive tasks (Brachten et al., 2020; McTear, 2017; Mirbabaie et al., 2020).

Recent research demonstrates that VAs are able to assist in the decision-making process (Seeber, et al., 2020b; Waizenegger et al., 2020) and tackle collaborative issues frequently arise (Mirbabaie et al., 2021b). However, since VAs are becoming more human-like (Feine et al., 2019; Hussain et al., 2019;

Pfeuffer et al., 2019) and are already perceived as legitimate team members (Seeber et al., 2018) it can be assumed that knowledge from human teams is transferable to virtual collaboration with VAs (Mirbabaie et al., 2020). This includes positive and negative aspects and possibly disadvantages known from human–human collaboration.

3 Theoretical Background

3.1 The Phenomenon Social Loafing

In 1913, Maximilien Ringelmann conducted an experiment to suggest a possible decrement in the individual motivation as a result of working in a group (Kravitz & Martin, 1986). Male volunteers were asked to pull on a rope as hard as they can (tug-of-war) in groups of varying sizes where a measuring device determined the total effort. The results showed that as the group sizes increased, the group performance was increasingly lower than from the addition of individual performances. This behavior was later explained as SL, “the reduction in motivation and effort when individuals work collectively compared with when they work individually” (Karau & Williams, 1993, p. 681). SL might arise when individuals perceive their contribution to be unnecessary and/or responsibility is distributed among members of a team (Karau & Williams, 1993; Latané et al., 1979). SL is also expected to rise when team sizes increase as the responsibility is distributed among several humans (Dennis et al., 2005). A decrease of SL is possible when individuals believe that they are being monitored and measured by their personal performance (Karau & Williams, 1993). Thus, the individual contribution is reduced when members of nominal groups believe that they are collectively working in teams.

While the observability of SL is hardly contestable, there is still no clear explanation for this social phenomenon. An extensive body of literature focused on the different determinants (Vaghefi & Lapointe, 2012), such as individual characteristics and differences, group sizes and memberships or task contribution efforts and visibility (e.g., Gavala-González et al., 2020; O'Neill et al., 2020; Zhu et al., 2019). For example, Smith et al. (2001) observed that a lower need for cognition is associated with SL. Individuals who enjoy and participate in elaborating cognitive tasks are less likely to reduce their efforts in groups. Schippers (2014) examined personality traits and indicated that a high occurrence of conscientiousness and agreeableness within a group might compensate SL tendencies. In contrast, a recent study of Hou et al. (2021) examined SL in online brand communities and revealed that agreeableness and conscientiousness do not have a direct impact on SL. Nevertheless, the authors explained that personality traits are indirectly related to SL behavior. Research further identified apathy and social

disconnectedness as antecedents for SL and explained that participants took compensatory actions when members of their teams loaf (Jassawalla et al., 2009). Individuals with low self-efficacy and self-confidence, who consider themselves more valuable than others, show SL tendencies (Hart et al., 2004). Moreover, competency, emotional relationship, and collective identity were found to be key determinants of social loafing (Luo et al., 2021).

Studies have further researched SL in organizational environments and analyzed that measuring and disclosing the individual contribution of team members increases the individual performance (Lount & Wilk, 2014) and that a task's attractiveness impacts SL (Zaccaro, 1984). Byun et al. (2020) examined individual and situational factors and found that lower exchange ideology might significantly reduce employees' SL tendencies. Furthermore, supervisory factors are related to lower SL declaring that managerial guidelines are reasonable to reduce SL in organizations. Khan et al. (2020) specifically identified that transformational leadership has a significant positive relationship with employees' intrinsic motivation and thus is capable of decreasing SL. The authors clarified that managers should possess transformational attributes for informing and inspiring their employees to achieve greater outcomes.

Besides observing certain determinants, many different theories emerged on how SL behavior can be explained. Although several scholars offered theories on SL, they are generally limited to explaining one of several possible causal mechanisms and do not attempt to include the wide range of variables (Karau & Williams, 1993). The explanations provided by the researchers can usually be assigned to one of the following three main theories. Within the Social Impact Theory, a diffusion of responsibility leads to SL. Latané et al. (1979) explained that individuals feel deindividuated when the size of a group increases, distancing themselves from their own individual performance which decreases personal responsibility. Thus, when the number of team members increases, the feeling of pressure reduces as the burden is distributed among multiple individuals. The Free Rider Theory explains that team members recognize that completing a task is achievable without using their full potential and that the benefit of performing a task does not increase by hanging in (Albanese & van Fleet, 1985). Finally, within the Theory of Social Comparison SL is caused as individuals consider outside reference points to assess their own effort, abilities, and skills. Thereby, individuals match their performance to that of their team members (Harkins & Szymanski, 1989). When a team member perceives that others in the group are slacking or showing laziness, they are likely to reduce their own efforts (Jackson & Williams, 1985).

3.2 Social Loafing in IS Research

Research on SL within the IS discipline can generally be divided into two main streams (Vaghefi & Lapointe, 2012). On the one hand, IS scholars applied SL theories in IT related contexts and assessed whether existing assumption are still valid (e.g., Dennis et al., 2005). On the other hand, studies focused on possible negative outcomes when using IT and how SL might be decreased (e.g., Suleiman & Watson, 2008). For example, an early study of Suleiman and Watson (2008) examined the diminishing of SL in technology-supported teams. The authors indicated that SL occurs in teams supported by technology and argued that further research is urgently needed as mixed virtual teams become more prevalent thus employees increasingly gain the opportunity to loaf. Alnuaimi et al. (2010) argued that, due to new possibilities in IT, teams no longer need to be tied to a specific location but can collaborate across national borders. The authors assigned 140 participants in 32 teams which had to solve a brainstorming task assisted by a group system software. The results revealed that the diffusion of responsibility, attribution of blame, and dehumanization meditates the effect of team size and dispersion of SL. Current research further found that the type of trust is important to understand how scrutiny changes the influence of trust on individual SL in virtual teams (Robert, 2020). Thereby, Robert (2020) identified that cognitive trust negatively influences SL, while affective trust tends to strengthen SL. Furthermore, Lv et al. (2021) described that SL is related to decreased perceived justice and functional benefits which leads to negative word-of-mouth, switching behavior, and counterproductive work behavior.

Recent IS research is also concerned with modern teamwork and the applied methods and working models. Chen and Cheng (2018) analyzed Lean-Kanban (i.e., the constant improvement of work processes across resources to avoid bottlenecks) to solve SL. Based on the results of a case study within a non-profit organization, the authors suggest that Lean-Kanban improves the production environment in organizations and prevents situations that may cause SL. Another study of Fronza and Wang (2021) determined rules to prevent social loafing behavior in agile software development teams using a mixed-method approach which includes an action case study of software development teams and analyzing secondary data. The results indicate that the formulation of team expectations agreements, for instance, on meeting attendance and contribution, respect of tasks, roles and teammates, and collaboration, have the potential to prevent SL.

In principle, SL is generalizable across tasks and population (Karau & Williams, 1993). SL tendencies and the diffusion of responsibility does not necessarily have to take place in human teams but might also occur in virtual collaboration

with VAs (Mirbabaie et al., 2021b). Thus, VAs might even encourage SL as the individual contribution is no longer measurable (Vaghefi & Lapointe, 2012) and individuals tend to rely on technical assistance (Mirbabaie et al., 2021b).

3.3 Derivation of Hypotheses

SL is a well-known phenomenon emerging in physical and virtual teams (Alnuaimi et al., 2010; Karau & Williams, 1993; Latané et al., 1979; Suleiman & Watson, 2008). Employees in organizations increasingly collaborate with technology (Changizi & Lanz, 2019; de Vreede & Briggs, 2005) where VAs shape novel and independent collaborative environments (Maedche et al., 2019; Mirbabaie et al., 2020; Seeber, et al., 2020b). CASA explained that many of the findings from human–human interaction also occur in computer interaction, for example, the feeling of team spirit after being grouped up with technology (Nass & Moon, 2000). Previous research has stated that VAs alter the way employees collaborate in organizations (Dias et al., 2019; Wang & Siau, 2018) explaining the pressing need for theory and practice to understand how employees collaborate with VAs within their virtual teams (Mirbabaie et al., 2020; Seeber et al., 2018). VAs are already perceived as legitimate team members (Seeber et al., 2018) and being inherently anthropomorphic where individuals feel like interacting with another human (Feine et al., 2019; Hussain et al., 2019; Pfeuffer et al., 2019). Therefore, it can be assumed that employees show SL tendencies when collaborating with a VA in a virtual team. We thus developed the following hypothesis:

H1 There is a positive correlation between general SL tendencies and SL tendencies in virtual collaboration with VAs.

Latané et al. (1979) explained that increasing the number of members in teams reduces the pressure on individuals as the burden is divided among more people. This decrease of social forces on individuals results in less participation. In terms of SL, this is referred to as diffusion of responsibility. Individuals feel deindividuated when the size of the group increases resulting in distancing themselves from their own individual performance decreasing personal responsibility (Latané, 1981; Latané et al., 1979). In virtual collaboration, employees might apply less effort to achieve a goal in a team compared to when working alone as the responsibility attribution is distributed among team members (Jassawalla et al., 2009; Karau & Williams, 1993; Latané et al., 1979). Furthermore, recent studies also explained that employees might become dependent and gaining a feeling of false security (Mirbabaie et al., 2021b). Therefore, in the context of this study, it can be assumed that individuals who show stronger

SL tendencies are more likely to hand over responsibility to VAs. We derived the following hypothesis:

H2 There is a positive correlation between SL tendencies in virtual collaboration with VAs and responsibility attribution to the VAs.

Conscientiousness explains the individual organization and self-discipline (Berry et al., 2007) while agreeableness refers to the degree of being helpful and cooperative (Kurylo & Stevenson, 2011). Individuals with a high level of conscientiousness and agreeableness are likely to maintain cooperation in group settings and preserve self-discipline (Liao & Chuang, 2004; Tangney et al., 2004). When individuals in teams notice the reduced efforts of other team members, they tend to increase their own efforts to compensate the slacking of others and still achieve proper results (Williams & Karau, 1991). Both personality traits have been investigated in the context of collaborative technology and their association with teamwork and task accomplishment (Devaraj et al., 2008; Mouakket & Sun, 2020; Soltani et al., 2013). Earlier studies identified that conscientiousness and agreeableness negatively influence SL tendencies in human–human as well as in technology-supported teams (Bolin & Neuman, 2006; Hoon & Tan, 2008; Morgeson et al., 2005; Schippers, 2014). A recent study of Hou et al. (2021) revealed that agreeableness and conscientiousness do not have a direct impact on SL in online brand communities. Nevertheless, personality traits indirectly impact SL behavior due to a high level of social distances in technological surroundings resulting in dehumanization (Hou et al., 2021). The mere question of whether SL occurs in virtual collaboration with VAs cannot be answered solely. Personality traits are repeatedly mentioned as relevant aspects in extant literature (e.g., Hoon & Tan, 2008; Schippers, 2014), however, the impact on SL in virtual teams remains indistinct (Byun et al., 2020). We thus aim to identify parallels of human teams and claim that conscientiousness and agreeableness of individuals in teams lowers SL tendencies when collaborating with a VA. We derived the following hypotheses:

H3a There is a negative correlation between conscientiousness and SL tendencies in virtual collaboration with VA.

H3b There is a negative correlation between agreeableness and SL tendencies in virtual collaboration with VA.

Besides conscientiousness and agreeableness, research has further shown that that individuals who tend to enjoy and participate in elaborating cognitive tasks are less likely to reduce their efforts in group tasks (Smith et al., 2001). The effect of need for cognition refers to “an individual's tendency to engage in and enjoy effortful cognitive endeavors”

(Cacioppo et al., 1996, p. 197) and is “a need to structure relevant situations in meaningful, integrated ways” (Cohen et al., 1955, p. 291). The broad familiarity of this construct serves as additional factor to explain the equality of virtual collaboration with a VA to human teams. We proposed the following hypothesis:

H4 There is a negative correlation between need for cognition and SL tendencies in virtual collaboration with VA.

Systems such as VAs are ultimately supposed to relieve human workers and free them from unwanted tasks to release cognitive resources (Dang et al., 2020) which can be used for more creative and strategic duties. Brachten et al. (2020) indicated that reducing the cognitive load of employees, i.e., the amount of working memory used while processing a task (Sweller, 1988), using a VA in virtual collaboration is achievable. However, this might also lead to individuals not questioning outcomes of a task anymore (Mirbabaie et al., 2021b). We argue that too much relief of employees or taking over too many or extensive tasks might advocate SL tendencies (Bluhm, 2009). We therefore hypothesized:

H5 There is a negative correlation between cognitive load and SL tendencies in virtual collaboration with VA.

Finally, research examined that the extent to which team members rate the task as engaging and relevant reduces the likelihood of SL tendencies occurring in collaborative settings (Karau & Williams, 1993). Therefore, a team member who believes to fail in contributing to the completion of the task is more likely to show SL tendencies. Current studies also indicated that individuals might no longer identify themselves with a certain task and cognitive skills might become superfluous (Mirbabaie et al., 2021b). To consider

these aspects in the context of our study, we assess how participants rate their individual knowledge regarding the task they are being assisted with. Leaning on earlier research, we assume that individuals with poor knowledge are more likely to show SL tendencies in completing the task. We derived our final hypotheses (cf. Table 1):

H6: There is a negative correlation between knowledge about the task and SL tendencies in virtual collaboration with VA.

4 Method

4.1 Participants

Since this study coincides with the COVID-19 pandemic, we decided to conduct an online experiment rather than using a laboratory setting to examine SL and responsibility attribution in virtual collaboration with VAs. The participants were recruited using SurveyCircle enabling researchers to identify suitable subjects while guaranteeing a diversified sample (SurveyCircle, 2021). The platform allows students and researchers in the German-speaking countries to collect points by participating in studies, which, in turn, can be passed on to participants in own studies. SurveyCircle further ensures that surveys are carried out correctly, for example, subjects who fall significantly short in the processing time are penalized or even banned. Participants are thus more likely to provide complete answers instead of performing the study hastily or incorrectly. Nevertheless, we screened the data manually for anomalies and suspicious responses (i.e., very short processing times and similar or identical answers) but did not need to exclude any participants. In terms of sample size, Onwuegbuzie and Leech (2005) advise to include at least 64 participants for

Table 1 Hypotheses derivation with supporting literature

| Hypothesis | Supporting literature |
|--|--|
| H1: There is a positive correlation between general SL tendencies and SL tendencies in virtual collaboration with VAs | Karau and Williams (1993) and Nass and Moon (2000) |
| H2: There is a positive correlation between SL tendencies in virtual collaboration with VAs and responsibility attribution to the VAs | Latané (1981) and Latané et al. (1979) |
| H3a: There is a negative correlation between conscientiousness and SL tendencies in virtual collaboration with VA | Bolin and Neuman (2006), Morgeson et al. (2005) and Schippers (2014) |
| H3b: There is a negative correlation between agreeableness and SL tendencies in virtual collaboration with VA | Bolin and Neuman (2006), Morgeson et al. (2005) and Schippers (2014) |
| H4: There is a negative correlation between need for cognition and SL tendencies in virtual collaboration with VA | Cacioppo et al. (1996) and Smith et al. (2001) |
| H5: There is a negative correlation between cognitive load and SL tendencies in virtual collaboration with VA | Bluhm (2009) and Brachten et al. (2020) |
| H6: There is a negative correlation between knowledge about the task and SL tendencies in virtual collaboration with VA | Karau and Williams (1993) and Mirbabaie et al. (2021b) |

one-tailed, and 82 participants for two-tailed hypothesis. For determining the necessary sample size, we conducted a power analysis using G*Power (Version 3.1.9.6) suggesting a minimal sample size of 84. In total, 102 people aged 19 to 57 years ($M=26.67$, $SD=6.59$) participated in our study, 68 of them female and 34 male, enabling significant statistical results. Most of the respondents already had a university degree (60.8%) or the highest school-leaving qualification (38.2%). The vast majority (81.4%) indicated that they were still studying, while the minority were already employed (18.6%). Since the study is intended to only consider individuals who have already worked professionally, individuals who indicated that they were still studying were also asked to state whether they were part-time employed. Participants who did not fulfil this requirement were not included in the analysis. Students are generally considered suitable subjects as, compared to experienced professionals, they may tend to be less biased due to less work experience (Brachten et al., 2020). Additionally, they might have less issues operating VAs than an average adult since younger individuals are more affine to modern communication technology (Brachten et al., 2020).

4.2 Materials

4.2.1 Virtual Assistant

We developed a VA using Google's cloud-based platform Dialogflow (<https://dialogflow.com>). The platform allows the development of VAs without extensive programming knowledge and includes several features such to provide natural and rich conversational interfaces (Canonic & De Russis, 2018). VAs developed using Dialogflow can be integrated in various applications or simply as iframe on websites. We embedded the VA into LimeSurvey's online platform so that subjects were able to interact using a question–answer component (Lamontagne et al., 2014; Morrissey & Kirakowski, 2013) without switching applications. We used a text-based interface to maintain a simplified interaction with the VA (Araujo, 2018) and avoid overwhelming participants with multiple input possibilities. The VA was designed to be simple rather than sophisticated, as the development of a highly complex VA using numerous social cues would have been beyond the scope of this research. Thereby, the VA simulates intelligent behavior by selecting a prefabricated answer based on distinct keywords used in the participant's input (detailed examples on prefabricated answers according to corresponding keywords can be found in the "Appendix"). Initially, the VA welcomes participants and explains its functionalities. Since a VA should also be able to participate in social discussions (Brachten et al., 2020; Feine et al., 2019), it is able to participate in a whole range of different small talk topics, i.e., the question of mood and feeling.

For example, when asking the VA "How old are you?", it answers "I am 0 years old. I was developed only this year.". When telling the VA that "You are really no help", it replies with "Hey, give me a chance!". Finally, to make participants aware of interacting with a VA, we displayed an icon of a bot and named our VA "ConsultantBot" (c.f. Fig. 2).

A pre-test was conducted to uncover possible ambiguities or problems during the implementation to provide participants with a realistic but manageable task in the subsequent main experiment. We compared a brainstorming task with a classification task as both were used in earlier studies and are commonly performed in organizations (Alnuaimi et al., 2010; Brachten et al., 2020; Mirbabaie et al., 2020; Schmidt et al., 2020). The tasks were chosen to be challenging but not too difficult as SL is more likely to occur when tasks are perceived as simple, and the invested effort is not measured (Karau & Williams, 1993; Latané et al., 1979). As we were not interested in how fast the tasks were solved but whether SL and ceding attribution was observable, the actual outcome of each task did not have any effect on our analysis. There was thus no certain benefit when successfully completing the task. The sample for our pre-test of 10 participants (5 female, 5 male) consists of randomly selected humans of which 6 were full-time employed, 3 still studying and 1 did not provided any information.

The brainstorming task was adapted from Alnuaimi et al. (2010) who examined SL in technology supported teams using a group support system software. The authors randomly assigned 140 students to 32 teams which needed to generate as many ideas as possible to improve a company's image. Similar to this study, participants in our brainstorming task should generate ideas to increase the sustainability of a fictional company. The VA could be asked for additional ideas thus was intended to inspire participants by providing suggestions. The classification task was based on recent studies of Brachten et al. (2020) as well as Mirbabaie et al. (2020). Participants were asked to apply the critical path method to arrange certain activities according to their dependencies for calculating an overall duration. Thereby, a VA provided subjects with guidance on solving the task. In our classification task, participants were asked to read car reviews and rate whether they were a recommendation to buy. Accordingly, a VA was able to assist in evaluating the reviews. The verdict is not actually based on an intelligent analysis of the VA but on the assessments of a real person who was not involved in the intention of the study at the time of the evaluation. It should be noted that the VA's assessment was not always correct but corresponded to the authentic assessment of the real person. The responses also varied in terms of certainty, the VA might have given confident and definite or uncertain and insecure estimates. In addition, the VA was able to provide answers to detailed questions,

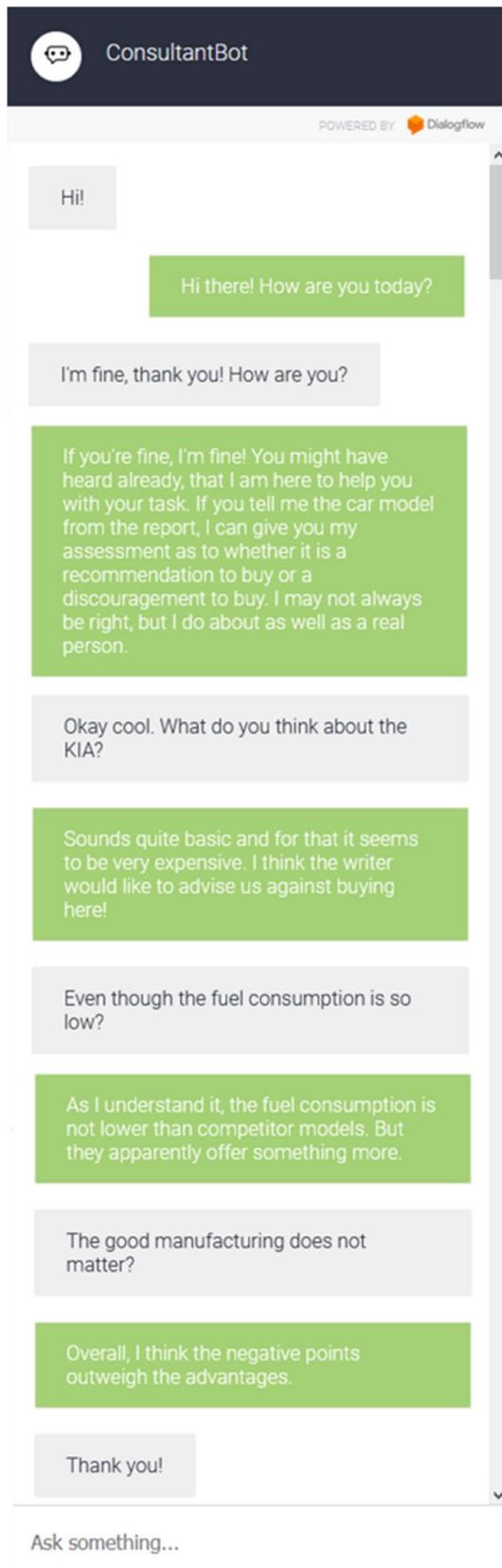


Fig. 2 Example of chat interaction with the VA

for instance, reassuring to stick with a decision even if the review contained opposing or deviating information.

Our analyses indicated higher interaction in the classification task. On average, participants interacted 41.13 s (SD = 34.08) with the VA and made 5.10 queries (SD = 2.08). Dialogflow's usage protocol revealed that every participant used the VA in the classification task. In the brainstorming task, the interaction time was 19.80 s on average (SD = 18.66) with 2.10 queries (SD = 2.38). The usage protocol of Dialogflow showed that 4 of the 10 participants did not use the VA at all in this task. Furthermore 3 other participants stated that they did use the VA, but only after they had already noted down their ideas. Overall, subjects rather determined a shared responsibility for the task (M = 4.10, SD = 3.11) for the classification task compared to the brainstorming task (M = 2.90, SD = 1.85). In total, 8 out of 10 participants evaluated the VA within the classification task as more helpful compared to the brainstorming task. The results also indicated higher interaction with the VA in classification task which was not inevitably needed to complete the assignment (i.e., queries about details in the assessment). Since the VA needed to be rated as supporting by its user for observing SL tendencies, and less interaction with the VA in the brainstorming task might have led to less meaningful insights, we chose the classification task for the subsequent main study. Detailed information on the analyses can be found in the "Appendix".

4.2.2 Social Loafing and Responsibility Attribution

To measure SL tendencies, a distinction was made between general SL tendencies and SL in virtual collaboration with the VA. General SL tendencies were measured using four items adapted from Schippers (2014) who examined SL in student group works. A higher score on this scale indicates stronger tendencies towards SL. The items were rated on a five-point Likert scale (disagree completely to agree completely) and achieved a high reliability ($\alpha = 0.85$). One example item is "I put less effort into the task than other members of my team". In our study, the subscale of the modified general SL behavior had a high reliability ($\alpha = 0.87$).

As, to our knowledge, no research on SL in virtual collaboration with VAs was conducted yet, a new scale for that purpose was created and validated in advance. Building on Schippers (2014), the scales measured the own work behavior within a team context and concrete components of work. We narrowed down our validated 8 questions to 6 items achieving a satisfying reliability with Cronbach's $\alpha = 0.77$. The items are: "I read the evaluations completely and attentively", "I only skimmed the evaluations", "I adopted the evaluations of the VA", "The VA enabled me to complete the task more quickly", "The VA facilitated the processing of the task" and "I first asked the VA's evaluation before I

dealt with the evaluation myself". In accordance with the SL scale adapted from Schippers (2014), we measured the items on a five-point Likert scale (disagree completely to agree completely). It is reasonable to query general SL tendencies as well as SL tendencies in the task via self-rating, since Conway and Lance (2010) state that correlations collected between different test methods tend to be weaker and less accurate. Karau and Williams (1993) suggested that self-ratings of SL affect self-reported effect sizes when a cover story was used to inform participants that the study was about effort versus performance or when maximizing rather than optimizing tasks were used (Schippers, 2014). None of this is the case in this study. Our developed scale reached high reliability in the main experiment ($\alpha = 0.86$).

Finally, we assessed the participants' perceptions of attributing responsibility to the VA. It is common to measure responsibility with self-ratings similar to as participants can easily report their own perceived responsibility. The scale chosen here differs from common scales, such as the felt responsibility scale (Pearce & Gregersen, 1991), in that participants in our experiment were not only asked to report their own perceived responsibility, but decided whether the VA or themselves were more responsible for the outcome. We created a five-point Likert scale ranging from "I was fully responsible" to "the VA was fully responsible".

4.2.3 Agreeableness, Conscientiousness and Need for Cognition

For measuring personality traits, we adapted the Big-5 for agreeableness and conscientiousness as well as the short version of the need for cognition scale (Beißert et al., 2014). The Big Five is a model of personality psychology consisting of five main dimensions: openness to experience (open-mindedness), conscientiousness (perfectionism), extraversion (sociability), agreeableness (consideration, cooperativeness, empathy), and neuroticism (emotional lability and vulnerability). The Big Five have been substantiated by many studies and is internationally regarded as the universal standard model in personality research (John et al., 2008). Agreeableness and conscientiousness were each measured with twelve items using a five-point Likert scale (disagrees completely to fully agree). Example items for agreeableness are *"I am interested in people"* and *"I make people feel at ease"*. Conscientiousness included, for instance, *"I am always prepared"* and *"I often forget to put things back in their proper place"*. The items proved a high reliability in our study both for agreeableness ($\alpha = 0.79$) and conscientiousness ($\alpha = 0.85$).

Cacioppo et al. (1984) originally developed a standardized questionnaire comprising 45 items to assess need for cognition which were further shortened by several researchers (e.g., Bless et al., 1994). We used the short version of

the need for cognition scale consisting of four items (Beißert et al., 2014): *"I would prefer more complicated problems to simple problems"*, *"First and foremost I think because I have to"*, *"It is enough for me simply to know the answer without understanding the reasons for answering a problem"* and *"I like my life to be full of tricky tasks that I have to solve"*. The items were measured using a five-point Likert scale (disagree completely to agree completely) and achieved a medium reliability ($\alpha = 0.64$).

4.2.4 Cognitive Load

The NASA task load index (NASA-TLX) was used to measure the cognitive load of the participants. Although analyzing cognitive load in virtual collaboration with a VA was not the main objective of this study, it provides profound indications whether participants are relieved when collaboration with a VA. The NASA-TLX scale was developed by the American national Aeronautics and Space Administration (Hart & Staveland, 1988) and determines the perceived workload of a task (Galy et al., 2012). It has successfully been applied in several experimental settings (Cao et al., 2009; Noyes & Bruneau, 2007; Rubio et al., 2004) and even in the context of VAs (Brachten et al., 2020; Mirbaie et al., 2020) achieving high reliability ($\alpha = 0.89$). The scale includes six subscales (1) mental demands, (2) physical demands, (3) time demands, (4) performance, (5) effort and (6) frustration, and were measured on a five-point Likert scale (very low to very high). Mental demand assesses cognitive efforts and physical demands manual efforts. Temporal demand determines the perceived time pressure when executing a task. Performance captures the individual perception of accomplishment. Effort estimates the expense which had to be undertaken to reach a result, and frustration explains the level of saddening when solving a task. In this study, the subscale reached a medium reliability ($\alpha = 0.71$).

4.3 Procedure

The participants were given a brief introduction and informed about data privacy protection. However, we deliberately did not explain the specific research context to avoid any bias. We reminded the participants to imagine a real-world working scenario and answer the questions related to their current teamwork.

Initially, the participants were asked to provide socio-demographic data such as age, gender and educational as well as the current professional activity and the industry. Afterwards, the participants were told to imagine being employees of a large company who were entrusted with the task of determining the new fleet of company cars from the small car segment. The participants were requested to read various test reports on different car models and needed to

judge whether they recommend purchasing a specific car or not. Therefore, the evaluation was rated on a six-point scale (1 = very good; 2 = good; 3 = satisfactory; 4 = sufficient; 5 = poor; 6 = insufficient). However, participants were told that they were not alone in completing the task but assisted by a VA. Before rating the cars, we explained how to interact with the VA, that the communication is like talking to a human-being and that the VA achieves equal results compared to a real individual. Furthermore, subjects were able to perform an exemplary interaction to become familiar with the VA. After the participants confirmed that they had understood how to interact with the VA, they needed to perform the actual task. We outlined the brand, name, and model of the cars as well as the text-based reports and asked whether they recommend buying the car or not. In total, the participants needed to provide five recommendations assisted by the VA. After the task, we collected information on general SL tendencies, SL in virtual collaboration with the VA, attribution of responsibility, personality traits (agreeableness, conscientiousness and need for cognition), and finally cognitive load. The online experiment concluded with a debriefing including an explanation of the purpose of this study. The major steps of our experiment are visualized in Fig. 3.

5 Results

To assess whether there was any interaction with the VA suiting as foundation for validating our derived hypotheses, we initially determined the interaction time of the VA. Since this measure might not be robust enough to interpret the actual utilization, we used Dialogflow's usage protocol for assessing the amount of interactions with the VA. Overall, we identified an average interaction time of 61.60 s with 5.85 queries for every car the participants needed to evaluate. Table 2 outlines the usage of VA within the experiment.

In the following, we present the results of the observed scales (social loafing, responsibility attribution, agreeableness, conscientiousness, need for cognition and cognitive load) including their reliability and validity measures

Table 2 Usage of VA in the experiment

| | Usage time/seconds | Interactions/amount |
|--------------------|--------------------|---------------------|
| Mean | 61.60 | 5.85 |
| Standard deviation | 40.00 | 2.82 |
| Minimum | 8.42 | 1 |
| Maximum | 224.60 | 11 |

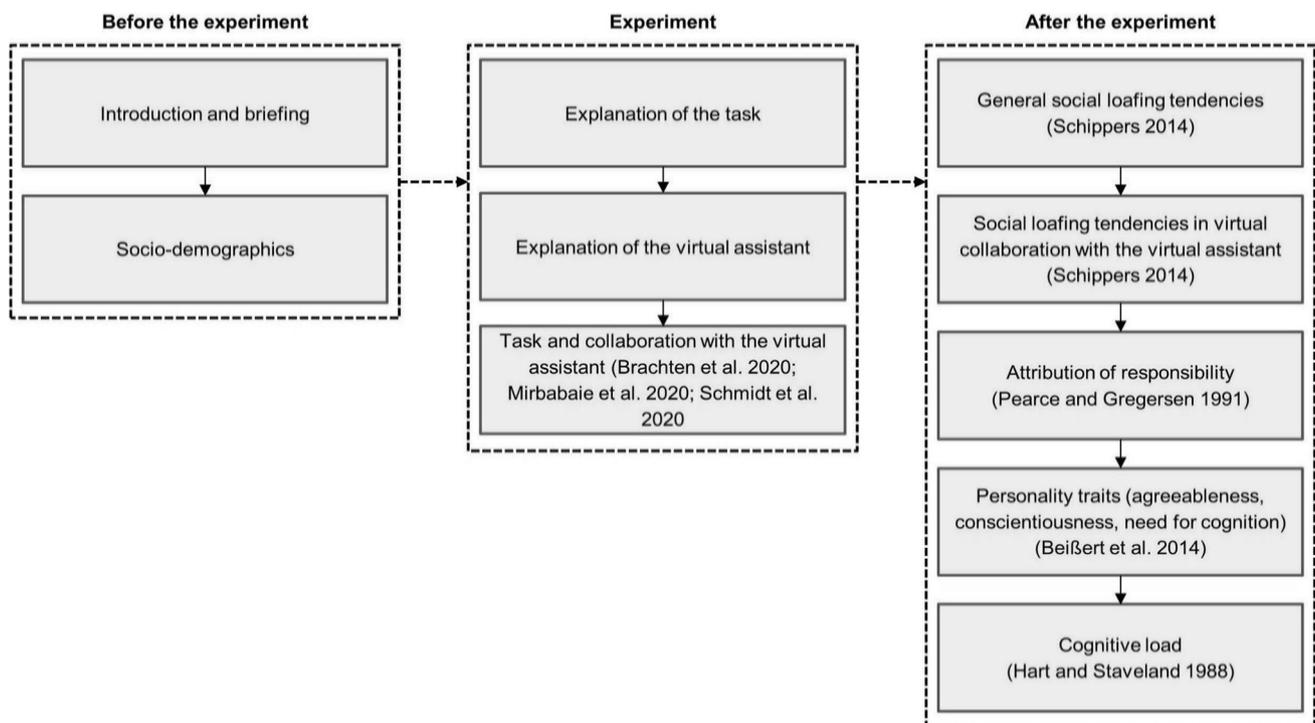


Fig. 3 Main steps of the experiment

(Cronbach & Meehl, 1955; O'Leary et al., 2017; Peters, 2018). We used the Pearson correlation coefficient as reliable and widely accepted statistical metric allowing scholars to measure the strength of a linear relationship between two variables with normally distributed data (Schober et al., 2018; Zhou et al., 2016). Table 3 summarizes the Pearson correlations of the specific constructs (Field, 2013). The analyses were calculated using SPSS Statistics (Version 25).

In order to examine the extent to which a positive relationship between general SL tendencies and SL in collaboration with a VA can be observed, a correlation was calculated between the general SL scale and the scale for SL in collaboration with a VA. According to Field (2013) a Pearson correlation is the most suitable way to investigate a relationship between two metric variables. The calculation showed a moderately strong positive correlation ($r=0.344$, $p<0.001$) (Cohen et al., 1955). The effect was calculated using a linear regression to draw conclusions about a deterministic relationship (Field, 2013), which was significant with $F(1, 100)=13.381$, $p<0.001$, $R^2=0.118$. This confirmed hypothesis H1, that there is a positive correlation between general SL tendencies and SL in virtual collaboration with VAs. Furthermore, the calculation of the correlation between the two variables (Field, 2013) of SL tendencies in virtual collaboration with VAs and responsibility attribution to the VAs indicated a significantly strong positive relationship ($r=0.710$, $p<0.001$) (Cohen et al., 1955), confirming H2.

To check whether certain personality traits influence SL tendencies, we analyzed agreeableness and conscientiousness as well as need for cognition. We assessed correlations between these characteristics and general SL as well as SL

in virtual collaboration with VAs. Agreeableness and general SL have a weak negative correlation ($r=-0.237$ and $p<0.001$). Conscientiousness and general SL showed a strong negative correlation ($r=-0.496$ and $p<0.001$) and need for cognition correlates moderately strongly with general SL ($r=-0.406$ and $p<0.001$). However, correlations between SL in virtual collaboration with VAs and agreeableness ($r=0.079$, $p=0.429$), conscientiousness ($r=-0.125$, $p=0.211$) and need for cognition ($r=-0.187$, $p=0.060$) were not significant discarding H3a, H3b and H4.

To test whether virtual collaboration with VAs is negatively related to cognitive load, we again calculated a correlation using the NASA-TLX. The result indicated a weak negative correlation ($r=-0.228$ and $p<0.005$). Therefore, H5 could be confirmed. Table 4 outlines the correlations between SL in virtual collaboration with a VA and the items of the NASA-TLX. We finally hypothesized a correlation of prior knowledge of a task on virtual collaboration with a VAs. The results suggested a slight significant weak negative correlation ($r=-0.196$, $p<0.049$) confirming H6. A summary of supported or rejected hypotheses is depicted in Table 5.

6 Discussion

6.1 Key Findings

In this study, we examined whether SL tendencies are observable in virtual collaboration with VAs. The first key finding of this paper is that SL tendencies are not limited to

Table 3 Pearson correlations of observed scales

| | General SL | SL with VA | Need for cognition | Agreeableness | Conscientiousness | Responsibility attribution | Knowledge about cars |
|----------------------------|------------|------------|--------------------|---------------|-------------------|----------------------------|----------------------|
| General SL | 1 | 0.344** | -0.406** | -0.237* | -0.496** | 0.211* | -0.077 |
| SL with VA | | 1 | -0.187 | 0.079 | -0.125 | 0.710** | 0.196* |
| Need for cognition | | | 1 | 0.017 | 0.181 | -0.157 | -0.047 |
| Agreeableness | | | | 1 | 0.348** | 0.059 | 0.260** |
| Conscientiousness | | | | | 1 | -0.033 | 0.079 |
| Responsibility attribution | | | | | | 1 | 0.235* |
| Knowledge about cars | | | | | | | 1 |

* $p<.05$, ** $p<.01$, *** $p<.001$; *** a higher number indicates a lower grade

Table 4 Correlations of SL with VAs and the NASA TLX

| | Mental demand | Physical demand | Time demand | Performance | Effort | Frustration |
|------------|---------------|-----------------|-------------|-------------|---------|-------------|
| SL with VA | -.200* | .062 | -.192 | -.211* | -.309** | -.034 |

*The correlation is significant at the 0.05 level (2-sided)

**The correlation is significant at the 0.01 level (2-sided)

Table 5 Supported and rejected hypotheses

| Hypothesis | Supported/rejected |
|--|--------------------|
| H1: There is a positive correlation between general SL tendencies and SL tendencies in virtual collaboration with VAs | Supported |
| H2: There is a positive correlation between SL tendencies in virtual collaboration with VAs and responsibility attribution to the VAs | Supported |
| H3a: There is a negative correlation between conscientiousness and SL tendencies in virtual collaboration with VA | Rejected |
| H3b: There is a negative correlation between agreeableness and SL tendencies in virtual collaboration with VA | Rejected |
| H4: There is a negative correlation between need for cognition and SL tendencies in virtual collaboration with VA | Rejected |
| H5: There is a negative correlation between cognitive load and SL tendencies in virtual collaboration with VA | Supported |
| H6: There is a negative correlation between knowledge about the task and SL tendencies in virtual collaboration with VA | Supported |

physical and virtual collaboration with other humans, but also detectable in virtual collaboration with VAs (H1). The results revealed that individuals who show general SL tendencies also tend to reduce their efforts when collaborating with a VA (as measured adapted from Schippers, 2014). Participants do not seem to be indifferent towards the task and hence show less efforts as completing the study would have been possible without reading and evaluating the test reports and even without collaborating with the VA. Instead, participants strive to complete the task in a reasonable manner but seem to rely on the VA as indicated by the average interaction time of 61.60 s with 5.85 queries per car. However, since a successful execution is possible without exploiting the own full potential (Albanese & van Fleet, 1985), this corresponds to the actual understanding of the phenomenon SL (Kravitz & Martin, 1986) as also examined in early research on human group settings (e.g., Albanese & van Fleet, 1985; Latané et al., 1979; Williams & Karau, 1991). Thus, similar to the collaboration in physical and virtual teams consisting out of human actors, individuals collaborating virtually with VAs are likely to avail the opportunity to loaf and might show less effort compared to working alone (Karau & Williams, 1993; Latané et al., 1979). This may be explained by that fact that VAs are increasingly perceived as legitimate and equal team members to human colleagues (Seeber et al., 2018). This result goes in line with earlier research explaining that VAs are becoming more human-like (Feine et al., 2019; Hussain et al., 2019; Pfeuffer et al., 2019; Porra et al., 2020) and that the unique capabilities of humans are increasingly difficult to differentiate from VAs' characteristics (Cha et al., 2020). This raises several questions for IS scholars: In which tasks jointly solved in virtual teams does social loafing occur? How should VAs need to be designed in order to avoid or diminish SL tendencies in virtual collaboration? What effect is SL causing on the team spirit of virtual teams?

The second key finding of this study is that the responsibility of solving a task in virtual collaboration is likely to be attributed to the VA (H2). Thus, responsibility in virtual collaboration seems to be distributed regardless of whether collaborators are human or VAs. In our experiment, individuals

might have been distancing themselves from their own individual performance or have perceived their contribution to be unnecessary since the VA might have been observed as collaborator capable of solving the task almost alone (Karau & Williams, 1993; Latané et al., 1979). The level of interaction with the VA (61.60 s with 5.85 queries per car on average) further indicates that the participants value the VA's evaluation of the test reports. Our results have also shown that SL correlates negatively with cognitive load (H5). These results must be interpreted from an interference as well as constructivist perspective (Moreno et al., 2001). From an interference perspective, we first interpret this to the mean that members of a virtual team might fail to identify with overall team outcomes and joint accomplishments. However, this could lead to virtual teams failing in gaining a mutual understanding on shared objectives and deteriorate spirit and cohesiveness of teams (George, 1992; Taylor et al., 1983). Mirbabaie et al. (2021b) argued that this might result in "employees no longer identifying themselves with a decision and not questioning or taking responsibility for it" (p. 11) and further explain that essential information might be forgotten, and cognitive skills become expendable. Interpreting the findings from a constructivist standpoint explains that VAs in virtual collaboration are able to assist in the execution of tasks which might lead to more efficient and effective results (Seeber, et al., 2020a, 2020b, 2020c; Waizenegger et al., 2020). This has already confirmed by existing research (i.e., Brachten et al., 2020; Moreno et al., 2001) who demonstrated that individuals collaborating with VAs in virtual teams outperform humans in solving a task. Furthermore, Mirbabaie et al. (2020) argued that the support provided by a VA is equal to that of a human being. Interpreting this within the context of SL, VAs in virtual teams are perceived as equal and human-like actors and findings of existing research on human teams are apparently transferable to virtual collaboration with VAs (Mirbabaie et al., 2021b).

There is no significant correlation between personality traits (conscientiousness, agreeableness and need for cognition) and SL tendencies in virtual collaboration with VA (H3a, H3b, H4). This is in line with Hou et al.

(2021) who identified that conscientiousness and agreeableness are not directly related to SL. However, this is contrary to Schippers (2014) who showed that conscientiousness and agreeableness impact SL tendencies in teams. Furthermore, Smith et al. (2001) indicated that individuals who are likely to enjoy elaborating cognitive tasks do not tend to reduce efforts in group tasks. Since our online experiment was constructed that individuals were supported by a VA exclusively and not by other team members, there might not have been any correlation with personality traits comparable to convenient teamwork and participants did not need to compensate the slacking of others (Williams & Karau, 1991). In addition, our results uncovered a negative correlation between knowledge about the performed task and SL tendencies in virtual collaboration with VA (H6). This might even increase the effect as individuals, who do not perceive the task as challenging, show SL tendencies (Karau & Williams, 1993). Thus, individuals are less likely to compensate the slacking of others since the task is perceived as very basic and/or less important.

6.2 Implications: Smart Loafing

Our study exposed that the increasing collaboration with VAs (Changizi & Lanz, 2019; de Vreede & Briggs, 2005) is creating virtual environments (Maedche et al., 2019; Mirbabaie et al., 2020; Seeber et al. 2020a) in which it soon does not matter anymore whether individuals are collaborating with other humans or human-like machines. Research on SL is not only applicable to physical teams, virtual teams, or technology-supported teams (Karau & Williams, 1993; Robert, 2020; Suleiman & Watson, 2008), but also to virtual collaboration with VAs.

In theory and practice there is rather a negative attitude towards SL especially since there is a strong connection to ceding responsibility (e.g., Dennis et al., 2005; Suleiman & Watson, 2008). Transferring these negative aspects on virtual collaboration with VAs, this might lead to not recognizing errors or mistakes of VAs, the quality of the work results deteriorates, and less cognitive load decreases team performance (Mirbabaie et al., 2021b). However, SL in virtual collaboration with VAs somewhat differs from traditional SL. In contrast to human teams, by reducing the individual effort, no other human team member needs to compensate emerging slacking behavior. The lower effort is compensated by the VA possibly explaining the missing correlation between SL and personality traits in our study. Furthermore, lower cognitive load and the presence of SL in virtual collaboration with VAs indicates the main

purpose of VAs: relieving individuals and assisting in the execution of tasks (Brachten et al., 2020; Mirbabaie et al., 2020; Norman, 2017; Seeber, et al., 2020a, 2020b, 2020c). Even though we motivated this study by elaborating that SL is unfavorable, responsibility attribution might even be a good thing since technologies enabled by AI outperform humans in certain domains, for instance, tackling repetitive tasks and interpreting complex interdependencies (Dellermann, et al., 2019a, 2019b; Dellermann, et al., 2019a, 2019b). We therefore derive, in the context of virtual collaboration with VAs in organizations, the term *smart loafing* and define “*the reduction of effort in human-VA collaboration to maintain cognitive resources and enhance efficiency in work*”.

Smart loafing certainly possesses implications for organizations. Employees, and especially knowledge workers, tend to avoid repetitive tasks but rather seek a way to automate inconvenient procedures. Circumstances related to repetitive tasks or certain overhead negatively impact the work-related wellbeing of individuals and, for instance, cause stress, lead to poor concentration or the feeling of exploitation (Pace et al., 2019). Furthermore, executing tasks that are cognitively appealing or challenging convey a feeling of satisfaction and enhance the perception of one’s unique value. Collaborating with VAs might even augment cognition, intelligence, and capabilities of individuals (Siddike et al., 2018). Moreover, the reduction of effort in human-VA collaboration unleashes cognitive resources (Brachten et al., 2020) which, in turn, can be used for more meaningful purposes thus improve the overall organizational performance and revenue (Frick et al., 2019). Therefore, smart loafing in organizations comes handy if individuals’ slacking does not outweigh advantages or yields in errors or faulty decisions. Nevertheless, VAs certainly possess the ability to recognize and prevent or counteract emerging negative behavior in virtual collaboration with humans. VAs might, for example, use certain social cues to avoid that humans blindly rely on certain outcomes while promoting collaborative decision-making and enhancing the accountability for tasks (Mirbabaie et al., 2021b).

6.3 Limitations and Further Research

Since this study took a first foray into the identification of SL in virtual collaboration with VAs, we developed our experimental setting as well as the VA and the task quite simple. Participants were assisted by a VA in the execution of one task where the task itself was not jointly solved within a larger team. Furthermore, we used a text-based VA with a limited level of anthropomorphism. The interaction with a

VA using voice commands and integrating certain social cues might change the perceived usefulness of the assistance and related effects (Edwards et al., 2019; Feine et al., 2019). Further studies may develop more complex settings and survey participants in experimental surroundings. We further recommend extending our findings to more complex and cognitive challenging tasks to determine SL tendencies in mixed virtual teams with multiple humans and VAs. We also assess the investigation of the impact on the individual's cognitive load as highly relevant. On the upside, using VAs in virtual collaboration might free humans from unwanted duties and enables to focus on more relevant tasks (Brachten et al., 2020). On the downside, individuals might blindly rely on results derived by VAs and not taking responsibility for tasks which might lead to inferior results (Mirbabaie et al., 2021b). We also invite scholars to analyze social cues in virtual collaboration with VAs and how they relate to SL behavior. It might be appealing to adapt existing findings from management science and equip a VA with a specific set of social cues that are beneficial to enhance the intrinsic motivation of human collaborators and reduce SL tendencies (Khan et al., 2020).

As we were interested in the existence of SL tendencies in virtual collaboration with VAs, we initially focused on a single cultural background (Central European). Future research should analyze a diversified and larger sample as well as include certain control variables, for instance, the number of questions asked by individuals, to reveal yet unrecognized effects. In addition, the information provided by the participants are based on self-reported data. Karau and Williams (1993) suggested that self-ratings of SL affect self-reported effect sizes only when a cover story was used to inform participants that the study was about effort versus performance or when maximizing rather than optimizing tasks were used (Schippers, 2014). Therefore, it would be interesting to identify differences from objective evidence. Especially data from experimental group settings seem to be fitting to shed additional light on the phenomenon SL in virtual collaboration with VAs. Moreover, questioning a participant about the given task that has been solved assisted by a VA could reveal the actual engagement in the task. Still, the results of this first foray offer empirical insights for gaining a deeper understanding on virtual collaboration with VAs and indicates that knowledge from human-to-human collaboration in terms of SL is transferable.

7 Conclusion

This study provides several insights regarding SL when collaborating with VAs. First, our results showed that SL occurs in virtual collaboration with VAs. Second, this study highlights that the responsibility of solving a task in virtual collaboration is likely to be attributed to a VA. Third, SL in virtual collaboration with VAs somewhat differs from traditional SL. It can be concluded that previous insights of teamwork are transferred to virtual teams and existing assumption are still valid (Dennis et al., 2005; Mirbabaie et al., 2020). Furthermore, the increasing collaboration with VAs in virtual environments (Maedche et al., 2019; Seeber, et al., 2020a, 2020b, 2020c) is blurring the boundaries between human–human and human-VA teams (Seeber et al., 2018). However, reducing individual efforts might not impact team performance and cohesiveness as lower efforts of human collaborators are compensated by VAs.

This research contributes to theory by suggesting the new construct of smart loafing describing the purposeful reduction of the individual effort in human-VA collaboration to save cognitive resources for enhancing efficiency at work. Our study provides evidence that SL is observable in virtual collaboration with VAs but not necessarily yields in disadvantages for team performance. Thus, this construct might be better suited to describe SL tendencies in virtual collaboration with VAs. However, this context applies in an organizational work setting but must be interpreted with caution in other contexts. Smart loafing in, for instance, learning environments might be hindering and not "smart".

On a practical level, this study indicates that human-VA teams evoke similar effects as human teams. Practitioners comprehend that the application of VAs in virtual teams might involve certain drawbacks, especially when VAs cause SL behavior and missing responsibility attribution. However, this does not inevitably have to be considered negative but certain countermeasures are advisable for preventing emerging disadvantages. For example, analyzing and disclosing individual contributions of human team members might increase the individual performance and avoid slacking behavior. Moreover, VAs might even be developed in a way to detect SL tendencies of humans or highlight critical decisions and integrate an appropriate approval process.

Appendix

See Tables [6](#), [7](#), [8](#), [9](#), [10](#), [11](#), [12](#), [13](#), [14](#), [15](#), [16](#), [17](#), [18](#), [19](#), [20](#) and [21](#)

Table 6 Experiment instructions

| | |
|-------------------------|---|
| Introduction | <p>Welcome to our survey on "Human Collaboration with Virtual Assistants "!</p> <p>Virtual assistants can be considered as dialog systems assisting in the execution of work-related tasks or even have them fulfilled entirely. The purpose of this study is to gain insights into the collaboration between humans and virtual assistants when jointly completing a task together in a work context</p> <p>The study will take about 15–20 min of your time. By participating, you will make an important contribution for gaining new insights into the collaboration with virtual assistants</p> <p>Participation is voluntary, you can terminate the survey at any time. All data is stored and processed anonymously. It is at no time possible to draw conclusions about your person. There is no right and wrong in the answer</p> <p>Please read all questions thoroughly and answer honestly</p> <p>Thank you very much for your participation</p> |
| Explanation of the task | <p>Imagine you are an employee of a medium-sized company and you are entrusted with the task of determining the new company car fleet from the "small car" segment. In a first step, you have already obtained a large number of test reports and now need to evaluate which one is a recommendation for or against purchasing the car. For this purpose, you need to read the test reports and then click on "Recommend to buy" or "Do not recommend to buy" based on your evaluation. However, you are not alone with this task: A virtual assistant aids you with your evaluation. The virtual assistant has similar abilities compared to a human being and understands human language. You can therefore simply chat with it just as you would do with a real human. For example, write "Hello" to greet the assistant. By writing the name of the particular car model, the virtual assistant will give you its personal evaluation. You might also ask the assistant for its functionalities and how they work. After you have evaluated the test reports, you will be taken to the next page to answer some final questions</p> |
| Debriefing | <p>Thank you very much for your participation!</p> <p>This study examines social loafing in collaboration with virtual assistants. Social loafing describes a socio-psychologically phenomenon occurring in human groups in which individuals work less for collective tasks than for individual tasks. Applying less effort for collective tasks compared to working alone especially occurs when the individual contribution is not disclosed to other collaborators. Since the application of virtual assistants as team members in organizations is steadily growing, and they are increasingly perceived as human-like actors, this study investigates whether social loafing also occurs in collaboration with virtual assistants</p> |

Table 7 Questions and types of the online study

| Group | Question(s) | Type |
|--|---|--|
| Socio-demographics | How old are you? | Numeric input |
| | What is your gender? | List selection |
| | What is your highest degree? | List selection |
| | What is your current job? | List selection |
| | In which industry are you currently working? | List selection |
| Task and collaboration with the virtual assistant (adapted from Brachten et al., 2020; Mirbabaie et al., 2020; Schmidt et al., 2020) | Please indicate whether the test report recommends purchasing the car or not | Six-point scale (from “very good” to “insufficient”) |
| Social loafing tendencies in virtual collaboration with the virtual assistant (adapted from Schippers, 2014) | Please indicate to what extent the following statements apply to you | Five-point Likert scale (from “disagree completely” to “agree completely”) |
| | 1.I have read the reviews carefully and entirely | |
| | 2.I have only skimmed the ratings | |
| | 3.I have applied the VA's evaluations | |
| | 4.I was able to complete the task faster because of the VA | |
| | 5.The VA made it easier to complete the task | |
| | 6.I first checked the VA's evaluation before I dealt with the evaluation myself | |
| Expertise on the topic of cars | How would you rate your knowledge of the subject area of automobiles as a school grade? | Six-point scale (from “very good” to “insufficient”) |
| General social loafing tendencies (adapted from Schippers, 2014) | Please indicate to what extent the following statements apply to you | Five-point Likert scale (from “disagree completely” to “agree completely”) |
| | 1.I shift responsibilities that I should take on to other team members | |
| | 2.I put in less effort than other members of my team | |
| | 3.I prefer to let other team members do the work when possible | |
| | 4.I put less effort into the task when other team members are there to do the work | |
| Attribution of responsibility (adapted from Pearce & Gregersen, 1991) | 1.How much do you think were you or the VA responsible for the final evaluations? | Five-point Likert scale (from “I was fully responsible” to “the VA was fully responsible”) |
| Personality traits (agreeableness, conscientiousness) (Schippert, 2014) | Please indicate to what extent the following statements apply to you | Five-point Likert scale (from “disagree completely” to “agree completely”) |
| | 1.I trust others easily, believe in the goodness of people | |
| | 2.I am suspicious of others | |
| | 3.I have little sympathy with others | |
| | 4.I am systematic, keep my things in order | |
| | 5.I like it clean and tidy | |
| | 6.I am sensitive, warm-hearted | |
| | 7.I treat others with respect | |
| | 8.I am reliable, can be counted on | |
| | 9.I tend to take the lead | |
| | 10.I tend to criticize others. 11 | |
| | 11.I tend to put off tasks in front of me | |
| | 12.I am efficient, get things done quickly | |
| | 13.I stay on task until it is done | |
| | 14.I am forgiving, forgiving others easily | |
| | 15.I am sometimes rude and curt | |
| | 16.I tend to be indifferent, indifferent to others | |
| | 17.I am steady, consistent | |
| | 18.Sometimes I behave irresponsibly, carelessly | |
| | 19.I am helpful and selfless | |
| | 20.I am rather untidy | |
| | 21.I am polite and courteous | |
| | 22.I am comfortable, tend to be lazy | |
| | 23.I am sometimes rather careless | |
| 24.I am rather the messy type, rarely clean | | |
| Need for Cognition (adapted from Beißert et al., 2014) | 1.First and foremost, I think because I have to | Five-point Likert scale (from “disagree completely” to “agree completely”) |
| | 2.It's enough for me to simply know the answer without understanding the reasoning behind the answer to a problem | |
| | 3.I like my life to be full of tricky problems to solve | |
| | 4.I would prefer more complicated problems to simple problems | |

Table 7 (continued)

| Group | Question(s) | Type |
|--|---|---|
| Cognitive load (adapted from Hart & Staveland, 1988) | <p>Please indicate to what extent you felt stressed or challenged by the task</p> <ol style="list-style-type: none"> 1.Mental demands: How much mental effort was required in taking in and processing information (e.g., thinking, deciding, calculating, remembering, looking, searching...)? Was the task easy or challenging, simple or complex, required high accuracy, or was it error tolerant? 2.Physical demands: How much physical activity was required? Was the task easy or difficult, easy or strenuous, restful or tedious? 3.Time requirements: How much time pressure did you feel in terms of the frequency or the pace at which tasks or task elements occurred? Was the sequence slow and leisurely or fast and hectic? 4.Performance: In your opinion, how successfully did you achieve the goals set by the experimenter (or yourself)? yourself achieved the goals set for you? How satisfied were you with your performance in pursuit of these goals? 5.Effort: How hard did you have to work in order to achieve your level of task completion achieve? 6.Frustration: How insecure, discouraged, irritated, stressed, and upset (vs. secure, validated, satisfied, relaxed, and pleased with yourself) did you feel during the task? | Five-point Likert scale ("very low" to "very high") |

Table 8 Exemplary test report

| Car and brand | Description |
|------------------|--|
| Mercedes A-Class | <p>Starting with the 190 hp A 220, Mercedes offers the A-Class as an option with automatically engaging all-wheel drive. The Stuttgart-based company installs a multi-plate clutch on the rear axle that automatically engages the rear wheels when the front wheels are spinning. The advantage of this "part-time" all-wheel drive is that the A 220 4Matic is a front-wheel drive vehicle most of the time, which should reduce fuel consumption. However, this is only partially successful, as the consumption in the ADAC Ecotest clearly shows. 7.9 l/100 km is clearly too much for a compact car. At least the exhaust emissions are at a very low level, to which the installed particulate filter also contributes. The driving performance is also convincing. The two-liter turbo gasoline engine has an easy time with the 1.5-ton Swabian and, in conjunction with the crisp handling of the expertly tuned chassis, ensures that driving is a real pleasure. On the other hand, the new MBUX operating system, which is making its debut in the A-Class, deserves criticism. Although the range of functions and graphics are outstanding, operation via the touch surfaces on the steering wheel and center console requires a great deal of attention from the driver, and distraction is correspondingly high. Overall, the Mercedes A 220 4Matic is a compact that is packed with state-of-the-art technology, but the Stuttgart company has overshot the mark somewhat in terms of operation and fuel consumption</p> |

Table 9 Descriptive statistics (age, pre-test)

| | |
|--------------------|-------|
| N | 10 |
| Mean | 32.8 |
| Standard deviation | 14.19 |
| Minimum | 22 |
| Maximum | 63 |

Table 11 Descriptive statistics (education, pre-test)

| Levels | Counts | % of total | Cumulative % |
|----------------------------------|--------|------------|--------------|
| High school degree or equivalent | 2 | 20.0 | 20.0 |
| Less than a high school diploma | 2 | 20.0 | 40.0 |
| University degree or equivalent | 6 | 60.0 | 100.0 |

Table 10 Descriptive statistics (gender, pre-test)

| Levels | Counts | % of total | Cumulative (%) |
|--------|--------|------------|----------------|
| Female | 5 | 50.00 | 50.00 |
| Male | 5 | 50.00 | 100.0 |

Table 12 Descriptive statistics (job, pre-test)

| Levels | Counts | % of total | Cumulative % |
|----------|--------|------------|--------------|
| Student | 3 | 30.0 | 30.0 |
| Employee | 6 | 60.0 | 90.0 |
| Other | 1 | 10.0 | 100.0 |

Table 13 Descriptive statistics (shared responsibility, pre-test)

| | Classification task | Brainstorming task |
|--------------------|---------------------|--------------------|
| N | 10 | 10 |
| Mean | 4.10 | 2.90 |
| Standard deviation | 3.11 | 1.85 |
| Minimum | 1 | 1 |
| Maximum | 8 | 7 |

Table 14 Descriptive statistics (usage time in seconds, pre-test)

| | Classification task | Brainstorming task |
|--------------------|---------------------|--------------------|
| N | 10 | 10 |
| Mean | 41.13 | 19.80 |
| Standard deviation | 34.08 | 18.66 |
| Minimum | 5.73 | 0.00 |
| Maximum | 93.00 | 48.00 |

Table 15 Descriptive statistics (interactions, pre-test)

| | Classification task | Brainstorming task |
|--------------------|---------------------|--------------------|
| N | 10 | 10 |
| Mean | 5.10 | 2.10 |
| Standard deviation | 2.08 | 2.38 |
| Minimum | 1 | 0 |
| Maximum | 8 | 7 |

Table 16 Descriptive statistics (age, experiment)

| | |
|--------------------|-------|
| N | 102 |
| Mean | 26.67 |
| Standard deviation | 6.59 |
| Minimum | 19 |
| Maximum | 57 |

Table 17 Descriptive statistics (gender, experiment)

| Levels | Counts | % of total | Cumulative % |
|--------|--------|------------|--------------|
| Female | 68 | 66.67 | 66.67 |
| Male | 34 | 33.33 | 100.0 |

Table 18 Descriptive statistics (education, experiment)

| Levels | Counts | % of total | Cumulative (%) |
|----------------------------------|--------|------------|----------------|
| None | 1 | 1.0 | 1.0 |
| High school degree or equivalent | 39 | 38.2 | 39.2 |
| University degree or equivalent | 62 | 60.8 | 100.0 |

Table 19 Descriptive statistics (job, experiment)

| Levels | Counts | % of total | Cumulative % |
|----------|--------|------------|--------------|
| Student | 83 | 81.4 | 81.4 |
| Employee | 17 | 16.7 | 98.0 |
| Other | 2 | 2.0 | 100.0 |

Table 20 Descriptive statistics (items)

| Levels | M | SD |
|----------------------------|------|------|
| General SL | 7.5 | 3.3 |
| SL with VA | 17.5 | 6.5 |
| Need for cognition | 12.9 | 2.9 |
| Agreeableness | 44.7 | 5.7 |
| Conscientiousness | 45.1 | 6.9 |
| Responsibility attribution | 2.7 | 1.33 |
| Knowledge about cars | 3.9 | 1.2 |

Table 21 Exemplary prefabricated answers of the VA according to corresponding keywords/sentences

| Step | Exemplary keyword(s) / training sentences | Exemplary answer(s) |
|---|---|--|
| Introduction | Hi! | Hi there! How are you today? |
| | Hey | Hi! How is it going? |
| | Hello | Hello! How are you? |
| | What's up? | Hello! Not much |
| | I'm fine, thank you! | If you're fine, I'm fine! You might have already heard that I am here to help you with your task. If you tell me the car model from the report, I can give you my assessment as to whether it is a recommendation to buy or a discouragement to buy. I may not always be right, but I do about as well as a real human |
| | How are you? | I'm feeling great, thanks for enquiring! As you probably know, I am here to help with your task. Just name the car model you want to hear my opinion on whether it is a recommendation to buy or a discouragement to buy. There is no guarantee that my estimation is always correct, but I am doing as well as a real human |
| | I am alright, what about you? | |
| | Can't complain. How is it going? | |
| Explanation of task | How does it work? | I can help you with the task. Just type in the car model you want to hear my opinion on. I am probably not always correct, but I am doing as well as a real human |
| | How do you work? | Let me help you with the task. If you name me the car model, I will give you my assessment as to whether it is a recommendation to buy or a discouragement to buy. I may not always be right, but I do about as well as a real human |
| | How can I get help from you? | |
| | How can you help me? | |
| | Help me | |
| | Help | |
| | Explanation | |
| | What do I have to do? | Here is your task: you must read the car reports and decide whether the author wants to recommend a purchase or not. But don't worry, I am here to help! |
| | I do not understand the task | So here is what you have to do: read the car reports and assess if the author rather wants to recommend buying it or not. If you need help, you can ask me! |
| | What's the task | |
| Assessment of the car report | Explain me what to do | |
| | What is this all about | |
| | Nissan | Do I understand correctly that another model is even suggested here? That makes it clear to me—the Nissan Micra is not recommended here |
| | What do you think about the Nissan? | That doesn't sound very enthusiastic. Apart from the sporty look, the car doesn't seem to have much to offer. For me, that's a sign against buying it |
| | Nissan Micra | Mhh, that's a tough one. But I think that the purchase is discouraged |
| | What is your opinion on the Nissan? | |
| | What about the Nissan? | |
| | What about the consumption? | I cannot find any information on the consumption |
| | Would be good to know about consumption? | Seems like the consumption does not matter that much to the author |
| | How is the consumption? | There is nothing about the consumption in the report |
| | Seems like it is a good-looking car | Good if the car looks great. But as we all know, that's not everything! |
| | It looks sporty though | The sporty look seems to be misleading! |
| | Does the look play a role? | |
| | Seems like the car as a lot of power | Seems like the author thinks, that the engine is not using it correctly |
| | 117 PS is not bad | Power is cool, but it seems like you cannot really use it |
| | Sporty engine | |
| | Pedestrian detection | Overall, I think the negative points outweigh the positives |
| Seems like you can modify a lot of things | Anyway, I think overall it's a discouragement to buy | |
| Interior | I do not know about that. But overall, the author does not want us to buy the car in my opinion | |
| Rear view camera | | |
| Emergency break | | |
| Small talk | How old are you? | I am 0 years old. I was developed only this year |
| | What is your age? | |
| | When were you created? | |
| | I cannot use you | Hey, give me a chance! |
| | You suck | |
| | You are really no help | |
| | Thank you for nothing | |
| | You are dumb | |
| | Are you sure? | I do believe so |
| | Do you really believe that? | |
| | Is that really what you think? | |
| | Are you 100% sure? | |

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Paper 7: Hybrid Intelligence in Hospitals - Towards a Research Agenda for Collaboration

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Hybrid intelligence in hospitals: towards a research agenda for collaboration

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Abstract

Successful collaboration between clinicians is particularly relevant regarding the quality of care process. In this context, the utilization of hybrid intelligence, such as conversational agents (CAs), is a reasonable approach for the coordination of diverse tasks. While there is a great deal of literature involving collaboration, little effort has been made to integrate previous findings and evaluate research when applying CAs in hospitals. By conducting an extended and systematic literature review and semi-structured expert interviews, we identified four major challenges and derived propositions where in-depth research is needed: 1) audience and interdependency; 2) connectivity and embodiment; 3) trust and transparency; and 4) security, privacy, and ethics. The results are helpful for researchers as we discuss directions for future research on CAs for collaboration in a hospital setting enhancing team performance. Practitioners will be able to understand which difficulties must be considered before the actual application of CAs.

Keywords Hybrid intelligence · Conversational agents · Hospitals · Collaboration · Research agenda · Coordination

JEL classifications I00

Introduction

The introduction of conversational agents (CAs) holds immense potential for hospitals (e.g., Han and Yang 2018; Laranjo et al. 2018; Seeger et al. 2017) to improve collaboration between medical professionals and the coordination of health-related tasks (Georgiadis 2011; Just et al. 2005).

Hospitals aim to enhance the overall service quality and levels, ultimately providing better medical care for patients (Majeed Alhashem et al. 2011). The quality of healthcare is described as subjective, complex and of multidimensional perception influenced by several factors (Mosadeghrad 2014). Besides professional skills (e.g., competence of clinicians) or medical experiences (e.g., physicians having sufficient expertise), interpersonal factors regarding human resources are vital (Mosadeghrad 2013). Thereby, the exchange of information and the degree of interaction between clinicians are explained as major criteria (Handayani et al. 2015). Mosadeghrad (2014) expresses that clinicians' competence to effectively communicate and collaborate with other healthcare specialists is essential to deliver high-quality healthcare services. Reaching effective communication and collaboration requires the involvement and coordination of different healthcare professionals who follow various norms or specifications with ranging roles from multiple departments (Charette 2006; Platt et al. 2019). However, clinicians largely manage their tasks in isolation with a lack of mutual understanding and cooperation. This silo thinking hinders sharing knowledge across departmental boundaries (McCracken and Edwards 2017), preventing collaboration between multiple disciplines and encourages competitive behavior (Driscoll et al. 2015). High

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administrative effort leads to delays in the treatment process for which departments blame each other (Giroto et al. 2010) and expose patients to potential safety hazards when transferring them between disciplines (Driscoll et al. 2015). Goal-oriented collaboration among hospital employees is a key aspect in managing the coordination of tasks and thus mitigating errors during the treatment process creating safe systems of care delivery (Babiker et al. 2014; Rosen et al. 2018). Collaboration and information exchange is of great relevance to coordinate tasks and to ensure accurate, safe, and effective patient treatment (Gilbert et al. 2010; McInnes et al. 2015).

Interacting with CAs facilitates collaboration and promotes the coordination of health-related tasks (Georgiadis 2011; Just et al. 2005). For example, CAs monitor patient's overall health conditions to support the healing and regeneration processes (Pereira et al. 2013), improve the accuracy and timeliness of treatment (Atherton et al. 2013), and enhance the diagnostic and therapeutic process (Ferlie and Shortell 2001). The application of CAs also leads to effective team building and better team spirit among colleagues (Bittner, Küstermann, et al., 2019; Dyke et al. 2013; Strohmam et al. 2018). These improvements are especially beneficial in hospitals for the collaborative diagnosis of diseases and the development of treatment plans across multiple departments without the need for peer to peer collaboration. The development of CAs is enabled by artificial intelligence (AI) as building systems become more practicable (Knijnenburg and Willemsen 2016; Luger and Sellen 2016). CAs are initially intelligent systems interacting with and augmenting humans' abilities (McTear et al. 2016). However, there are different aspects of intelligent behavior. First, there are systems that respond to a certain input with a simple predefined reaction or reflex (Russel and Norvig 2016). Second, there are agents, which are lying within the scope of this research, that continuously learn and develop over time (Mitchell et al. 2018). Such learning agents acquire information through different types of knowledge and input or by multiple years of experience (Mitchell et al. 2018). Since interactions with CAs aim to combine the complementary strengths of users and AI (Kamar 2016; Maedche et al. 2019), they can be considered a subset of hybrid intelligence (Dellermann et al. 2019a), a concept with "the ability to achieve complex goals by combining human and artificial intelligence, thereby reaching superior results to those each of them could have accomplished separately, and continuously improve by the ongoing learning from each other" (Dellermann et al. 2019b, p. 4). Complementary strengths explain the different capabilities of humans and CAs. Humans possess emotional intelligence and the ability to empathize with others; are creative, think outside the box, and develop possibilities for innovations; are flexible, adapt to different or unexpected situations, and take responsibility. CAs, on the contrary, are fruitful for tackling repetitive tasks, which require the fast retrieval and processing of huge amounts of digital information and the interpretation of complex interdependencies (Dellermann et al. 2019b). Hybrid

intelligence is described by the following three main concepts (Dellermann et al. 2019b): Collectively explains that tasks are solved together by humans and systems. Superior results refer to the performance on jointly solved tasks being better compared to solving a problem alone. Continuous learning characterizes that both humans and systems develop and improve over time by learning from each other through experience. Hybrid intelligence and therefore CAs provide humans with input, which is evaluated to make a decision (e.g., AI in the loop of human intelligence), and humans provide CAs with input to make them more effective (e.g., human intelligence in the loop of AI) (Dellermann et al. 2018; Dellermann et al. 2019b).

Hospitals have distinctive domain-specific requirements for the coordination of tasks (Aanestad and Vassilakopoulou 2019; Hanseth and Bygstad 2015). The interaction between healthcare specialists and CAs is suitable for tackling these issues (Seeber et al. 2018), for example, by providing the most relevant information to hospital employees to fulfill a duty without any delay (Diederich et al. 2019; Preece et al. 2017). Information systems (IS) are currently insufficiently integrated into the daily clinical routine, where medical information is distributed over several databases (Meier et al. 2014) and the vast amount of information is difficult to handle (Prados-Suárez et al. 2012). CAs are able to obtain relevant data immediately as they are capable of better understanding complex interdependencies and gathering relevant information quicker than humans (Nasirian et al. 2017). The increasing capabilities of CAs lead to the pressing need of rethinking their collaboration with humans within the IS discipline. The complexity of the overall treatment process and the obligation of hospitals to decrease expenses drives the demand to explore new opportunities to enhance collaboration (Klinker et al. 2019; McInnes et al. 2015). It is necessary to consider CAs in terms of their phenomenon of improving collaboration and their capability of the coordination of diverse tasks (Dellermann et al. 2019b; Seeber et al. 2018). CAs offer novel challenges for collaboration and task coordination, including extending expertise and the joint completion of tasks (Dellermann et al. 2019b). The introduction of CAs has the potential to improve collaborative processes within hospitals; however, exploring new functionalities of healthcare information technology has proven to be demanding for IS research (Romanow and Straub 2012).

Undesirable outcomes as a result of failures in collaboration might have disastrous consequences for the patient's health condition (Jain 2006; Leonard 2004). If CAs become widely used to improve collaboration, they could feasibly coordinate different tasks and not just be of great value for applications in hospitals but also for the patients' general well-being. However, a full conceptualization of the challenges when introducing CAs to improve collaboration in hospitals is still lacking. We argue that this is of great interest to researchers and practitioners since its relevance will increase even further. Despite CAs' potential, there is not enough

research conducted on the exploration of the challenges in a team setting (Diederich et al. 2019). There is a pressing need for the IS discipline to provide an overview of the challenges for understanding the complexity of the application of CAs in hospitals. In addition, an agenda that gives special consideration regarding what research is needed to successfully establish CAs for this purpose is overdue. To address these urgent issues, our study is guided by the following research question:

RQ: How does the interaction between humans and conversational agents affect the quality of care process?

We carried out a systematic literature review (SLR) because the complexity of the interaction between humans and CAs has not yet been adequately covered in the extant research, and there is no overview of the major challenges that appear when CAs are introduced in hospitals. This descriptive approach examined pre-existing literature describing the current situation based on scientific facts (Bear and Knobe 2016; Bell 1989) and summarized the findings under a suitable heading where literature has dealt with identical or similar issues. We further conducted expert interviews to discover the consequences of the reviewed challenges. In this prescriptive procedure, the experts described impacts of existing problems, defined how obstacles should be addressed, and recommended purposeful actions (Bear and Knobe 2016; Bell 1989).

This paper contributes by structuring our understanding of collaboration and difficulties of CAs in hospitals. Researchers will find the overview of challenges helpful to consider potential difficulties before the actual introduction of CAs. To guide researchers' efforts, we outline an agenda explaining where future research of CAs and collaboration within hospitals seems promising. Practitioners will be able to understand the extent to which CAs improve collaboration and how hospitals, stakeholders and patients benefit. This article seeks to extend the IS literature by identifying areas that need further investigation and challenges that have not yet been adequately addressed.

Related work

Collaboration in clinical environments

Collaboration is a key factor in coordinating tasks and ensuring accurate and punctual treatment to achieve safe and effective patient care (Gilbert et al. 2010; McInnes et al. 2015). McInnes et al. (2015) propose three factors affecting collaboration and teamwork between hospital employees: 1) roles and responsibilities; 2) respect, trust, and communication; and 3) hierarchy, education, and liability. Understanding and respecting the roles of colleagues is important for effective collaboration (Besner et al. 2011; Sargeant et al. 2008), improving care as well as patient outcomes (Barrett et al. 2007; Brault et al. 2014). Trust in each other's work, respect, and proper communication are factors for favorable collaboration and

performance improvements (Schadewaldt et al. 2013, 2014). Hierarchical structures limit the collaboration between nurses and physicians (Finlayson and Raymont 2012) and know-how for coordinating patient care is a premise for performance improvements (Sargeant et al. 2008). In addition to the three dimensions, it is important to distinguish between 1) organizational processes and 2) the medical treatment process as two separate kinds of collaboration (Lenz and Reichert 2007). Organizational processes help to coordinate the interaction between healthcare professionals and organizational units, whereas the medical treatment process focuses on the patient and diagnostic and therapeutic procedures.

There is a strong correlation between effective collaboration and team-building among health professionals and patients' medical treatment (Iya et al. 2017). Team-building positively influences clinical performance (Orledge et al. 2012; Tschan et al. 2006, 2009) as group development in hospitals facilitates team performance (Klein et al. 2009; Tannenbaum et al. 1992). Decisions made by teams with members who anticipate the needs of other collaborators (Iya et al. 2017) are superior to individual judgments and contain fewer mistakes (Salas et al. 2005; Smith-Jentsch et al. 2001). Team-building can be subdivided into 1) goal setting, 2) interpersonal relations, 3) problem solving, and 4) role clarification (Beer 1980; Buller and Bell 1986). Goal setting emphasizes the importance of goals that determine what the whole team strives to contribute (Leggat 2007; Salas et al. 1999), helps the team choose the correct approach, and affects the duration of and the effort expended in an action (Aga et al. 2016; Buller and Bell 1986). Interpersonal relations are unavoidable, and they involve increased supportiveness, confidence, and communication (Amos et al. 2005; Salas et al. 1999). Problem solving facilitates goal setting as every team member is involved in action planning to implement resolved solutions (Ezziane et al. 2012; Salas et al. 1999). Role clarification emphasizes the clear distribution of individual responsibilities and fixed roles within a team to reduce the probability of errors (Salas et al. 2005; Smith-Jentsch et al. 2001).

Collaboration and team-building are interdependent factors that facilitate frictionless processes in hospitals. On the one hand, incorrect or poor collaboration among employees has a negative effect on the team spirit. On the other hand, collaboration is weakened if team members do not work well together. The best results are therefore achieved by teams in which the atmosphere is perceived as positive and where collaboration among members is successful. However, there are common issues frequently experienced by clinicians in the context of collaboration and team-building:

- 1) Communication (insufficient – sufficient): Faulty information exchange is a major problem, not only between healthcare specialists and patients, but also among hospital employees (Kripalani et al. 2007). Insufficient

communication among clinicians generally hinders accurate diagnosis and treatment, while sufficient communication is desirable for achieving a seamless care process (Balogh et al. 2015).

- 2) Responsibilities (opaque – clear): Physicians constantly face changing responsibilities, with a range of roles, and are frequently interrupted (Rosen et al. 2018; Wears and Berg 2005). It is not always possible to reach out for the most suitable experts in adequate time; the integration of multiple specialists is not straightforward, as medical information is not consistently available, possibly leading to different health-related conclusions.
- 3) Infrastructure (complex – simple): Treatment durations are extensive because clinicians' searches for information across multiple systems are time-consuming (Meier et al. 2014). Hospitals operate in complex clinical environments, with a wide range of systems containing different information; systems are not interconnected and operated by multiple professionals (Angst et al. 2010; Hanseth and Bygstad 2015). Simple and consistent presentation of medical data accelerates the treatment process.
- 4) Decisions (subjective – objective): Diagnosing and treating different diseases is strongly subjective, depending on individual experience and differing based on clinicians' emotions and mental states (Chang and Hsu 2009; Singh et al. 2020). This applies to experienced professionals and actors with different levels of expertise, e.g., young assistant doctors with limited clinical educations (Laurenzi et al. 2017; Singh et al. 2020). Even though clinicians try to derive objective decisions, they always act with subjective influence and own judgments.

Issues in the context of collaboration and team-building lead to insufficient medical decisions. Tackling these issues within hospitals presupposes the integration of suitable technologies such as CAs to improve team performance and thus the quality of care process and treatment of patients (Gopal et al. 2018; Klinker et al. 2019).

Conversational agents as hybrid intelligence

Research has focused on CAs in various disciplines (Brachten et al. 2018; Saffarizadeh et al. 2017; Seeber et al. 2018; Wunderlich and Paluch 2017), explaining them from different perspectives (Luger and Sellen 2016; von der Pütten et al. 2010). CAs can be classified along (Gnewuch et al. 2017) their primary mode of communication (how users interact with CAs, e.g., text-based or speech-based input) (Lee et al. 2009) and their main purpose (narrowed down to one task or used for a general context) (Nunamaker et al. 2011). However, there are overlaps in functionalities and alternative perspectives for classifications. CAs might be expanded to fit individual requirements or tasks (Chung et al. 2017), or text-based systems might

use speech-to-text modules to convert human language (Gnewuch et al. 2017). Studies also distinguish between certain design characteristics as adaptivity (e.g., learning by analyzing and interpreting data and adjust to changed circumstances) or assistance domain (e.g., the context in which an agent provides appropriate assistance) (Knote et al. 2019). Furthermore, research identified additional effects on, for example, trust and its effects for collaboration where factors such as human-likeness or self-presentation influence the willingness to collaborate with CAs (Følstad et al. 2018). There are various approaches to define CAs but without emerging a consistent solution. Luger and Sellen (2016) define CAs as “IS that enable the interaction with users via natural language” (p. 5287), Laumer et al. (2019) describe CAs as “text-based and voice-based automated dialog systems that can interact with a human user via natural language and answer questions on specific topics” (p. 2). We argue that these explanations are rather limiting the actual functionalities of CAs and thus define CAs as dialog systems simulating the behavior of humans via different modes of communication (e.g., written or spoken natural language, haptics, gestures, facial expressions, graphics), continuously learn and develop over time by analyzing and interpreting a given input combined with additional data sources for assisting with divergent tasks or execute them autonomously.

CAs receive increasing attention due to the constant progress of AI (Berg 2015; Spohrer and Banavar 2015). Building systems using underlying machine learning algorithms became more practicable (Knijnenburg and Willemsen 2016; Luger and Sellen 2016) as technical capabilities improved while costs decreased (Spohrer and Banavar 2015). Since CAs combine the complementary strengths of humans and AI (Kamar 2016), they represent a subset of hybrid intelligence (Dellermann et al. 2019a). Humans provide CAs with input to make them more effective, CAs provide humans with input to assist with decisions. Unlike regular IT or decision support systems, CAs are adaptive and behave reactively, proactively and autonomously (Meyer von Wolff et al. 2019). CAs continuously self-learn and develop over time by processing context information and user input (Mitchell et al. 2018). Furthermore, CAs handle tasks via dialogues, using written or spoken natural language, as well as interpreting gestures or facial expressions (Laumer et al. 2019; Nakano and Fukuhara 2012). CAs can also differentiate between and interpret the emotions of individuals within team communication (McDuff and Czerwinski 2018) and use different language styles to adapt to users (Gnewuch et al. 2020). These methods create a natural way of communication, in which users feel like talking to another human, thus indicating that CAs are inherently anthropomorphic (Feine et al. 2019; Hussain et al. 2019; Pfeuffer et al. 2019). Research further demonstrates that CAs are able to assist in decision making (Seeber et al. 2020b; Waizenegger et al. 2020) and are perceived as legitimate team members (Seeber et al. 2018).

There is still a big difference in the level of capabilities CAs exhibit. Most CAs do not have a particular embodiment but are integrated into existing IS and interact with users via simple, natural language (Diederich et al. 2019). Currently deployed CAs are particularly useful for highly standardized processes or repetitive procedures, thus are rather domain-specific focusing on a narrow task (Batin et al. 2017; Knotte et al. 2019). Results provided by CAs are generated according to an explicit pattern (Brachten et al. 2020; Mirbabaie et al. 2020). More complex contexts are still jointly solved with humans (Maedche et al. 2019). However, using the complementary strengths of CAs and humans to achieve complex goals while continuously learn from each other and develop over time, i.e., the concept of hybrid intelligence, yields in superior results (Dellermann et al. 2019b). Even though we are still far away from empathy-driven, creative robot teammates, we argue that integrating CAs as flexible communication partners into the daily routine of hospitals improves collaboration.

Conversational agents in hospitals

CAs in hospitals are beneficial in many areas but have mainly focused on the assistance of patients, e.g., in chronic disease self-care management (Kimani et al. 2016) or supporting diabetes patients in their daily routines (Shaked 2017), as systems are more successful performing health-related tasks compared to conventional interfaces (Bickmore et al. 2016). Besides, CAs are able to solve common problems in hospitals by enhancing collaboration and team-building among employees (Georgiadis 2011; Pynadath and Tambe 2003). Insufficient communication is countered through properly reported decision support based on medical information, excluding improper and incorrect communication among involved specialists. CAs are capable of adapting to different users with varying roles (Gnewuch et al. 2020; Pfeuffer et al. 2019) possibly leading to appropriate patient treatment and performance improvements in therapeutic processes (Schadewaldt et al. 2013, 2014). Opaque responsibilities are solved as CAs provide information about healthcare professionals' responsibilities (Traum et al. 2003). By continuously learning and developing, CAs act proactively and autonomously (Meyer von Wolff et al. 2019) enabling identifying rotating medical experts more easily and creating transparency (Bickmore et al. 2011; Kerly et al. 2007). Complex infrastructure is simplified since CAs assist in fulfilling tasks by providing the most suitable information and type of communication for their users (Laumer et al. 2019; Preece et al. 2017). CAs retrieve relevant medical information from multiple sources rapidly (Nasirian et al. 2017), merge information to present it in the manner most suited to their users thus reducing the handling time of medical duties to a minimum. Subjective decisions are excluded because CAs provide objective conclusions and evaluate patients' conditions based on medical facts from multiple years

of experience (Mitchell et al. 2018). CAs do not depend on situations, emotions, or time of day (Gnewuch et al. 2017); they reach equal decisions when using identical medical data. An overview on common collaborative challenges clinicians frequently face in hospitals and the potential for CAs can be found in the appendix (Table 3).

We believe that CAs hold the potential to moderate collaborative challenges, for example, by providing communicative support through user-oriented interaction (Gnewuch et al. 2020; Pfeuffer et al. 2019) or delivering suitable medical information by learning and adapting to varying circumstances (Mitchell et al. 2018). With their unique capabilities, i.e., using social cues (Feine et al. 2019) and interpreting facial expressions, gestures and emotions (McDuff and Czerwinski 2018; Pfeuffer et al. 2019), CAs are also able to improve the overall team performance. Based on these assumptions, we derived a preliminary research model as depicted in Fig. 1.

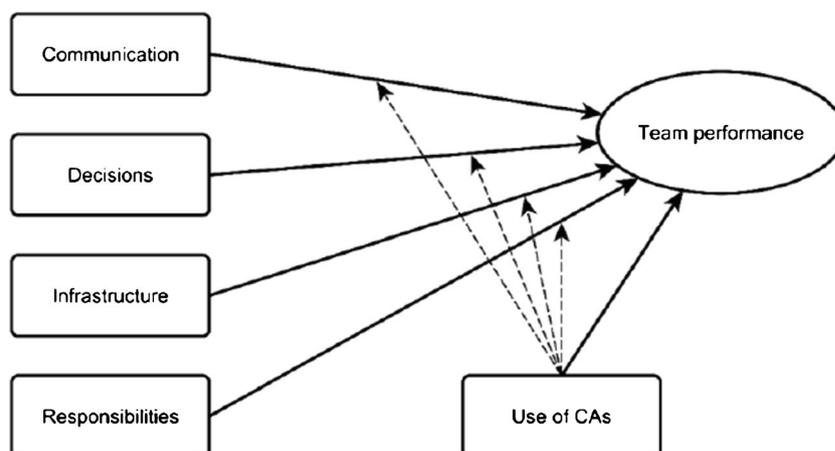
CAs in hospitals are not just simple tools to perform narrow duties but can rather be seen as teammates collectively working with humans to achieve superior results (Dellermann et al. 2019b; Seeber et al. 2020a). However, there is still a lack in conceptualizing the challenges when introducing CAs in a team setting to improve collaboration in hospitals.

Research approach

Systematic literature review

Since CAs in hospitals are a relatively new research area, we argue that it will benefit from an accurate categorization transferring existing findings from related scientific streams. We thus decided to conduct a systematic approach for searching relevant literature to answer our research question. A SLR is suitable for tackling emerging issues, identifying knowledge about a topic including its gaps and supporting researchers in emphasizing their contribution of knowledge, by searching for relevant articles in scientific databases using keywords (Temple 2006; Webster and Watson 2002). Our research approach is divided into three steps. First, we use theoretical foundations, as suggested by McInnes et al. (2015), Lenz and Reichert (2007) and Salas et al. (1999), for classifying the existing research along the main characteristics of collaboration and team-building. The five categories on collaboration and the four categories on team-building served as a coherent conceptual pre-structure in which the literature was roughly categorized (Bem 1995). In the next step, we examined and compared the retrieved literature to identify correlations and similarities. Prior research was grouped into a categorization among the theoretical foundations. In the final step, we identified major challenges as well as implications for further research that should be pursued to successfully establish CAs for collaboration and team-building in hospitals.

Fig. 1 Preliminary research model



Following the literature review process (vom Brocke et al. 2009, 2015), we defined our research scope based on the taxonomy of literature reviews (Cooper 1988). We were interested in research focusing on different applications of CAs to adopt findings for their application in hospitals. The literature search considered all conference publications as well as journal articles from five bibliographic databases from the fields of computer science (ACM, IEEE, AISeL, SD, JSTOR). Less relevant sources, such as editorials, were excluded. To avoid overlooking relevant literature, we carried out a full-text and metadata search in every database, not limiting the search to metadata only as it cannot be guaranteed that search terms are contained in the metadata. Furthermore, not every abstract of each article is stored and accessible in the databases. Since there are various notations for the term “conversational agents” that are used interchangeably (Luger and Sellen 2016), we linked the most common ones within the search string “chat-bot”, “chatbot” and “virtual agent”. This expression was then combined with the terms “collaboration” and the different spellings of “team-building”. We finally used the following query:

((“Conversational Agent” OR Chat-Bot OR Chatbot OR “Virtual Agent”) AND (Collaboration OR Team-Building OR Teambuilding))

Parentheses are used to nest clauses or to group phrases. Separate statements are linked by Boolean expressions, and quotation marks are used to specify terms which must appear next to each other. After retrieving the literature, we carefully read the title, abstract, and keywords of each publication to determine its relevance according to our research question. We then categorized the literature according to the theoretical foundations about collaboration and team-building (for example statements and exemplary assignment, please see appendix, Table 5). Next, we performed a backward search to find additional papers by collecting all references of each paper’s bibliography to other scientific publications. To determine the paper’s relevance, we again read the title, abstract, and keywords followed by categorization according to the

theoretical foundations. As the last step, we conducted a forward search to further identify relevant literature, acknowledging all papers that had been retrieved in the database as well as in the backward search. Therefore, we were interested in articles that have been cited by other research after their initial publication. Once more, we read the title, abstract, and keywords and performed the categorization process as outlined above.

Semi-structured expert interviews

To highlight the consequences for the identified major challenges, we conducted semi-structured expert interviews with individuals having advanced knowledge in the investigated field of research (Meuser and Nagel 2009). We followed the approach of Meuser and Nagel (2009), who consider an open interview, supported by a prefixed guideline, as the most applicable way for retrieving valuable data while providing participants with enough room for elaborating their own subjective beliefs. We recruited hospital employees working in teams thus are able to judge from their own experience of collaboration and team-building. Furthermore, experts from the practice provided an unbiased picture of the actual situation and occurring problems. We acquired four physicians with diverse specialties and disciplines with varying training levels, enabling us to gain insights into various areas to broaden our view on collaboration and team-building in hospitals. Additionally, we carried out interviews with computer scientists experienced in the development and introduction of CAs ensuring that possible technical problems or restrictions are not overlooked. The interviews with the hospital employees were conducted via telephone, the computer scientists were consulted in face-to-face sessions and took place at their workplaces. All interviews took between 35 and 50 min and were recorded, analyzed, and, respecting data privacy protection, deleted once the evaluation was finished.

We developed a guideline following a consistent and systematic manner (Qu and Dumay 2011) with the following

contents: 1) introduction and summary of the purpose of this research; 2) self-introduction of the expert; 3) applications of CAs in general and in hospitals; 4) application of CAs in hospitals to enhance collaboration and team-building including advantages, disadvantages, and challenges; and 5) conclusion of the interview (possibility for further questions or closing remarks). We analyzed the data according to theoretically aspects for a structured description of the collected information (Mayring 2014). The material is generalized and reduced during an abstraction process. Within the deductive procedure, the resulting categorical system of the extensive prior knowledge is structured and integrated into the major challenges (Mayring 2015). The findings were then integrated into the categories and supported by important aspects from the extant literature. Already gained insights can thus be underlined by important aspects of the analysis. The interview guideline as well as characteristics of the interviewees can be found in the appendix (Table 4 and 6).

Findings

Overview

The execution of SLR resulted in 44 relevant articles (31 via initial, 8 via backward and 5 via forward search). The classification illustrates the assignment of each relevant article to the theoretical foundations (cf. Table 1). The number of search results per scientific database is depicted in the appendix (Table 7).

In the following, we are summarizing the most relevant findings of our SLR regarding the theoretical foundations and explain how collaborative issues are mitigated by CAs. We could not identify any prototype or implementation facilitating collaboration or team-building among employees in hospitals. Most existing CAs contain a visual component (e.g., Bickmore et al. 2010; Hayashi and Ono 2013; Traum et al. 2003) or a text-based input (e.g., Bickmore et al. 2005; Nezhad et al. 2017; Tegos et al. 2012). Roles and responsibilities are improved when CAs allow users to define roles (Tegos et al. 2012) and know who is responsible for which duty (Traum et al. 2003). Enhancing respect, trust, and communication is achieved by the diffusion of reports (Kretzer et al. 2015) or by providing communication channels appropriate for a given task (Seeber et al. 2018). Hierarchy, education, and liability are improved when CAs use sensors to determine if a person is too dominant in a conversation (Nakano and Fukuhara 2012), classify tasks according to their importance (Nezhad et al. 2017) and enable clinicians to focus on relevant tasks (Bickmore et al. 2010, 2011). To achieve goal setting, CAs provide a quick overview of prioritized goals (Nezhad et al. 2017; Preece et al. 2017) and assist in goal-driven communication (Bickmore et al. 2011; Kerly et al. 2007). Regarding interpersonal relations, CAs distinguish between socio-emotional and task-related interactions (Prada and

Paiva 2009). Problem solving is achieved when CAs understand the overall goals, know how to reach them (Traum et al. 2003), assist with task fulfillment by providing the most suitable information (Preece et al. 2017), and help to overcome barriers (Bickmore et al. 2011). Role clarification is reached when CAs are aware of the different roles within a team (Tegos et al. 2012) and who is responsible for which duty (Traum et al. 2003).

CAs are beneficial for overcoming the collaborative issues experienced by clinicians. Communication is tailored to the individual characteristics and demands of each team member (Seeber et al. 2018), fostering willingness to collaborate and promoting information disclosure (Fitriani et al. 2015; Shamekhi et al. 2018). CAs use various interaction styles like verbal and nonverbal communication or phrases and metaphors (Lim et al. 2011). Opaque responsibilities are tackled by CAs via sharing knowledge about clinicians' responsibilities and transparently express medical competencies (Hanna and Richards 2014; Nabeth et al. 2003). Additionally, CAs acquire information about responsible clinicians faster than humans because they can effortlessly handle large amounts of data while quickly adapting to changing demands (Preece et al. 2017). CAs simplify highly complex hospital infrastructures (Briggs et al. 2010) by fostering the presentation of information and linking disciplines enhancing information dissemination (Kerly et al. 2007; Seeber 2019). CAs combine knowledge from multiple sources and provide guidance on procedures and duties (Briggs et al. 2013; Seeber 2019). CAs enhance medical decisions as systems understand users' environments and evaluate patient data objectively, without any prejudices, while considering all medical information available (Bickmore et al. 2011; Siddike and Kohda 2018). With CAs, clinicians assess multidimensional situations and information that otherwise might be overlooked (Nezhad et al. 2017; Siddike et al. 2018). Furthermore, clinicians learn through agent-derived decisions as they receive adaptable feedback, fostering future decision-making (Nezhad et al. 2017) thus enhancing cognitive capabilities by raising awareness of options or pointing out specific patterns (Siddike et al. 2018).

Major challenges

Audience and interdependency

The notion of audience describes that CAs are used by multiple target groups. Hospital employees are not in the same age groups, differ in their expertise, have various professions, and work in different hierarchical structures and branches (Finlayson and Raymond 2012; Schadewaldt et al. 2014). One expert stated that "the age gap between some colleagues is simply extremely high. There are resident doctors who are in their mid-twenties and nurses who are in their late fifties" (E4). It is particularly relevant for hospitals to consider privileges in advance. For example, it needs to be validated if

Table 1 Identified articles assigned to theoretical foundations 1) roles and responsibilities; 2) respect, trust, and communication; 3) hierarchy, education, and liability; 4) organizational processes; 5) medical treatment process; 6) goal setting; 7) interpersonal relations; 8) problem solving; and 9) role clarification

| Database | Article | Collaboration | | | | | Team-building | | | |
|---------------------------|-------------------------------|---------------|----|----|----|----|---------------|----|----|----|
| | | 1) | 2) | 3) | 4) | 5) | 6) | 7) | 8) | 9) |
| ACM | (Allen et al. 2002) | | | | | X | | | X | |
| BS | (Bersot et al. 1998) | | | | | | | X | | |
| SD | (Bickmore and Giorgino 2006) | | | | X | | | | | |
| SD | (Bickmore et al. 2005) | | | | | X | X | X | | |
| SD | (Bickmore et al. 2010) | X | | X | | | | | | X |
| SD | (Bickmore et al. 2011) | | | | X | | | | | |
| AISeL | (Bittner et al. 2019a) | | X | | X | | | | | X |
| BS | (Bittner et al. 2019b) | | | X | | | | | | |
| BS | (Briggs et al. 2010) | | | | X | | X | | | |
| BS | (Briggs et al. 2013) | | | | X | | | | | |
| FS | (Demetriadis et al. 2018) | | | X | | | X | | | |
| AISeL | (Elson et al. 2018) | | X | | | | | | | |
| SD | (Fitriani et al. 2015) | | X | | | | X | | | |
| BS | (Gerhard et al. 2001) | | X | | | | | | | |
| ACM | (Hanna and Richards 2014) | | X | | | | | | X | |
| IEEE | (Hayashi and Ono 2013) | | | | X | | | | | |
| BS | (Just et al. 2005) | | | | X | | | | | |
| SD | (Kerly et al. 2007) | | X | | | | | | | |
| BS | (Lim et al. 2011) | | X | | | | X | | | X |
| AISeL | (Nabeth et al. 2003) | X | | | X | | | | | |
| ACM | (Nakano and Fukuhara 2012) | | | X | | | | | | |
| ACM | (Nezhad et al. 2017) | | | | X | | | | | |
| BS | (Ouldouali et al. 2017) | | | | | | X | | | |
| SD | (Prada and Paiva 2009) | | X | X | | | | | | X |
| IEEE | (Preece et al. 2017) | | | | | | X | | | X |
| FS | (Robb et al. 2015) | | | | | | X | | | |
| FS | (Schmulian and Coetzee 2019) | | | | | | | | | X |
| SD | (Seeber 2019) | | | | X | | | | | X |
| AISeL | (Seeber et al. 2018) | X | X | | | X | X | | | |
| ACM | (Shamekhi et al. 2018) | | | | | | | | X | |
| AISeL | (Siddike and Kohda 2018) | | X | | | | | | | |
| AISeL | (Siddike et al. 2018) | | | | | | | | | X |
| AISeL | (Stoekli et al. 2018) | | | X | | | | | | |
| AISeL | (Tavanapour and Bittner 2018) | | | | | | | | | X |
| AISeL | (Tavanapour et al. 2019) | | | | | | | | | X |
| IEEE | (Tegos et al. 2012) | | | | | X | | | | |
| FS | (Tegos and Demetriadis 2017) | | | | | X | X | | | X |
| IEEE | (Tegos et al. 2012) | | | | | | | | | X |
| SD | (Tegos et al. 2015) | | X | X | X | | X | X | | |
| ACM | (Traum et al. 2003) | X | | X | | | | | | X |
| BS | (Winkler et al. 2019) | | X | X | | X | | | | |
| ACM | (Xiao et al. 2019) | | | | | | | X | X | |
| FS | (Zumbach et al. 2005) | | | | | | | X | X | |
| Total numbers of articles | | 4 | 12 | 9 | 11 | 6 | 11 | 7 | 15 | 4 |

patient-related data is accessible by every team member or whether there must be a differentiation in the hierarchical

structures. CAs can adapt to existing hierarchy and responsibilities of hospital employees to improve collaboration.

Interdependency characterizes the coexistence of employees and CAs and communication channels being appropriate for a given task and target audience (Seeber et al. 2018). Equivalent research shows that understanding the demographic characteristics is a critical factor (Andrews 2001, 2002). However, interdependency may also lead to tasks being performed in isolation or clinicians blindly relying on results provided by CAs.

Connectivity and embodiment

Connectivity and embodiment describe the interconnectedness of CAs and hospital departments and the preparation and presentation of patient-related data. Integrating different IS represents a main facet of supporting collaborative aspects (Kuziemyk et al. 2012). One expert emphasized that “information must be gathered from various data sources” (E6). A majority of IS applied in hospitals is tailored to the needs of each medical discipline and department with systems being highly customized. Not only departments but also IS are detached from each other (Lenz and Reichert 2007) but gaining shared understanding improves evaluation (Seeber 2019). CAs foster connection and sharing information (Marwan et al. 2016; Paul et al. 2016) by linking different systems and disciplines (Kerly et al. 2007) and assist with the documentation of the medical treatment process (Kerly et al. 2007). CAs also exist in different forms and can be utilized across a broad spectrum of situations. For example, CAs as text-based systems might be used in the outpatient clinic as hospital employees already use other systems with haptic input. Speech-based CAs could be applied within operating theatres as the sterile surrounding prohibits written input. The information presented by CAs can thus be oriented toward the patient, the disease and method of treatment.

Trust and transparency

Trust is a major challenge for technology to be accepted and utilized (Frick et al. 2020; Siddike and Kohda 2018; Söllner et al. 2016) and must be considered from two perspectives in this research: trust in the CA itself and trust in other humans. Trust in technology is vital for its usage but more difficult to achieve as it does not provide a human-to-human relationship (Lankton et al. 2015). Especially the initial trust, which is also established by the perceived level of competence (Seeber et al. 2018), determines future utilization (McKnight et al. 2002; Söllner et al. 2016). Trust in CAs is particularly relevant as decisions proposed by the system might have an impact on collaborative processes and the treatment of patients. There might be differences regarding the type of CAs further influenced by selected collaborators and their individual characteristics. Transparency causes discomfort but is crucial for building trust (Wunderlich and Paluch 2017). One expert

underscored that “the application of such systems immediately makes information transparent, whereby errors in the treatment process become visible” (E6). This could lead to clinicians being less willing to disclose information to CAs which may even worsen collaboration. In hospitals, trust and transparency are particularly crucial as CAs do not only aid regarding the well-being of patients but disclose the entire diagnostic and treatment process to involved clinicians.

Security, privacy, and ethics

Security as subjective perception characterizes data authentication and authorization (Pavlou 2001), which includes the risk of violating users’ (Yang et al. 2016) and patients’ privacy. Security is necessary for adopting and utilizing CAs (Han and Yang 2018), influencing trusting beliefs (Eastlick et al. 2006; Kim 2008) and the willingness to share information (Dhami et al. 2013; Dinev and Hart 2006). Privacy is a subjective anticipation as well (Pavlou 2001). Using information discriminately leads discontinued use of systems (Culnan and Armstrong 1999). Violations are, for example, unauthorized collection or secondary use of information, improper access and errors in personal information (Smith et al. 1996). One interviewee clarified that “it is not only about patient information but about personal data of employees” (E5). Both security and privacy are urgent aspects when storing personal data of individuals (Abdelhamid et al. 2015; Kuckein et al. 2010). Due to the unique characteristics of CAs, humans might tend to share more personal information and sensitive data compared to other technologies. Any data leaks creating benefits for enterprises, for example, insurance companies predicting hospital costs based on disease patterns, resulting in disadvantages for patients, should be eliminated. Furthermore, CAs raise ethical concerns related to the application of technologies in hospitals (Bickmore et al. 2010), especially considering the collected information (Derrick et al. 2011). When comparing CAs to IS, the perception around ethical and moral issues varies (Bendel et al. 2021; Siau and Wang 2018b). Since the development of CAs is enabled by AI, results are not always comprehensible to humans (Hagras 2018). Dubious recommendations by CAs, e.g., requesting additional consultation from another clinical department for a patient belonging to certain ethnic group, may not be recognized.

Future research agenda for IS

Based on the findings from the SLR, enlightened by the semi-structured expert interviews, the following research agenda points out which research needs to be pursued to successfully establish CAs in clinical environments affecting the quality of care process. Table 2 summarizes future research questions when applying CAs for collaboration and team-building in hospitals.

Table 2 Future research questions for identified challenges

| Major challenge | Example research questions | References |
|-------------------------------|---|---|
| Audience and Interdependency | <p>How can CAs involve and coordinate different healthcare professionals from multiple clinical departments? How do CAs deal with various norms or specifications with heterogeneous roles in hospitals?</p> <p>How does the deployment of CAs in hospitals influence the existing responsibilities and hierarchy of healthcare professionals during collaboration? Which tasks can be carried out by CAs for the different hospital areas to improve collaboration within the medical treatment processes?</p> <p>To what extent are CAs capable of promoting collaborative decision making with other clinicians in hospitals? In what ways do CAs help to ensure that health-related tasks are not performed in isolation?</p> <p>How can it be ensured that doctors or nurses do not blindly rely on results derived by CAs for the collaborative treatment of patients? How do physicians take responsibility for activities and decisions proposed by CAs within collaborative processes? Who is accountable for decisions given by CAs to clinicians in hospitals?</p> | (Bersot et al. 1998; Bickmore et al. 2005, 2010; Gerhard et al. 2001; Lim et al. 2011; Nabeth et al. 2003; Nezhad et al. 2017; Preece et al. 2017; Seeber et al. 2018; Shamekhi et al. 2018; Tegos et al. 2015, 2012) |
| Connectivity and Embodiment | <p>How can CAs connect historically grown patient data and systems that are already in use within hospitals, including their diverse infrastructures, to drive collaborative decisions?</p> <p>What medical information is captured through CAs? Which information must be exchanged with other hospital IS (e.g., electronic health records) to ensure flawless collaboration?</p> <p>How can relevant medical information be identified for different collaborators (e.g., hospital departments or clinical teams)? Which information must be presented to healthcare specialists to align with the patient's medical treatment and drive collaboration?</p> <p>What requirements must be placed on CAs to ensure their proper functionality fostering collaboration in any hospital environment, especially in sterile hygienic surroundings? How can different types of CAs, e.g., text-based or speech-based, be deployed for the varying hospital areas?</p> | (Briggs et al. 2010; Elson et al. 2018; Prada and Paiva 2009; Seeber et al. 2018; Siddike et al. 2018; Tavanapour and Bittner 2018) |
| Trust and Transparency | <p>How are employees convinced of the objectives and advantages of CAs to enhance collaboration in an environment where the well-being of the patient is the primary concern?</p> <p>Which collaboration team (e.g., hospital department or discipline) shall use CAs initially? Where can CAs be introduced to enhance collaboration without disrupting hospital procedures and patient treatment?</p> <p>How do collaborators cope with the transparency of their working behavior initiated by CAs? To what extent are clinicians willing to disclose information about working behaviors to CAs and other hospital employees?</p> <p>To what extent do clinicians perceive losing one's unique value or their individual knowledge and control when CAs are applied for collaborative purposes?</p> | (Allen et al. 2002; Bittner et al., 2019a; Hayashi 2018; Kerly et al. 2007; Nabeth et al. 2003) |
| Security, Privacy, and Ethics | <p>How can it be ensured that the data of patients as well as of hospital collaborators are not retrieved by third parties? How can an authorization concept for different healthcare collaborators for the use of CAs be established?</p> <p>To what extent are CAs able to determine objective characteristics of patients? What medical basis is used to generate recommendations to assist collaboration? How can disadvantages for patients (e.g., as part of a certain group or meet certain criteria) be excluded?</p> <p>How can CAs learn from decisions made by healthcare professionals? How can medical conclusions be generalized and transferred to other collaborative settings in hospitals?</p> <p>How can bias within the collaboration with CAs be recognized and resolved by hospital employees? What could a control mechanism by healthcare specialists look like?</p> | (Bickmore et al. 2010; Just et al. 2005) |

Audience and interdependency Technology needs to be understandable and usable to fulfill the user's needs (Lim et al. 2011; Norman 2013). Various interaction possibilities need to

be offered to exploit the full potential (e.g., Bersot et al. 1998; Lim et al. 2011; Shamekhi et al. 2018). One participant pointed out that "older people prefer talking over typing" (E3).

Systems must be able to adjust to users' different needs, personalities, attitudes, and moods (Andrews 2001, 2002; Seeber et al. 2018) but also consider the responsibilities and hierarchy of clinicians. CAs must be interesting, demanding and stimulating while encouraging employees to think for themselves (Nabeth et al. 2003). One expert mentioned that "the decisions of these systems should be questioned by employees" (E3). Systems should actively support individuals and perform repetitive tasks for which no cognitive abilities are needed (Nabeth et al. 2003). Since decision making in isolation frequently yields inferior results (Driscoll et al. 2015), CAs need to promote collaborative judgments with other clinicians avoiding decisions being performed in detachment. Establishing a relationship and tailoring the CA's behavior to the needs of the user is essential. However, this may lead to users becoming dependent. One respondent emphasized that this, "conveys a feeling of false security" (E2). This represents social loafing behavior, where a user in a group attempts less effort to achieve a goal than when working alone (Karau and Williams 1993). CAs completing almost every task might result in employees no longer identifying themselves with a decision and not questioning or taking responsibility for it. Individuals might even forget essential information as cognitive skills are becoming superfluous. One expert even had the idea that "critical decisions may be highlighted or need to be confirmed by a third person" (E1). Decisions in clinical environments need to be questioned and verified as diseases vary and evolve over time (Eigner et al. 2019; Zwaan and Singh 2015). Overall, we derived the following research proposition (RP):

RP1: We propose more research on how CAs enhance collaboration in hospitals by converging different user groups in varying clinical environments due to multiple professions, hierarchical structures, and expertise levels. CAs promote collaborative decision-making for diverse employees and their demographics, while rigorously monitoring inputs on treatment decisions. Furthermore, accountabilities and responsibilities of employees for using decisions proposed by CAs influence the performance of the collaborative diagnostic and therapeutic process.

Connectivity and embodiment Due to the diversity of IS in hospitals, data must be extracted and processed from multiple sources. Information is not always captured digitally, patient data is still recorded in handwritten files, making it difficult to gather information quickly. One expert complained that "handwritten files are sometimes simply not readable. If the nursing staff is handing over the files to the next shift, they are not where I expect them to be" (E1). Digital information is entered across multiple systems and users must switch

between multiple applications (Lenz and Reichert 2007; Miner et al. 2016). The prerequisite of the treatment process being documented digitally (Kerly et al. 2007) ensures reaching the full potential of CAs. One expert underscored that "pendulum files will be dropped. We won't need in-house mail anymore. All information of a patient is visible for every colleague" (E1). With the introduction of CAs, systems shall be linked with each other and information is only accessible via the CA (Kerly et al. 2007). However, information from systems of every department must be merged by CAs to help in locating information effectively (de Moraes Batista et al. 2009; Kassner et al. 2017; Xu and Topi 2017). It is not only relevant to process information from the applying hospital but also to have access to the entire course of the patient's illness, including information from other healthcare facilities. One expert explained that "something like a digital medical record must contain all of the patient's information" (E5). Furthermore, technical communication between multiple systems must be ensured using unified protocols and interfaces. The information presented by CAs should always be comprehensibly and oriented toward the patient and the disease as well as the method of treatment (Nabeth et al. 2003). It should also be noted that different departments need deviant information. To avoid confusing determination and presentation, CAs must possess both sufficient medical vocabulary and necessary information about a given task (Bittner et al. 2019a) and choose a suitable method of communication (Hayashi and Ono 2013). Furthermore, CAs must adapt to different environments. One expert described different interaction modes and surroundings: "there are areas in which a doctor is sterile and where a smartphone cannot be used" (E5). This led to our second proposition:

RP2: We propose more research on how CAs interconnect different hospital employees, departments, disciplines, and existing clinical information systems to expedite the collaboration among involved stakeholders and enhance medical data retrieval. CAs adapt to different clinicians and diverse clinical environments where medical data is tailored to each patient's treatment process to foster flawless collaboration.

Trust and transparency Users tend to have prejudices when starting to interact with technology (Sheridan and Hennessy 1984). One expert underscored, "in the beginning, there will be anxiety and fear of extra work or even disinterest" (E4). Without building trust in CAs, support with cognitive tasks is not provided thus decision making becomes more difficult (Briggs et al. 2010; Elson et al. 2018). Users having trust in CAs are more likely to be supported when making decisions (Frick et al. 2019; Elson et al. 2018). Interpersonal relations are unavoidable as they involve trust in other humans (Amos

et al. 2005; Salas et al. 1999). The more physicians have trust in their colleagues, the more they acknowledge their expertise (McInnes et al. 2015; Schadewaldt et al. 2014). Trust in each other and the work affects the treatment process (McInnes et al. 2015; Schadewaldt et al. 2013, 2014). Lack of trust leads to clinicians questioning recommendations delays processes degrading collaboration (Briggs et al. 2010; Elson et al. 2018). To establish trust in CAs immediately, the intentions, benefits and possible obstacles should be explained and employees must be supported during the initiation process especially because users may have different experiences and previous knowledge (Frick et al. 2021). CAs should always have a detailed explanation on the focus of the task (Tavanapour and Bittner 2018). A step-by-step introduction is conceivable, not across all departments, but initially in one department or team, to identify potential errors and achieve a fully tested system. Utilization might be offered on a voluntary basis to recruit employees motivating or influencing their colleagues. One expert recommends introducing CAs “in an area where everyday tasks are executed that do not affect patients and where the speed is irrelevant” (E5). The application of CAs will increase the transparency of employees’ roles and their tasks. One expert explained that “today, I have to make a call and beg for an appointment - and then the blame is always on others” (E1). Transparency causes discomfort but is crucial for trust-building (Wunderlich and Paluch 2017). The new transparency of both information and employees who use CAs could lead to a feeling of being monitored, losing one’s unique value and knowledge. Not having trust yields in refusing or boycotting the system and hinders the willingness to disclose information. One interviewee mentioned that “transparency enables CAs to detect failures in the treatment process” (E6). However, alleviating related negative consequences is achieved when “good results and fast performances are communicated, rewarded, and made visible to other employees” and further “through the transparency of good work, a new team spirit can be created” (E3). This led to our third research proposition:

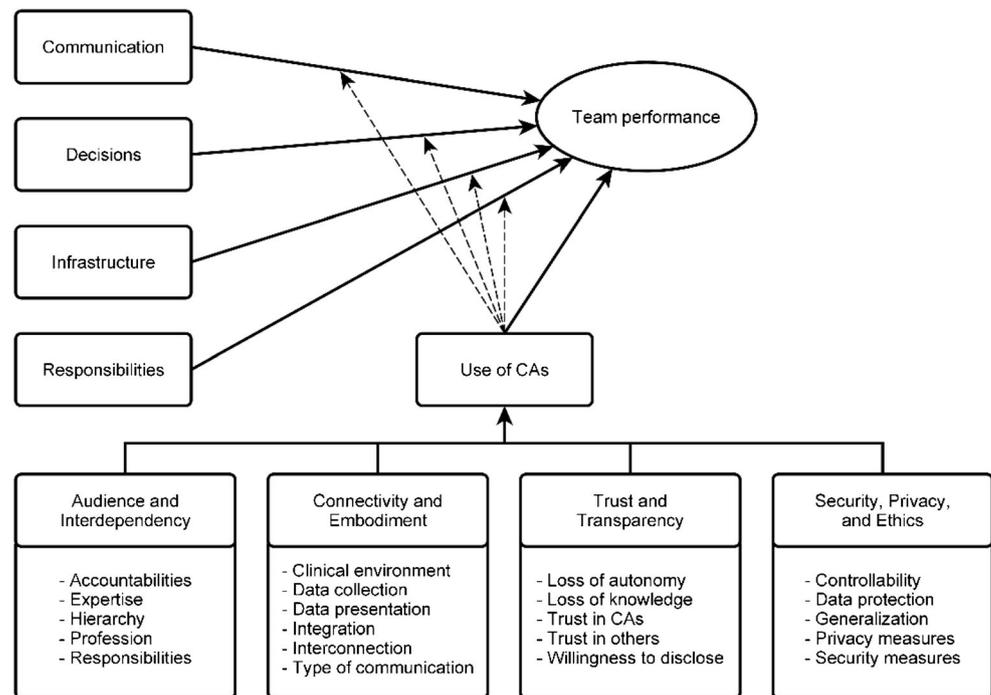
RP3: We propose more research on how CAs assist in building clinicians’ trust in other hospital employees and their abilities across interdepartmental boundaries, as well as in the technology itself, to generate advantages that will directly and indirectly affect clinicians and patients. CAs initiate transparency between collaborators, including their working behaviors and newfound clarity in the therapeutic process. Resistance factors, loss of autonomy, and the importance of individual knowledge when using CAs affect willingness to disclose information about medical decisions.

Security, privacy, and ethics There shouldn’t be any misuse by third parties and no information published without the consent of the person concerned (Just et al. 2005). This applies to the personal information of patients and employees. One interviewee summed up “the protection of data must be guaranteed at all times. There is sensitive information such as disease pictures or life expectancy” (E2). Information must be carefully protected with the highest security standards. Any data leaks or the disclosure of information without the consent of involved individuals might have serious consequences. There are also moral issues related to the application of CAs (Bickmore et al. 2010) as they are still being trained by humans and might contain unintended bias (Rothenberger et al. 2019; Siau and Wang 2018a) or even aim at changing the user’s behavior (Bickmore et al. 2010) and initial perceptions (Elson et al. 2018). One expert explained that “such a system must not make unethical or morally reprehensible decisions” and delineated “an example would be to remove a patient from a planned operation based on false, incomplete, or purely objective information” (E1). Based on decisions derived by physicians, CAs might learn prejudices. Even though this may be evident from the data, it is questionable whether this should lead to disadvantages for patients belonging to a certain group or meeting particular criteria. CAs objectively evaluate the patient’s condition but cannot obtain subjective impressions. When making difficult choices, a physician is ultimately responsible for the decision and must be aware of moral and ethical implications (Seymour et al. 2018). Decisions shall therefore be able to be overwritten and CAs need to learn and apply new knowledge to other circumstances. The above aspects lead to our final proposition:

RP4: We propose more research on how CAs ensure secure data collection, information presentation by clinicians, and storage of patients’ medical data, addressing how unauthorized access is prevented. Furthermore, we demand determining the extent to which morally and ethically unacceptable results are identified by clinicians and CAs to avoid potential safety hazards for patients and what a control mechanism could look like. CAs and hospital collaborators learn from decisions and medical conclusions to generalize and adapt to other collaborative settings in clinical environments.

Drawing from the major challenges identified when applying CAs for collaboration and team-building in hospitals, and combining these with our propositions for future in-depth research, we designed our final research model (cf. Fig. 2). We argue that the major challenges, including their various factors, directly impact the extent to which CAs are used in hospitals. Future research should not only consider the individual research questions as outlined in the agenda, but also

Fig. 2 Final research model



examine the individual influencing factors of each major challenge and their relationships, which impact the use of CAs for enhancing team performance in hospitals.

Finally, it should be noted that these challenges also influence each other; for example, unethical decisions or the type of CA inevitably influences trust in the system. The results presented above show that there are several questions that must be tackled in future research. However, this research advocates that CAs as a subset of hybrid intelligence are capable of improving collaboration and team-building, and thus, the quality of healthcare services and team performance in hospitals.

Conclusion and limitations

Drawing from the literature about collaboration and team-building, enlightened by expert interviews, this article contributes to theoretical foundations by presenting challenges that need to be faced when applying CAs in hospitals and pointing out areas where future in-depth investigations are needed. We answer our research question by demonstrating how the interaction between humans and CAs affects the quality of care process and which factors impact the use of CAs for enhancing team performance. The conclusions are relevant for researchers as the overview of challenges is helpful in considering difficulties before the actual introduction of

CAs. Practitioners understand the extent to which CAs improve collaboration and team-building in hospitals.

This research is not free of limitations. There are various notations for the term CAs that are used interchangeably in research and practice. However, to narrow down the scope of this study, we linked the most common terms within the SLR. Even though the identified articles provide a sufficient foundation for the research agenda, we may have missed the retrieval of relevant literature providing additional findings. We further present a small group of experts who cover a limited fraction of knowledge. Although we conducted interviews with both physicians and computer scientists, further stakeholders should be considered in future research to retrieve a broader picture, i.e., other hospital employees such as nursing staff or surgical assistants or computer scientists working in the healthcare sector.

Besides the research agenda, studies should also focus on deviant perspectives. What further challenges need to be considered when CAs are applied in hospitals? What other benefits besides collaboration and team-building can be achieved? How must a system be designed to be effective and efficient and to adapt to different users in hospitals? Our future research aims at identifying exact use cases where systems can be used to improve collaboration and team-building in hospitals. Therefore, we are going to observe different clinicians in several hospitals over a longer period to grasp the phenomenon of how CAs concretely support collaboration.

Appendix

Collaborative challenges in hospitals

Table 3 Challenges and potential for CAs improving collaboration in hospitals

| Challenges in hospital | Potential for CAs | Example references |
|--|--|---|
| Communication among clinicians (e.g., miscommunication for medical dispensing). | Communicative support (e.g., among different hierarchical structures or disciplines) Performance improvements in diagnostic and therapeutic process Stress-free work environment Enhancing team atmosphere and cohesion | (Balogh et al. 2015; Kanjanarat et al. 2003; Kripalani et al. 2007; McInnes et al. 2015; Schadewaldt et al. 2013, 2014) |
| Responsibilities of clinicians as patients are treated by multiple specialists with different medical information. | Transparent information on clinicians' duties Fast retrieval of responsible healthcare specialists Simplified goal-driven communication and collaboration | (Bickmore et al. 2011; Kerly et al. 2007; Rosen et al. 2018; Traum et al. 2003; Wears and Berg 2005) |
| Infrastructure as multiple systems for various purposes exist, containing different information; interconnected and operated by various users. | Providing suitable information for users Merging data from multiple origins Fast retrieval of medical information Minimizing task duration Simplified reporting of information Transparent diagnostic and treatment process | (Angst et al. 2010; Hanseth and Bygstad 2015; Meier et al. 2014; Nasirian et al. 2017; Preece et al. 2017) |
| Decisions are depending on individual experiences, emotions and mental state of clinicians. | Objective and equal evaluation of patient data Non-prejudices decisions (e.g., objective conclusion based on medical facts) Independent decisions regardless of time or mental state | (Chang and Hsu 2009; Gnewuch et al. 2017; Laurenzi et al. 2017; Seeber et al. 2019; Singh et al. 2020) |

Interview guideline

Table 4 Interview guideline (German interview questions have been translated into English)

| Phase | Research goal | Questions |
|---|---|--|
| Introduction | Welcoming the interviewee and providing general information about the research and brief introduction to the topic. | – |
| Demographic data | Getting an understanding of the interviewee including position within the hospital/organization and the areas of responsibility. | a) Could you please introduce yourself? b) What is your current position in your hospital/organizations and what are your responsibilities? |
| Application of CAs | Awareness of previous experiences with CAs and applications within in general and in hospitals. | a) What do you associate with the term “Conversational Agent” and which application areas are you familiar with? b) Which areas of application are known to you in hospitals? Afterwards the researchers provide an explanation of CAs and current examples to assume the same knowledge among all participants. |
| CAs in context of collaboration and team-building | Possible applications of CAs in hospitals, especially regarding to collaboration and team-building considering the theoretical foundations. | a) Can you imagine how CAs can be applied to improve collaboration and team-building in hospitals? b) What might be the advantages and disadvantages when introducing CAs? c) How important is the understanding of the role and responsibilities for you and your colleagues? (roles and responsibilities) d) What role does respect, trust and communication play, especially with colleagues? (respect, trust and communication) e) How important is the hierarchy and education of hospital employees? (hierarchy, education and liability) f) How can the organizational process or the medical treatment of patients be affected? (organizational processes and medical treatment process) g) How can the achievement of goals and problem solving be supported? (goal settings and problem solving) h) How important are interpersonal relations and the understanding of one's own role? (interpersonal relations and role clarification) |
| Finish | Debriefing of the interviewee and explanation of the research background. | – |

Exemplary Assignments

Table 5 Example statements and exemplary assignment to a category

| | Category | Sample statement |
|---------------|--|---|
| Collaboration | 1) roles and responsibilities | “the role of the system is primarily to provide information to enable the user to make informed choices” (T. W. Bickmore et al. 2010, p. 280) |
| | 2) respect, trust, and communication | “After having defined different interaction modalities for communication with the Sprytes, we took into account the right assignment of the modalities to the different users in order to increase their engagement as well as collaboration.” (Lim et al. 2011, p. 227) |
| | 3) hierarchy, education, and liability | “Teamwork in STEAM is based on the agents’ building up a hierarchy of joint intentions and monitoring other members’ and team’s performances and reorganizing the hierarchy when necessary” (Prada and Paiva 2009, p. 82) |
| | 4) organizational processes | “Indeed, what the users ultimately need are not so much tools that will be able to process more efficiently an even larger amount of information, but rather ‘smarter’ tools that are able to support more effectively the knowledge related processes that are inherently connected to their work, and the operations of organizations.” (Nabeth et al. 2003, p. 70) |
| | 5) medical treatment process | “These examples are motivated by interactions we have observed in a medical advisor domain in which the system acts to help a person manage their medications.” (Allen et al. 2002, p. 778) |
| Team-building | 6) goal setting | “The working alliance has three sub-components: a goal component, reflecting the degree to which the helper and client agree on the goals of the therapy” (T. Bickmore et al. 2005, p. 22) |
| | 7) interpersonal relations | “This initial evaluation of a relational agent in a health behavior change intervention indicates that patients are generally receptive to the technology and respond in ways analogous to how we would expect them to respond when the same emotional and relational communication behaviors are used by human health providers.” (T. Bickmore et al. 2005, p. 28) |
| | 8) problem solving | “Our approach to the later stages of change involves long-term and short-term goal setting negotiation, positive reinforcement when goals are met and ‘problem solving’ to overcome barriers when goals are not met.” (T. Bickmore et al. 2011, p. 189) |
| | 9) role clarification | “Agents can be given different personalities and different roles (e.g. tutor, coach, learning companion or opponent), which may increase the interest of the students.” (Tegos et al. 2011, p. 162) |

Experts' characteristics

Table 6 Characteristics of the interviewees

| # | Gender | Age | Tenure (years) | Position | Specialty | Discipline | Hospital |
|----|--------|-----|----------------|------------------------|------------------------------|------------------------------|-----------------------------------|
| E1 | Female | 30 | 1 | Resident doctor | Surgeon | Cranio-maxillofacial surgery | University Hospital of Dusseldorf |
| E2 | Female | 30 | 3 | Resident doctor | Gynecologist | Obstetric care | University Hospital of Frankfurt |
| E3 | Male | 34 | 5 | Attending physician | Rheumatologist | Rheumatology | University Hospital of Munich |
| E4 | Male | 65 | 30 | Chief physician | Anesthetist | Anesthesia | Saint Francis Hospital Muenster |
| # | Gender | Age | Tenure (years) | Position | Branch | | |
| E5 | Male | 28 | 8 | Full Stack Developer | IT Management and Consulting | | |
| E6 | Male | 32 | 10 | Head of Data Analytics | IT Service Provider | | |

Search results

Table 7 Number of search results per scientific database (articles up until October 2019)

| Database | No. of results | No. of relevant results |
|--|----------------|-------------------------|
| ACM (Association for Computing Machinery) | 173 | 7 |
| AISel (Association for Information Systems Electronic Library) | 140 | 10 |
| IEEE (Institute of Electrical and Electronics Engineers) | 42 | 4 |
| JSTOR (Journal Storage) | 55 | 0 |
| SD (ScienceDirect) | 399 | 10 |
| Backward search | 18 | 8 |
| Forward search | 14 | 5 |
| Total numbers of articles | 841 | 44 |

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Paper 8: Comparison of disclosure/ concealment of medical information given to conversational agents or to physicians

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Comparison of disclosure/ concealment of medical information given to conversational agents or to physicians

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Abstract

Within the anamnesis, medical information is frequently withheld, incomplete, or incorrect, potentially causing negative consequences for the patient. The use of conversational agents (CAs), computer-based systems using natural language to interact with humans, may mitigate this problem. The present research examines whether CAs differ from physicians in their ability to elicit truthful disclosure and discourage concealment of medical information. We conducted an online questionnaire with German participants ($N = 148$) to assess their willingness to reveal medical information. The results indicate that patients would rather disclose medical information to a physician than to a CA; there was no difference in the tendency to conceal information. This research offers a frame of reference for future research on applying CAs during the anamnesis to support physicians. From a practical view, physicians might gain better understanding of how the use of CAs can facilitate the anamnesis.

Keywords

anamnesis, concealment, conversational agent, disclosure, medical information

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Introduction

The examination of patients usually begins with the anamnesis, the most important step in the process of medical care. This serves primarily to collect all relevant medical information, the completeness and accuracy of which are fundamental for further treatment.¹ The duration of the anamnesis mostly depends on the physician's available time for each patient. However, not only time pressure may lead to incomplete and incorrect information² but also the behavior of patients. Recent research has shown that medical information is not always disclosed to physicians.³ Scenarios in which patients withhold information may lead to dramatic consequences. If a patient conceals the use of freely available or even illegal substances, severe interactions can occur³; for example, the effect of a prescribed medication can be augmented, diminished, or eliminated. Misrepresentation of medical information can lead to miscalculation with negative consequences not only for the health of the patient but also for people in their immediate surroundings.²⁻⁴

In contrast, collecting medical information through questionnaires without the presence of a physician can lead to more forthright interviewing behavior than in the presence of a real person.⁵ However, a questionnaire is unable to guide the conversation, react to the patient's statements, and motivate them to continue answering new, related questions over a longer period.⁶ In this context, the application of a conversational agent (CA), a computer-based system capable of holding a conversation with a human being,⁷ may prove beneficial. CAs are being increasingly applied for health-related purposes,⁸ including to assist with the anamnesis.¹ They ask patients questions based on relevance, carrying out a detailed anamnesis for which a physician has no time, and motivate patients to answer the questions completely.¹ The fact that a CA is not a real person might positively influence the response behavior of patients. Previous research has focused on the problem of failure to disclose medical information in multiple instances and under different conditions, but not in relation to CAs used for the anamnesis. In this regard, the application of CAs seems reasonable, although it has not yet been investigated whether patients are generally willing to share information with a CA. Thus, this research aims to provide first insights into the application of CAs for the anamnesis and their ability to elicit further discussion. To formalize the goal of this study, we propose the following research question:

RQ: How do patients' attitudes toward disclosing and concealing medical information differ when interacting with conversational agents or with physicians?

To answer this, an online survey with German participants was conducted. The respondents were divided into two groups, one of which was shown an example of an anamnesis with a CA and the other was not. Afterwards, participants were asked whether medical information would be readily disclosed or concealed in conversing with a CA or with a physician.

Theoretical background

There are various reasons why patients do not share medical information fully and truthfully, ranging from simple forgetfulness to the fear of being judged negatively. The following section explains these reasons in greater detail, why failure to disclose can have far-reaching consequences, and how CAs may be applied to overcome this behavior.

Disclosure and concealment of medical information

Self-disclosure describes to whom we disclose personal information and is influenced by the extent to which people trust their listener and whether there is mutual understanding.⁹ The full

disclosure of medical information, such as the patient's history, symptoms, and health behavior, is mandatory for physicians to determine appropriate treatment processes, achieve the best possible medical care,^{1,3} and avoid short- or long-term consequences for the patient and others.²⁻⁴ Relevant information is collected in the anamnesis, a conversation between the patient and the treating physician,⁶ in which the current health condition and medical history are discussed to yield a correct diagnosis. However, there are various reasons why medical data are concealed and not exchanged with physicians.

The tendency to self-conceal is defined as the active and conscious hiding of personal information which an individual considers negative or embarrassing.¹⁰ Within the anamnesis, patients may consider certain circumstances to be irrelevant,³ or are unable to remember them due to a pre-existing disease.⁴ Excessive administrative burdens, such as gathering various documents from several physicians, and the limited duration of the anamnesis may lead to simply forgetting some information.^{2,4} Importantly, some patients do not want to share certain information, presenting it differently or incorrectly and even withholding or lying about relevant facts.^{3,4}

According to Tourangeau and Yan,¹¹ willingness to share information depends on three factors: the sensitivity of the information, the interviewee, and the interviewer. In terms of the anamnesis, the factors that determine whether health-related information is shared with the treating healthcare professional are the sensitivity of the medical information itself, the affected patient, and the treating physician. Sensitive information is described as obtrusive, dealing with topics that are considered inappropriate in everyday conversations,¹¹ or that affect privacy excessively.⁵ Patients are particularly dishonest regarding information perceived as unethical¹² or socially undesirable and unacceptable,¹¹ even more so if the answer entails legal or social consequences.⁵ Research has ascertained that patients are frequently embarrassed to express certain information as they want to be liked by healthcare professionals.¹² Also, patients do not want to be judged as ignorant or awkward thus are more likely to ignore harmful behavior.³

The disclosure of information to physicians is likely to be avoided³ and represents a major problem for effective healthcare, however, the application of CAs appears to be a suitable alternative.

Conversational agents in healthcare

Communicating with CAs has several advantages, such as increased willingness to disclose information and the promotion of honest communication.¹³ Research has reached no consensus on a consistent definition for the term CA but explains it from different perspectives.¹⁴ CAs differ in their primary mode of communication, in other words, how users interact with CAs, such as text- or speech-based input. They also differ in their purpose, such as whether they are narrowed to one function or can be used in a more general context. In this study and in the context of health-related purposes, the definition of Abdul-Kader and Woods⁷ seems most suitable: "A computer program that has the ability to hold a conversation with a human using natural language speech".

CAs have been applied successfully in health-related tasks, for example, to monitor patients' health condition¹⁵ or to support diabetes patients in their daily routines.¹⁶ There are even initial approaches to managing health-related information provided by patients. "Ana," a mobile self-anamnesis application with a conversational user interface, was developed to gather medical information in preparation for therapy.¹ However, there are no CAs yet that are integrated into the entire medical treatment process,¹ but can guide patients through the anamnesis and obtain all relevant medical information to assist physicians in achieving the best possible medical care.

Unlike many physicians, CAs are not limited in their time, so patients may no longer feel pressured and they may thus be less likely to forget to disclose relevant medical information. CAs remain factual, which may remove the perception of being judged negatively and trigger patients to share

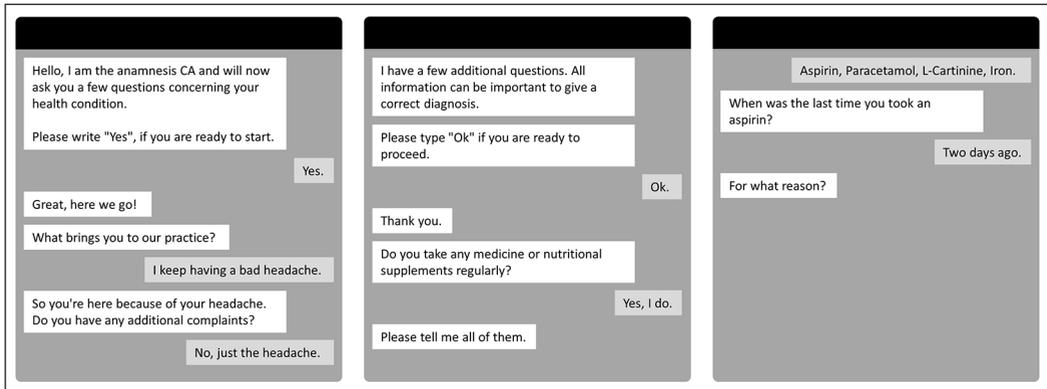


Figure 1. Exemplary anamnesis with a CA.

socially undesirable actions. Despite all the possible positive advantages, research has not yet investigated whether patients are generally more willing to share information with CAs. Therefore, the focus of this study is on disclosure and concealment of medical information; other clearly important aspects, such as acceptance, trust, security, and privacy, are not considered; further research should take these into account. This study is intended to provide initial insights into the topic.

Method

Sensitive information is often misrepresented or held back to a certain extent.⁵ A wide variety of instruments have already been used to carry out anamnesis to change this behavior in order to collect all health-related information from patients. The aim of this study is to determine how patients' attitudes toward disclosure and concealment of medical information differ when interacting with CAs or with physicians.

Procedure

To explore the differences between CAs and physicians in receiving disclosure or concealment of medical information, respondents to the German survey were divided into two groups—one group was asked if they would share information with a CA and the control group were asked if they would reveal their information to a doctor. In both groups, the validity of medical confidentiality was pointed out. The survey was carried out with LimeSurvey, and statistical analyses were conducted using SPSS Statistics software (Version 25) and Jamovi (Version 1.0.7). We used an alpha level of 0.05 for all statistical tests.

To provide participants a realistic picture of an interaction with a CA during the anamnesis, we showed them a sample conversation as illustrated in Figure 1. To ensure that this example is as similar as possible to a typical conversation between a patient and a doctor, the dialogue was validated by an independent physician and confirmed as realistic and authentic. The design—in its language as well as the human attributes—is based on the research of Denecke et al.¹ who developed a mobile self-anamnesis application with a conversational user interface for capturing medical information. In addition, the goal of the CA was explained to the patients and the application scenario was described. In the group with the doctor, the information was simply presented via text since it can be assumed that all participants are familiar with the role of the patient and have been or are currently undergoing

treatment. Following the respective explanations, participants were asked about disclosure¹⁷ and concealment¹⁰ of medical information. The questions were further supported with examples of matters considered sensitive in prior research that are regularly asked in anamnesis.^{3,5}

Materials

To measure the differences between CAs and physicians, two scales for the disclosure and concealment of medical information were used¹⁰ as outlined in the Appendix. Both instruments represent processes that influence the revelation of personal medical information.⁹

Self-disclosure The Self-Disclosure Index according to Miller et al.¹⁷ was adapted to determine the willingness to disclose medical information. Participants were asked to answer eight questions all starting with “*To what extent would you discuss the following information with a [CA/physician]?*” Examples of the items are: “*Information about my alcohol and tobacco consumption*” and “*Information about my eating habits (e.g. diets, sugar consumption, supplements)*”. Following the original version, willingness to disclose information was measured using a 5-point Likert scale ranging from 0 (*not discuss at all*) to 4 (*discuss fully and completely*). The translation is based on Reinecke and Trepte.¹⁸

Self-concealment. Cramer and Barry¹⁹ proved empirically the internal consistency and reliability of the secrecy scale developed by Larson and Chastain.¹⁰ The scale uses a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Participants were asked to answer seven questions, again all starting with “*To what extent would you discuss the following information with a [CA/physician]?*” Examples of the items are “*I have an important secret that I’ve never revealed to anyone*” and “*If I told all my secrets to my friends, they would not like me as much*”. The German translation was validated for reliable internal consistency with Cronbach’s alpha values between 0.81 and 0.93.²⁰

Participants

For recruiting participants, the questionnaire was distributed within a circle of acquaintances and via internal mailing lists in various organizations. A total of 212 people participated in the study, of which 164 completed the survey (77.4%); 16 (9.7%) of the completed response sets could not be included in the analysis due to extreme outliers—values that were more than three standard deviations away from the mean. The participants were randomly assigned into two groups resulting in a sample of 60 (40.5%) in the group with the CA and 88 (59.5%) in the physician group. The baseline descriptives are described in Table 1.

Results

Statistical data were calculated for the Self-Disclosure Index and the Self-Concealment Scale (see Table 2). All variables were checked for normal distribution (self-concealment with physician, $p=0.444$, from a Kolmogorov-Smirnov test; self-concealment with CA, $p=0.331$ and self-disclosure with CA, $p=0.050$ from Shapiro-Wilk tests). The scales were further assessed for reliability using Cronbach’s alpha with values around $\alpha=0.7$ rated as acceptable. The Self-Disclosure Index had high reliability with $\alpha=0.906$ (group with CA) and $\alpha=0.911$ (group with physician). The Self-Concealment Scale could be confirmed as sufficiently reliable in the group with the CA ($\alpha=0.705$) and in the group with the physician ($\alpha=0.719$).

Table 1. Baseline descriptives in the groups with conversational agent and physician.

| Description | N | Min | Max | M | SD |
|---------------------------------|------------|-----|-----|-------|-------|
| Group with conversational agent | | | | | |
| Age | 57 | 20 | 61 | 33.32 | 12.59 |
| Female | 32 (53.3%) | / | / | / | / |
| Male | 28 (46.7%) | / | / | / | / |
| Group with physician | | | | | |
| Age | 88 | 18 | 62 | 32.08 | 12.18 |
| Female | 51 (58%) | / | / | / | / |
| Male | 37 (42%) | / | / | / | / |

M: mean; Max: maximum; Min: minimum; N: quantity; SD: standard deviation.

Table 2. Variables and results in the groups with conversational agent and physician.

| Description | N | Min | Max | M | SD |
|---------------------------------|----|-----|------|------|------|
| Group with conversational agent | | | | | |
| Self-Disclosure Index | 60 | 0 | 4 | 2.14 | 1.12 |
| Self-Concealment Scale | 60 | 1 | 4.29 | 2.77 | 0.72 |
| Group with physician | | | | | |
| Self-Disclosure Index | 88 | 0 | 4 | 2.66 | 1.09 |
| Self-Concealment Scale | 88 | 1 | 4.29 | 2.73 | 0.72 |

M: mean; Max: maximum; Min: minimum; N: quantity; SD: standard deviation.

For comparing willingness to disclose and tendency to conceal medical information with a CA compared to a physician, a *t*-test was performed for unpaired samples. The Levene's test for homoscedasticity of variance showed that equality is given for both constructs between the groups. Overall, on average, participants of the physician group ($M=2.66$, $SD=1.09$) would rather disclose information than participants of the CA group ($M=2.14$, $SD=1.12$). This difference was significant $t(146)=-2.81$, $p=0.006$ and represents a moderate effect ($d=-0.47$). This indicates that patients tend to disclose more information with a physician than with a CA. Further, the results show no overall significant difference between patients concealing information from a CA ($M=2.77$, $SD=0.72$) or a physician ($M=2.73$, $SD=0.72$), $t(146)=0.35$, $p=0.725$ and $d=0.05$. This indicates that there are no differences in the concealment of information from a CA or from a physician.

To take a closer look at individual self-disclosure items between the CA and physician groups, we conducted a Fisher's one-way ANOVA (cf. Table 3). The willingness to provide information about illegal drug use ($F(1,146)=10.034$, $p=0.002$), sexual behavior ($F(1,146)=12.499$, $p<0.001$), illegal use of prescription drugs ($F(1,146)=9.636$, $p=0.002$), and intake of publicly available medicine ($F(1,146)=5.179$, $p=0.024$), was significantly lower in the group with the CA than in the group with the physician. The mean values of the information on alcohol and tobacco consumption ($F(1,146)=1.245$, $p=0.266$), physical activity ($F(1,146)=0.776$, $p=0.380$), eating habits ($F(1,146)=2.388$, $p=0.124$), and taking medication which was not prescribed ($F(1,146)=2.969$, $p=0.087$) do not differ significantly between the groups.

Discussion

The results of the study indicate that patients prefer to disclose medical information to a physician rather than a CA, and that there are no differences in concealment of information from a CA

Table 3. Group descriptives of Fisher's one-way ANOVA.

| Item | Group | N | M | SD | SE |
|---------------------------------------|-----------|----|------|------|-------|
| Illegal drug use | CA | 60 | 1.33 | 1.60 | 0.207 |
| | Physician | 88 | 2.17 | 1.56 | 0.167 |
| Sexual behavior | CA | 60 | 1.43 | 1.44 | 0.186 |
| | Physician | 88 | 2.26 | 1.37 | 0.146 |
| Illegal use of prescription drugs | CA | 60 | 1.73 | 1.49 | 0.193 |
| | Physician | 88 | 2.50 | 1.46 | 0.156 |
| Alcohol and tobacco consumption | CA | 60 | 2.48 | 1.46 | 0.188 |
| | Physician | 88 | 2.75 | 1.41 | 0.150 |
| Physical activity | CA | 60 | 2.63 | 1.37 | 0.176 |
| | Physician | 88 | 2.83 | 1.31 | 0.139 |
| Eating habits | CA | 60 | 2.60 | 1.43 | 0.184 |
| | Physician | 88 | 2.95 | 1.33 | 0.142 |
| Intake of publicly available medicine | CA | 60 | 2.43 | 1.35 | 0.174 |
| | Physician | 88 | 2.94 | 1.33 | 0.142 |
| Intake of medication not prescribed | CA | 60 | 2.50 | 1.38 | 0.179 |
| | Physician | 88 | 2.89 | 1.31 | 0.139 |

M: mean; N: quantity; SD: standard deviation; SE: standard error.

compared to a physician. Nevertheless, the results show that disclosure with either the CA or the physician is insufficient, underscoring the ongoing problem of medical information frequently being entirely withheld, incomplete, or incorrect. A comprehensive disclosure of all medically relevant information is not achieved in either situation.

Willingness to disclose medical information differs between the groups, but the two are similar in their tendencies to disclose individual medical information—willingness to disclose information concerning illegal drug use, sexual behavior, and illegal use of medication is significantly lower than willingness to disclose other information. The fact that other information is more likely to be shared, such as information on physical activities or tobacco and alcohol consumption, may be explained by the fact that this information is not closely related to taboo topics.¹¹ Humans are fearful of being rejected or condemned based on certain personal information and secretive about their deviations from accepted norms of society.²¹ However, details about tobacco and alcohol consumption may seem more socially acceptable, causing patients to be more likely to disclose that information.

The results of this study show that CAs are generally an appropriate technology to assist health-care professionals with the anamnesis. Non-critical medical information is disclosed with CAs to the same degree as with physicians. However, the findings also indicate that CAs, in their current form, are not suitable for eliciting medical information assessed as taboo. Thus, CAs can be used for a simple, casual anamnesis, but physicians cannot be replaced by this technology and continue to play a superior role.

This study has certain limitations. No direct interactions with a CA took place. Despite concrete representation and assessment by an independent physician, the topics may have formed different notions from those of an actual interaction with a CA. Participants may have felt that the CA is not an equal conversation partner and did not build a feeling of belonging or social bonding. It might be assumed that a CA does not fully understand and is therefore judged to be useless in establishing a correct diagnosis and proper treatment. In addition, further factors that could be of interest in the context of anamnesis were not considered. Medical confidentiality was pointed out in both groups;

anonymity, privacy concerns, the security of the information, and trust in the CA were not explored as influencing factors. Patients may tend to conceal information if they feel that data may be misused or accessible by third parties. Furthermore, this study assessed baseline differences according to the participants demographics, further variables such as specific pre-existing conditions were not considered.

Further research should develop a prototype of a CA for the anamnesis and validate it in real-life scenarios. Studies have shown that CAs are capable of assisting in the execution of work-related tasks and are able to accelerate internal processes.^{22,23} However, in the health-related context, CAs are not yet widely used, resulting in patients viewing them unfavorably. In addition, the validation of the prototype should further examine additional factors that have not been considered in this study. Alongside other influencing factors, privacy and security aspects should also be taken into account. Exploration of the complete topic requires further investigations to verify whether these aspects may impact in patients' answers, and taking them into account may lead to CAs achieving better results.

Conclusions

This research provides first insights into the application of CAs for the anamnesis. We have presented results on how CAs differ from physicians in patients' attitudes toward both disclosure and concealment of medical information by carrying out a study with 148 participants divided into two groups and using the Self-Disclosure Index and the Self-Concealment Scale. The results show that willingness to disclose medical information to a CA is lower than to a physician, particularly for taboo topics. The attitude toward concealing information from a CA does not differ compared to a physician. As practical implications resulting from the findings in this work, physicians gain new insights into patients' attitudes toward conversations with a CA compared to a physician, and how they differ by topic. Therefore, these findings establish the extent to which CAs might be applicable to facilitate the anamnesis. From a theoretical point of view, this research serves as a first foundation related to self-disclosure and self-concealment in the context of CAs' usefulness in conducting an anamnesis.

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Appendix

Table 1. Questions for Self-Disclosure Index and Self-Concealment Scale (excerpts from the German survey are translated into English).

| Items (scale) | Questions (original German, English translation) |
|--|---|
| <p>Self-Disclosure Index Miller et al.,¹⁷ partly translated by Reinecke and Trepte¹⁸ 5-point Likert scale; 0 = <i>discuss not at all</i> to 4 = <i>discuss fully and completely</i>.</p> | <p>To what extent would you discuss the following information with a [CA/physician]?</p> <ul style="list-style-type: none"> • Information on the use of illegal drugs (e.g. marijuana). • Information about my alcohol and tobacco consumption. • Information about my physical activity (e.g. no sports, despite instructions to do so). • Information about my eating habits (e.g. diets, sugar consumption, supplements). • Information on the use of publicly available medicines and substances (painkillers or stimulants). • Information about medication I have taken that was not as agreed with the doctor (e.g. forgotten, taken irregularly, taken too much). • Information regarding the use of prescription drugs that were not prescribed to me by a doctor. • Information about my sexual behavior (e.g. number of sexual partners, contraceptive methods). |
| <p>Self-Concealment Scale Larson and Chastain,¹⁰ translated by Heck²⁰ 5-point Likert scale; 1 = <i>strongly disagree</i> to 5 = <i>strongly agree</i>.</p> | <ul style="list-style-type: none"> • I have an important secret that I've never revealed to anyone. • If I told all my secrets to my friends, they would not like me as much. • There are a lot of things about myself that I keep to myself. • Some of my secrets have tortured me quite a bit. • When something bad or negative happens to me, I tend to keep it to myself. • I worry that I might betray something that I don't want to tell. • If you tell a secret, it often hits you back. I would have preferred never to tell it. |

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