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Conversational Agents in Organisations:
Strategic Applications and Implementation Considerations

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ABSTRACT

Conversational agents (CAs) promise to create significant organisational value by transforming how organisations operate and serve customers. Yet, the malleability of this technology poses challenges to both researchers and practitioners because of the wide range of strategic applications they can enable. Drawing on the lens of routine capability, this study investigates strategic applications of CAs and their associated implementation enablers and challenges. Via an exploratory case study of eight organisations that have successfully implemented CAs, this paper contributes to the literature on the value and implementation of conversational agents in particular and cognitive technologies in general by developing a typology of CA strategic applications and their implementation considerations. For practitioners, the findings highlight the interplay between technology, user, and project management factors that need to be addressed to ensure the successful delivery of the value of CAs.

KEYWORDS

Chatbots, Conversational Agents, IT Adoption, IT Implementation, Routine Capability, Strategic Applications

INTRODUCTION

Major developments in Artificial Intelligence (AI) have resulted in many industries and organisations looking into AI applications in processes, operations, and customer interaction to achieve gains in efficiency and organisational outcomes (Borges et al., 2021). Conversational agents (CAs) are one such application of AI that can mimic human conversations through text or voice-based interfaces. Two types of CAs have been gaining traction in the world of technology: chatbots (text-based) and digital assistants (text or voice-based). The use of chatbots has become prevalent through major messaging platforms such as Facebook, Slack, WeChat, and WhatsApp. Facebook itself has over 10, 000 chatbots that interact with its users (Devaney, 2016). It is estimated that the market size of chatbots will reach $1.25 billion by 2025 (Grand View Research Centre, 2017). In the space of digital assistants, major technology giants such as Amazon, Apple, Google, and Microsoft have invested considerably in

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the development of digital assistants for consumer applications (e.g., Google Assistant, Microsoft's Cortana, Amazon's Alexa, or Apple's Siri). The digital assistant offerings by these companies have been adopted by millions of consumers (Hao, 2018). Advancements in CA technology have gained the attention of organisations looking to use CAs in areas such as customer experience and internal operations (Meyer von Wolff et al., 2020). Interest for CAs among organisations is high, and Gartner predicts that chatbots, conversation user interfaces and virtual assistants will gain significant interest from customer service and support leaders (Omale, 2020), as well as transform the digital workplace in the next 2 to 10 years (Rimol, 2020).

It is evident that organisations strive to tap into the potential in leveraging CAs for benefits and value creation. CAs can provide customers with enhanced experience via personalised services and build strong relationships with customers (Huang & Rust, 2021). Moreover, CAs can transform organisational operations (Tarafdar et al., 2019). However, research into the applications of CAs in organisations is scant. More attention has been paid to the development, technical, and design aspects of CAs. The varieties of strategic applications of CAs in an organisational setting remain underexplored (Io & Lee, 2017). Early research on the application of CAs in organisations have looked at use cases in the consumer domain (Chung et al., 2018), workplace CAs for supporting employees (Feng & Buxmann, 2020; Meyer von Wolff et al., 2020), and machine learning (ML) techniques for CAs in various business domains (Bavaresco et al., 2020). Notably, different from traditional, task-oriented enterprise systems, CAs consisting of sophisticated cognitive and emotional features present new technical and organisational challenges when implementing CAs (Huang & Rust, 2021; Jang et al., 2021). Failed implementations can be costly, not only preventing benefit realisation but also detrimental to the reputation, as is the case with Microsoft chatbot Tay (Neff, 2016). It is vital for organisations to identify the needs for CAs, present justification evidence, and prepare an implementation plan to address risks ahead (Peffers & Santos, 2013). However, limited literature offers a holistic understanding of why and how organisations adopt CAs to support organisational capabilities - that is, to understand the rationale behind a CA investment and consider the foundations of successful implementation. The lack thereof limits the IS community's ability to develop refined theoretical understandings of the factors that affect CA's creation of value and their successful implementation, limiting the community's ability to provide evidence-based advice to practitioners about such matters.

Therefore, this study fills this gap by developing a typology of CA use in organisational routine capabilities (Swanson, 2019) and their associated implementation challenges. Specifically, this paper pursues two research objectives: (1) discover the types of strategic applications of CAs that organisations have implemented; (2) identify enablers and challenges for the implementation of CAs. To fulfil the objectives, the study explores the following research questions: (a) what strategic rationale stands behind the business application of CAs in organisational capabilities? and (b) what challenges and enablers impact the implementation of CAs to support these organisational capabilities?

We elicited insights from the perspectives of CAs experts in organisations that have implemented CAs. Our results contribute to the CA adoption literature by developing an emerging typology that conceptualises what purposes CAs can be used for and what kinds of value CAs can generate in organisations. It also contributes to an understanding of the implementation factors which can enable or derail the creation of organisational value via the application of CAs. Organisations can draw lessons from these findings to enhance their decisions on the adoption and implementation of CAs.

LITERATURE REVIEW

Artificial Intelligence and Conversational Agents

The definition of AI is still fuzzy as there are many understandings of what AI entails both from academic researchers and practitioners (Davenport & Ronanki, 2018). AI has been broadly defined as "programs, algorithms, systems or machines that demonstrate intelligence" (Shankar, 2018, p. vi).

Other AI researchers have described AI in greater detail, highlighting the capabilities, mechanisms, and goals. For instance, Kaplan and Haenlein (2019) define AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (p. 17). A technology is intelligent if it has "the ability to learn from various types of data and learn from massive amount of data (i.e., big data) and update thoughts or actions" (Huang et al., 2019, p. 45).

AI systems can be categorised into mechanical task support, cognitive task support, and emotional support (Huang et al., 2019; Huang & Rust, 2021; Kaplan & Haenlein, 2019). Mechanical AI systems can execute repetitive tasks, aiming to provide stable, consistent and reliable performance (Huang et al., 2019). Examples include remote sensing, machine translation, and clustering algorithms. AI systems help cognitive tasks via autonomously learning, adapting and recognising patterns and regularities in the data using machine learning, neural networks, and deep learning to process the data to arrive at new conclusions or decisions (Huang et al., 2019; Huang & Rust, 2021). Examples include text mining, speech recognition, and facial recognition technologies. AI systems can also be designed to interact empathetically with people and analyse human feelings and emotions using technologies such as sentiment analysis, natural language processing (NLP), and text-to-speech technology (Huang et al., 2019; Huang & Rust, 2021). Examples include embodied and embedded virtual agents and robots (Huang & Rust, 2021). The emotion-aware well-being chatbot, EMMA (Ghandeharioun et al., 2019), is an example of this category.

CAs, as specific applications of AI systems, primarily come in the form of chatbots and digital assistants and can serve various tasks, depending on how organisations intend to leverage them. Chatbots are conversation agents that receive natural language inputs through text-based user interfaces, with replies being in text form as well (Abu Shawar & Atwell, 2007). Weizenbaum (1966)'s ELIZA is often cited as the first chatbot designed to simulate natural language communication between humans and machines. Back then, chatbots were limited in terms of functionalities and most lacked the capabilities needed to interact with humans effectively. For instance, Weizenbaum (1966) described ELIZA as technically challenged in identifying keywords, identifying a context within the chosen keywords, choosing appropriate text transformation rules, effectively generating responses without using keywords, and lacking a platform for editing the chatbot scripts. However, since then, AI progression has made it possible to design CAs capable of scientific intelligence, social skills and general wisdom (Kaplan & Haenlein, 2019). CAs now are "able to recognise patterns, perform rule-based analysis from very large amounts of data, solve both structured and unstructured problems, recognise voices, process natural language, learn, and interact with other computers and humans" (Siddike et al., 2018, p. 1640). As a result, we see an increase in CAs that take the form of digital assistants such as Google Assistant, Microsoft's Cortana, Amazon's Alexa or Apple's Siri and many others. Digital assistants are differentiated from chatbots because they rely on speech input and output modalities or a combination of both and use speech recognition technology to process speech-based inputs to converse with users (Ciechanowski et al., 2018).

The interest in chatbots and AI-based assistants from the research community is growing as we observe a profusion of terms such as virtual assistants/agents (e.g., Sinatra et al., 2021), chatbots (e.g., Meyer von Wolff et al., 2020), cognitive assistants (e.g., Berry et al., 2011), virtual colleagues (e.g., Feng & Buxmann, 2020). Chatbots and assistants may differ in capabilities, modalities (text- or speech-based; or both), and business application areas, but they rely on the same underlying AI technologies. Therefore, to be inclusive, this study adopts the umbrella term conversation agents (CAs), which is defined as computer entities that aim to emulate human communication (Radziwill & Benton, 2017). CAs are considered a class of dialogue systems (all types of computer systems that converse with humans); however, CAs different from dialogue systems such as interactive voice response (systems that ask you to press a number on the phone to proceed) because interactive voice systems rely on decision trees and lack the autonomy and intelligence present in CAs (Radziwill & Benton, 2017). CAs can converse with users through a text or voice interface, and the term "agent" represents a degree of intelligence and a capacity for autonomous action (Sjödén et al., 2011). For typical CAs, the minimal available functionalities are making calls, sending text messages, setting reminders, controlling music players, and interacting with navigation tools (Riccardi, 2014). The most advanced CAs can understand, represent and process domain knowledge, learn and generate new knowledge by processing data using ML (Maedche et al., 2019).

The Core Technologies of CAs

The key elements that enable CAs to perform their purposes are natural language processing (*NLP*), machine learning (*ML*), deep learning *(DL),* and knowledge bases (*KBs*). *NLP* enables computers to mimic how humans interpret language and effectively process large chunks of language data (Chowdhury, 2005). Using NLP, algorithms and models are developed to manipulate information from speech or text inputs to perform desired tasks such as machine translation, speech recognition, and natural language text processing (Jain et al., 2018). NLP is a crucial component of CAs as it enables natural conversations with users. *ML* is an extension of AI, which enables a "machine" or the system to learn, make predictions regarding future data, and perform decision making under uncertainty (Murphy, 2014). The ML algorithms are crucial to CAs because they allow CAs to learn from users' inputs and become more effective at recognising users' voices, subtleties and nuances in language, context, and intent. ML also enables CAs to adapt and evolve, improve their interactions with users, automatically solve problems, uncover or produce certain behaviours through past experiences (Brill, 2018; Jordan & Mitchel, 2015).

Deep learning *(DL)* is an algorithmic approach for implementing ML. Nonetheless, DL goes beyond traditional ML techniques by utilising artificial neural networks (ANNs) (Wang et al., 2021). ANNs are inspired by neural networks present in human brains that deal with information processing and communication patterns (Marblestone et al., 2016). DL algorithms allow machines to learn multiple levels of representation corresponding to different levels of abstraction and concepts (Deng, 2014). For CAs, DL allows for more enhanced learning capabilities. By applying ANNs, CAs can be trained to select more appropriate responses when conversing with users (Serban et al., 2017), and learn how to differentiate background noises, reverberations and speaker variation, thereby improving speech recognition and reducing error rates. *KB* is a technology for storing structured and unstructured information used by systems. A KB contains facts about a specific domain of interest that are used to create inferences. A KB is an essential component of CAs as it provides knowledge that forms the basis for CAs' responses during interaction with users. KBs can also influence the scope and type of responses given by CAs (Tarau & Figa, 2004). Commercial CAs such as Alexa and Google Assistant have large KBs, enabling them to have an extensive range of responses for various topics, whereas some CAs, such as a banking CA, may only have access to specialised banking KB. The scope of a KB can impact CAs' level and quality of intelligence. KBs with well-designed rules and structures enhance ML and DL capabilities of CAs, making them learn faster and effective in determining and picking the relevant information for responses (Viswanathan, 2017).

Strategic Applications and Implementation Considerations of CAs

Current research on applications of CAs delves into their design, considering usability, security, and privacy issues (de Barcelos Silva et al., 2020). For instance, some inquiries have examined how anthropomorphism (i.e., perceived humanness) influences the adoption of CAs (Sheehan et al., 2020) and the impacts of information security and privacy expectations on trust toward CAs (Castro et al., 2018). Although the design of CAs is essential for successful adoption, it is equally important to consider the strategic value of CAs, that is, how their benefits are framed to justify their adoption, and implementation, which can reveal particular challenges.

To theoretically ground our examination of the strategic applications of CAs that can be made, we draw on the notion of organisational capabilities. Capabilities are central to theories of how organisations derive value from socio-technical bundles of people, information, process, and technology (Sambamurthy et al., 2003). The strategic management literature has traditionally emphasised the importance of dynamic capabilities in enabling organisational survival and the pursuit of competitive advantage (Teece et al., 1997), for which technology can serve as an enabler (El Sawy & Pavlou, 2008). For this inquiry into the value generated by the strategic application of CAs, we adopt the theoretical lens of technology as routine capability (Swanson, 2019). This lens considers that technological devices, such as CAs, are embedded in organisational routines: patterns of action aiming to accomplish some organisational task. It is via a technology's use and execution within those patterns of action that value is derived. Due to their malleability and potential to be recombined with other technologies (Henfridsson et al., 2018), CAs have the potential to digitise and transform several kinds of organisational routines by altering established patterns of action.

For instance, previous research suggests CAs possess information processing (e.g., information capture and provision) and business process management (e.g., process guidance and execution) affordances and can generate value such as increased productivity, reduced cost, improved well-being, and process efficiencies (Feng & Buxmann, 2020; Meyer von Wolff et al., 2020). Strategic applications are not limited to internal processes but also include customer service and product experience journeys. Davenport and Ronanki (2018) found that organisations use natural language processing chatbots, intelligent agents, and ML applications to provide 24/7 customer service process support and offer information for employees' inquiries related to IT- and HR topics. More recently, CAs have demonstrated the potential to be companions with humans and improve well-being (Skjuve et al., 2021). Nevertheless, the business impact of CAs that support social relationships with users remains unclear. Although a social CA influences interaction experience, a "friendship" relationship with a CA does not directly change consumers' perceptions of a brand (Youn & Jin, 2021). Table 1 illustrates various CA strategic applications in routine capabilities that have been identified via the practitioner literature.

To realise the value of embedding CAs within their routine capabilities, organisations need to consider and address various technical and organisational challenges when implementing AI (Bavaresco et al., 2020; Robert et al., 2020; Sestino & De Mauro, 2021). The examination of the adoption and implementation challenges of digital innovations such as CAs is a longstanding concern of the IS discipline (Fichman, 2004; Lucas Jr et al., 2008). It is well known that many factors at the individual level, such as user involvement and participation (Barki & Hartwick, 1994; Markus & Mao, 2004), and at the organisational level, such as top management support and absorptive capacity (Roberts et al., 2012; Sharma & Yetton, 2003), need to be considered for the successful implementation of technology in an organisation.

The literature on CAs indicates that the most common challenge affecting CA implementation success involves technological issues. These include CA intelligence (Nadarzynski et al., 2019) and autonomy (Mimoun et al., 2012) to support users without human intervention. Some researchers have found that many CAs lack the ability to stick to the conversational context, be engaging and convincing as the conversation with a user progresses (Sheth et al., 2019). Organisations also face the challenge of ensuring that their CAs can correctly understand user requests or handle complex requests and offer quality responses to users (Kvale et al., 2019). Some CAs are not intelligent enough to recognise emotions in user requests and respond empathetically (Shum et al., 2018). Apart from CA capabilities, the availability and readiness of technology resources are other obstacles affecting CAs implementation success. Many organisations lack technological capabilities to handle, mine enough quality data from CA interactions with users and analyse it to increase service quality, improve user support (Castro et al., 2018; Clark et al., 2019), develop and train CAs (Jang et al., 2021) and improve their CA capabilities (Bavaresco et al., 2020). Proper performance measures to evaluate and improve the quality of CA interactions with users are also an obstacle (Chakrabarti & Luger, 2015).

The technical aspect of the implementation is not the only hurdle to overcome. Research suggests that many CAs are abandoned because they are unable to meet user expectations experience and fail to increase user experience and satisfaction (Castro et al., 2018; Kvale et al., 2019). A lack of trust

Table 1. Illustrative examples of the current applications of CAs in organisational routine capabilities as identified from the literature

Application Areas	Routine Capability	Examples
Sales	Sales lead capturing via information processing and provision	RapidMiner, a company that provides analytical and visualisation software solutions to data scientists and data-driven organisations (Power, 2017), implemented a CA called LeadBot to capture high-value sales leads through conversation with users while blocking noise from low-value users. RapidMiner was able to automate the lead qualification process using the CA, to capture leads 24/7, and dedicate sales resources to vital customers.
HR	Employee support via information provision	Bupa, an international healthcare company, implemented a chatbot named Cyan to support employees during the relocation of the company's office (Tangoworks, 2018). Cyan could instantaneously answer employee's questions had regarding the relocation, allowing HR to focus resources on the relocation itself. Bupa progressively expanded the KB of Cyan, enabling it to answer more employee questions (McGrath, 2018).
	Recruitment via information processing and provision	Marriot International, a global hospitality group, launched the Marriot Careers (MC) chatbot on its Facebook Messenger to enhance job-seekers' job search and application experience (Hallam, 2017). MC converses with job-seekers and provides information on job openings based on positions and locations. Using the Marriot KB and specialised algorithms, MC can also recommend to job seekers the role they best align with based on their conversations (McManus, 2017).
Customer service	Customer service via process guidance and information processing	Amtrak, a railroad company operating over 300 passenger trains in the U.S. and Canada, implemented a virtual assistant named Ask Julie on its website to support its train booking system and reduce the load on customer service representatives. Ask Julie provides customers with train information and booking assistance. By deploying the assistant, Amtrak reduced customer service costs and increased revenue per booking (NEXT IT, 2016).
Banking	Mobile banking and customer services via process guidance and information processing	Bank of America, one of the largest financial institutions in the U.S., introduced a digital assistant called Erica into its mobile banking app to improve customer interactions. Erica can provide account information, schedule payments, transfer money and suggestions on savings or debt management (Bank of America, 2021). Bank of America accumulated a large KB due to the high volume of customer logins and payment transactions, which increased Erica's predictive analytics and cognitive capabilities, and enabled personalised customer experience (Coram, 2017; Hudson, 2018).
Commerce	Mobile shopping via process guidance, process execution, and information processing	Starbucks, a U.S. coffee company and coffeehouse chain operating globally, launched the My Starbucks Barista digital assistant on its Starbucks mobile app to converse with and help customers place orders and make payments before arriving at their store. The assistant has streamlined the ordering process, delivering speed and convenience (Bishop, 2016).
Healthcare services	Healthcare recommendations via process guidance, information processing, and relationship development	Mayo Clinic, a U.S. non-profit healthcare provider and medical research institute, implemented a digital medical assistant on their website to alleviate the burden on emergency rooms. The digital assistant uses Mayo Clinic's algorithms to provide personalised empathy-first healthcare guidance and recommendations on care options based on self-reported patient symptoms (Mayo Clinic, 2019).
Insurance	Insurance policy and claims via information provision and process execution	Lemonade Insurance, a U.S. based insurance company whose business model is driven by its use of chatbots, uses Maya, a chatbot that uses behavioural economics to deliver personalised insurance policies to customers in 90 seconds and handle claims and payments in less than 3 minutes. This swift customer service has enabled Lemonade to transform the insurance experience and achieve massive cost savings (Collier & Jeory, 2019).

due to concerns of fairness, transparency, and accountability partially contribute to less favourable attitudes (Shin, 2020, 2021; Shin & Park, 2019; Shin et al., 2020). Additionally, organisations require extensive investment to develop CA algorithms, manage quality datasets, set up the relevant IT infrastructure, and hire skilled and qualified staff (Jang et al., 2021). Managers responsible for CA services often do not have sufficient skills and knowledge in CA to secure initial and subsequent resource commitment to a CA implementation; they sometimes face organisational scepticism and resistance (Jang et al., 2021).

Problematisation: Despite the various sources of value attributed to CAs by the academic and practitioner literature, there has been a little systematic empirical examination of how they are strategically applied to support organisational capabilities, especially *routine capabilities* (Swanson, 2019). Furthermore, among a mix of technical and people-related challenges, it remains unclear what challenges are salient when organisations intend to adopt and implement CAs, and how those challenges change depending on the nature of their application in routine capabilities (Meyer von Wolff et al., 2020). This research aims to advance our understanding by first developing a typology of routine capabilities that CAs can support, that is, the types of business applications and patterns of action they can enable. Second, our analysis of the literature also points to a need to develop a conceptual model of their associated implementation challenges, which could be used as a platform by future research to develop more refined theoretical assessments (e.g. moderators and mediators) of CAs value and implementation success.

METHODOLOGY

The topic of organisational use and implementation of CAs is an emergent phenomenon. It is important to understand the context surrounding the organisational use of a CA, such as why an organisation decides to adopt it and what setting they are using it. We, therefore, adopted an exploratory case study approach to explain, describe, illustrate and enlighten our inquiry about the organisational use and implementation of CAs. For this reason, the cases in this study are organisations that have adopted and implemented CAs. For each organisation, we relied on an empirical data collection strategy that involved analysing and synthesising insights from CA experts and practitioners that have been involved in the implementation of CA for organizational purposes. We used the New Zealand CIO 100 list as a starting point for identifying potential cases. The CIO 100 list presents a list of organisations recognised for innovation and technological transformation, increasing the likelihood that these organisations have adopted CA solutions. We also used personal connections and online public forums such as LinkedIn, Reddit, and Facebook to advertise the study. Multiple cases were chosen to increase the diversity and breadth of information. We used Criterion-i as the purposive sampling strategy (Palinkas et al., 2015) to select cases. The selection criterion for the cases was that an organisation had to have a live CA, which was available for use by either external customers or internal personnel. In total, eight cases were identified and included in this study, as shown in Table 2.

The primary method of data collection was semi-structured interviews. Except for E-Commerce A, interviews were conducted with CAs developers, implementors, or product owners from the selected case organisations. These interviewees were either involved in the development of CAs or are currently managing CAs at their respective organisation. They were highly knowledgeable about the capabilities and use of CAs in their organisations, how the organisation could or was benefiting from CAs use, and implementation challenges. In total, eight individuals were interviewed: one from each case organisation. Interviews were conducted in August and September 2018 and lasted between 30 to 60 minutes. Interviews were recorded with the permission of the interviewees. The interview questions focused on the organisations' application of CAs in organisational routines and activities, the value they expected to derive from this application, CAs functionalities, realised benefits, and implementation challenges. During the interview, interviewees were asked further questions if their

Table 2. Case organisations and interviewee roles and positions in case organisations

Case Organisations	Interviewees' Roles and Positions
Airline A: a multinational airline in New Zealand. Seeing many of its competitors investing in AI technologies, the airline also saw the need to enter the space to avoid falling behind. They saw an opportunity in using a CA for *customer service*, so they developed a customer service chatbot on their website and mobile app.	Product Owner; Product Owner
Bank A: a multinational Australasian bank. The innovation team at Bank A identified digital assistants as valuable tools for *getting information to their customers,* and that voice-based interfaces would increasingly become prevalent in the future. Bank A intended to be the first to market with this technology.	Product Owner; Innovation Manager
SaaS A: a New Zealand software company that provides a cloud-based accounting platform to its clients. SaaS A heavily relies on its platform's uptime to maintain customer satisfaction. Therefore, they implemented a chatbot on their Slack communication platform to assist teams with *incident management* during platform outages.	Developer; Engineer
SaaS B: a New Zealand event management software company with a heavy reliance on its website to generate sales leads. The company had an issue where visitors to the site simply browsed and left without leaving information. To *capture customer information and increase leads*, they implemented a chatbot on their website to be the first point of contact for visitors.	Implementor; Marketing Manager
E-Commerce A: a New Zealand online marketplace for buying and selling goods. Like SaaS A, they are reliant on their website staying up. To support individuals with varying degrees of skills if the site went down, they implemented a *support* chatbot on Slack which guided individuals and teams through the recovery process.	Business user representative; Test Analyst
Start-Up A: a non-profit legal start-up in New Zealand. They were set up to develop and promote AI systems for public benefit and advancing access to justice. The start-up experimented with chatbots to see if they would be a useful way of *increasing access to legal resources*. They developed a chatbot aimed towards students and student law, with a rental law chatbot for tenants currently in development.	Developer/Implementor; Executive Director
Vendor A: an AI vendor that assists clients in transforming their business with AI. They provide chatbot solutions to clients that are both small and large enterprises. Their clients choose to adopt chatbots primarily due to a lack of *customer support resources and a need for lead generation* in competitive markets.	Developer/Implementor; Founder
Vendor B: digital services and social media consultant in New Zealand. They cater primarily to small to medium-sized enterprises and offer chatbot implementation services. Being a small organisation with limited resources, their clients adopt chatbots to increase *customer engagement, sales and assist with business transactions.*	Developer/Implementor; CEO

statements needed elaboration or additional information was required. Following the interview, each interviewee was sent a typed transcript to review.

Data Analysis

To identify the applications of CAs in routine capabilities and their associated implementation challenges from the interview data, we engaged in thematic analysis (Fereday & Muir-Cochrane, 2006) via a cycle of deductive and inductive analysis techniques to create codes and identify themes in the data. All interview transcripts were imported into NVivo data management software. The first stage of analysis took a deductive approach where higher-level code categories were developed a priori based on the research questions and objectives, which included "CA Solutions" (i.e., general description of the CA business application and how it is embedded in routine capabilities, what it does), "Challenges" (i.e., implementation challenges experienced surrounding CA), and "Realised Benefits" (i.e., benefits realised from CA use in a particular organisational capability).[1] We developed the code manually, scanned the relevant codes, and grouped them under high-level codes. This was followed by inductive analysis, where the text that had been organised into the higher-level code categories was scanned, and new inductive codes were created. These codes were more specific and described the data in more detail. For example, data that pointed towards the benefits of using CAs was assigned the deductive code "Realised Benefits". This data was then inductively analysed, and new codes such as "Customer Experience (CX) Enhancement" and "Time Savings" emerged that illustrated specific types of benefits organisations had realised. The first two authors coded the documents and compared the coding results. Differences in coding were discussed and reconciled.

After coding was completed, text segments of each of the codes were examined for similarities and differences. During this process, themes and patterns were identified in the data, and commonalities were found between the datasets of each case. For instance, the routine capability theme "process facilitation" emerged when the "guidance" code (i.e., CA's affordance to guide users on what to do in a process), the "documentation" code (i.e., CA's affordance to create documentation on what has been done and said during an interaction with CA), and the "reminders" code (i.e., CA's affordance to send reminders/alerts to users in the chat) all indicated that CA facilitated business processes and helped employees perform tasks by providing structures (guidance), keeping tracking of what happened (documentation), and checking if tasks were done properly (reminders). The theme was then associated with Realised Benefits through the identification of causal statements made by the interviewees. For example, process facilitation improved communication as evidenced in SaaS-A, where the CA's capabilities in guidance and documentation assisted newcomers' onboarding process: "*if you are someone who is just starting and you join a production channel, you can see if there are issues going on, whereas before it might have been out of your view*" (Developer). Figure 1 illustrates the process of coding for the process facilitation theme.

We continued refining the themes and ensured they were broad enough to cover the relevant set of ideas in the codes and specific enough to avoid repetition with other themes. Figure 2 represents seven business applications. We further group them under three routine capability clusters: relation, process, and information. The meaning of each application and associated challenges and enabling conditions (summarised in Figure 3) is discussed in the Findings section.

Figure 1. Example of Data Analysis Process

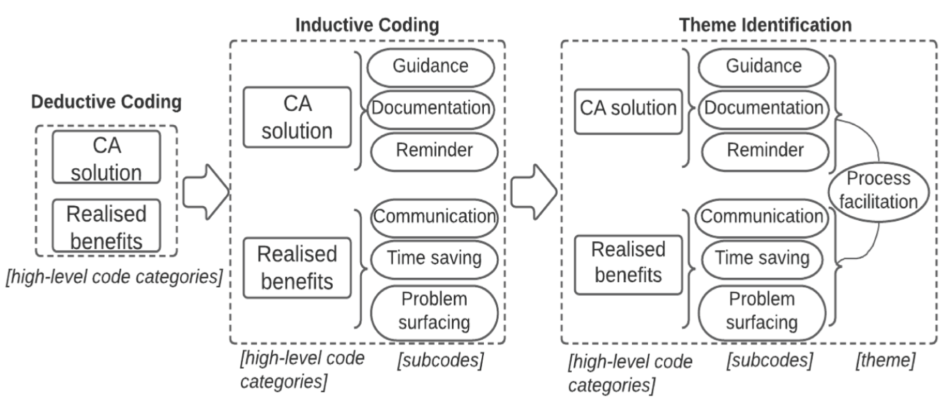


Figure 2. Typology of CAs' Applications in Routine Capabilities

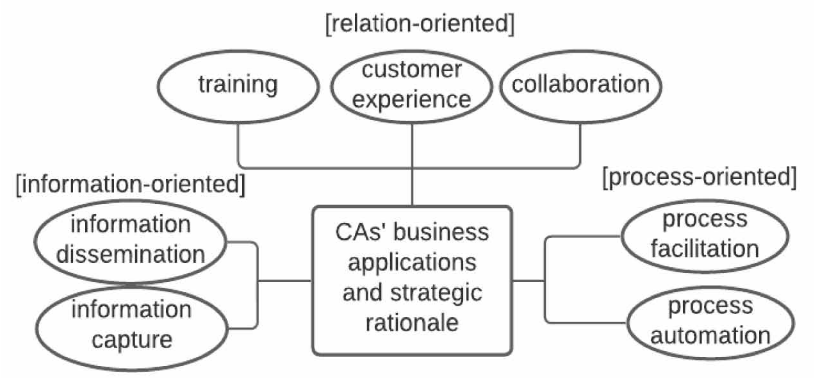
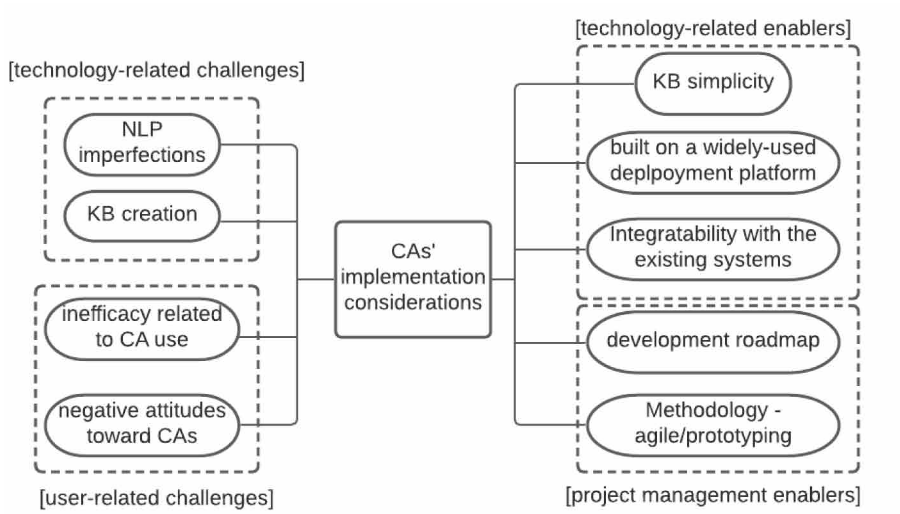


Figure 3. CA Implementation Considerations



FINDINGS

Typology of the Strategic Application of Conversational Agents in Routine Capabilities

Collaboration

Collaboration was one of the strategic applications found in SaaS A and E-Commerce A. Organisations adopted CAs *to assist users with collaboration, communication and coordination efforts*. These organisations integrated the CA with their Slack platform to better coordinate individuals and teams, information documentation and retrieval. During the incident or disaster management process at both organisations, the CA would open up new Slack channels for specific incidents and group the relevant members together and assign leaders. The CAs also saved the conversation history of channels and documented key information related to the incident, allowing for easier retrieval of information. For

SaaS A, the use of a CA solved visibility issues around which team members should be a part of incident response.

The most widely recognised benefit was the increase in communication and collaboration within the organisations. Both SaaS A and E-Commerce experienced an uptake in communication between members. They also saw that more collaboration occurred across teams and senior members of the organisations who were able to contribute their knowledge and expertise to solve incidents. Another benefit was a greater awareness of issues that were occurring in the organisations. By facilitating communication and collaboration, the CAs made issues visible to all users. For both SaaS A and E-Commerce A, this meant breaking down siloed teams.

Customer Experience (CX)

The CX application was found among organisations that had created CAs catered towards customer use. For this strategic application, *organisations used the CAs to communicate and interact with customers*. Bank A used their CA as a part of their omnichannel strategy to provide multiple channel options for their customers. The CA gave customers an additional choice in how they interacted with the company. Bank A's humanoid CA (i.e., with human avatar and human voice) offered an immersive and enhanced customer experience. Airline A also displayed a similar intention with their CA. The CA was added to an already vast array of channels that their customers use. For Airline A, having the CA as an additional CX Channel meant that customers could have their questions and queries answered anytime. The fact that a CA could be a channel to be accessed at any time was also expressed by Vendor A. Many of Vendor A's clients previously had no digital channels to communicate with their customers. A CA provided the organisation with a CX channel that they could use to engage customers 24/7 and increase the number of interactions they had.

Information Capture

Another application of CA in routine capabilities involves leveraging CAs *to capture information through their conversations with users*. Functionalities such as Q&A, qualification, and documenting conversations are used to gather key pieces of information required by organisations or discover new insights. SaaS B uses their CA to capture information of website visitors to help generate high-quality sales leads. By asking website visitors specific questions regarding their visit, the CA can provide the organisation with insights into what products customers are looking for and categorise them into high-value and low-value leads. Vendor A and Vendor B had clients who also shared a similar use of information capture for qualifying and generating leads.

For Airline A, information capture with CA came indirectly. While the organisation's original intention was to use the CA as a CX Channel, they inadvertently found that they could use its conversations with customers to gather rich insights into the problems customers face and how they communicate with the organisation. Having deployed the CA on their website and mobile app, Airline A now uses the CA's conversation logs to identify user experience and CX improvements for various channels.

The information capture routine capability allows organisations to gather key insights and data regarding users or customers. Organisations can use this information to identify areas of improvement. When combined with the CA's ability to function 24/7, organisations can constantly capture information through their CAs.

Information Dissemination

CAs are used *to disseminate or spread information to the relevant stakeholders of the organisation*. Using Q&A and informational CA functionalities, organisations can easily and quickly provide users will relevant information. While this use case is prevalent among many case organisations, it was predominantly present in Start-up A as it matched their mission of advancing access to justice. Start-up

A uses the CA to widen access to legal information. Their CA provides information on school- and student-related law to New Zealand students and parents. Besides, the CA allowed for scalability of capacity and 24/7 availability of information.

Process Automation

We also found that organisations use CAs *to automate tasks or processes such as scheduling, documentation, ordering, payments, coordinating, qualifying, and executing third-party programs*. Process automation is particularly vital for Vendor B, whose clients are small-medium enterprises (SMEs) with limited resources. Vendor B provided examples of two of its clients who have implemented CAs to automate their ordering and payments processes. Both clients used CAs for e-commerce purposes, automated the front-end processes and integrated the CAs with back-end systems, allowing processes to run 24/7. The CA-integrated processes streamlined the process, saving time and cost. SaaS B had CA automate their software demo scheduling process, allowing customers to book a software demo without contacting a salesperson, increasing process efficiency. Previously salespeople would have back and forth interaction with customers to organise a time for software demos. Customers could now schedule demos based on the salesperson's calendar using the CA, allowing instant confirmation.

Process Facilitation

CAs are also used *to facilitate processes*. Process facilitation differs from process automation in terms of how actively a CA is involved in the process. In process automation, a CA digitises and executes the entire process. In process facilitation, a CA proactively assists or guides a user through the process, making it easier for them. This use case was demonstrated in SaaS A and E-Commerce A, which used CAs to facilitate their incident management processes by guiding individuals and teams through the processes step-by-step, providing key information where necessary. The CAs would also send reminders and alerts to the relevant individuals, including activities that need to be completed for each stage of the process. Using the CAs to facilitate processes ultimately leads to improved coordination and confidence among teams and faster process completion time.

Training

The training application was exclusively found in SaaS A's use of its CA. Using the CA, SaaS A's users could run a training simulation of their incident management framework to tinker with the CA and practice for an actual incident. SaaS A's internal teams also used the CA to run their own practice training to become more familiar with the process and increase team members confidence in partaking in the process. Though not currently using their CA for training, Bank A expressed future intentions to use the CA as a training assistant for employee induction.

Summary

These seven types of strategic applications in routine capabilities can be collapsed into a trichotomy between information-oriented, process-oriented, and relation-oriented CAs. Information-oriented CAs sense and capture information and help organisations better understand their employees and customers. Proper processing of information can be used to strengthen KB. Then, CAs can disseminate information with high quality to relevant users. Process-oriented CAs play an essential role in improving process experience and outcomes. Process-oriented CAs can follow best practices and reduce time and efforts in the context of standardised processes. When humans need to intervene in the process, process-oriented CAs can facilitate human agents from multiple aspects, such as documenting what has been done, guiding through the process, and reminding users of the implications of various decisions and actions. Relation-oriented CAs attempt to build bonds with human actors, such as customers and employees, by increasing trust, enhancing collaboration among human actors, and developing human skills. Table 3 summarises the functionalities and benefits associated with each CA routine capabilities, alongside examples and quotes for illustration.

CA Implementation Challenges and Enablers

Our analysis has surfaced four types of implementation considerations: technology-related challenges, user-related challenges, technology-related enablers, and project management enablers.

Technology

NLP and KBs were identified as the technology-related challenges that organisations experience. The NLP challenges represent the difficulties that CAs face when users ask questions in ways that the CA cannot understand. Users, at times, engage with the CAs in unexpected ways, leading to a break in the conversation flow. Airline A and Bank A particularly faced the challenges of identifying complexities in how customers communicated with CA, which NLP engines could not handle. Some organisations found it challenging to create KB content and predict the type of questions users would ask and how they would ask them. They had to have a KB that was both broad and deep at the same time. Start-up's Executive Director said this about content creation. "*You want to end up with a manageable set of answers that are both as generic as possible, to match all the different ways that people ask something. But are also as specific as they need to be to, to be actually useful to people. It's kind of a thorny problem.*" While this was a challenge for complex KBs, KBs that comprised basic and easy-to-understand content make it easy for the NLP engine to manage and provide a better user conversation experience. In Start-up A's case, the plain legal publishing content from its parent organisation proved to be great for the CA's KB, as it was simple and easily translatable.

Deployment platforms and integration capabilities were identified to be enablers of use. By using various deployment platforms, organisations were able to leverage network effects when deploying CAs. Deploying the CAs on online platforms that internal or external users widely use enabled CAs usage. For instance, SaaS A and E-Commerce A deployed their CAs on Slack, a communication platform extensively used by their internal users. Start-up A deployed their CA on Facebook because many of its target users are present on Facebook groups. Integrating CAs with existing applications and systems also influences CA use. SaaS B's integrated its CA with the marketing automation and scheduling systems, which led to a more seamless workflow.

Users

User ability to use CAs and attitudes toward CAs were identified as user-related issues that challenged the use of CAs. A user's inefficacy to use the CA effectively can cause the CA to fail. SaaS A's experienced CA failure as a result of incorrect user input. "*There are times it [CA] failed for a variety of reasons. For example, if someone revokes a key or if someone uses it incorrectly by not putting the right message"* (SaaS A). SaaS B and Airline A experienced issues where users were not using the CAs as intended, either by not following instructions or conversing in ways unsuitable for the CA, such as communicating with slang and writing long paragraphs. "*Yesterday we had a situation where the user responded "Nah not really", but there were two multiple-choice options, yes or no. They wrote instead of choosing an answer*" (SaaS B). "*Sometimes people will come in, and they might write this massive paragraph and there's potentially, you know, eight different intents. The bot just can't match for that basis. There's no way that even we would be able to answer it, let alone the bot*." (Airline A)

SaaS A mentioned that many failings are due to incorrect usage and not a result of CA issues. However, even in these instances, the fault is always attributed to the CA. User attitudes towards CAs and AI as a broader concept also influence organisations' use of CAs. Vendor A's CEO said that many of its client's customers still prefer a live chat service with a human over a CA, which can be a barrier for adoption. "*We see that conversation with real people is still very high compared to bots. A big challenge you know is that if you look from a customer perspective, they are still far more comfortable dealing with humans*." The wider media and Hollywood also play a role in creating a

Table 3. CA Routine Capabilities and their Associated Functionalities and Benefits

Routine Capability	Functionalities	Benefits	Sample Quotes
Collaboration (relation-oriented)	Informational Coordination, Documentation, Simulation, Scheduling Integration	Tracking, Awareness, Communication and Coordination (C&C), Problem surfacing	"*It [CA] also will automatically assign a lead of the incident, so who's leading it, who's checking, who's being the communication point between these people which you can change, and it also sets up a discussion of what the actual incident is.*" (E-Commerce A) "*…for teams, it facilitates opening a new channel to discuss incidents. It will spin up a new slack channel, and it will archive it once the incident is over. So you can benefit from not having to worry about coordinating your response*." (SaaS A)
Customer Experience (CX) (relation-oriented)	Informational Chit Chat, Scheduling, Qualification, Q&A, Forwarding, Payments, Ordering	Customer Channel (choice variety), CX Enhancement, Anonymity, Accessibility, Customer Support, Customer Engagement, Availability, Customer Insights, Access	"*The customer value obviously is you can get help in whatever channel you want whenever you want it, so hopefully you know we can be more responsive.*" (Bank A) "*Basically, we are able to engage and support you know for a midsize client like 500 to 2000 customers a month, where it was almost zero before…now there is a better customer experience 24/7.*" (Vendor A)
Training (relation-oriented)	Informational, Q&A, Guidance, Simulation	Awareness, Confidence	"*People can now run their own incidents. There's training channels and all that so you can experiment with it and simulate a production incident*" (SaaS A) "*We have been looking into using it as a training assistant, to induct people into the organisation's way of thinking, and answer those commonly asked questions for employee experience*." (Bank A)
Information Capture (information-oriented)	Documentation Qualification Q&A	Tracking, Awareness, Customer Insights, Monetary gain, Leads	"*The most unexpected benefit of the chatbot has actually been that rich data that we have. When we started this journey, we didn't have the richest data around the problems that customers were having, and now we've tapped into what is a constant stream of consciousness into customers in our digital channels.*" (Airline A) "*We felt like there were a lot of people on our website who would be clicking around and who would leave the site without leaving their information. We wanted to provide a less full-on contact touchpoint where they could interact with us; we could clarify any questions, where we could qualify them in or out*." (SaaS B)
Information Dissemination (information-oriented)	Q&A, Informational, Forwarding	Access, Availability, Accuracy, Scalability	"*The 24/7 line. The phone line is only manned when there are people available. But this is always available, and it's very scalable. It doesn't matter how many people are talking to it. More or less, it will be able to handle it. And also, that sort of precision when it works well, that sort of getting precisely the answer you want, rather than having to search through screens of stuff*." (Start-up A)
Process Automation (process-oriented)	Guidance, Coordination, Forwarding, Documentation, Qualification, Informational, Execution, Ordering, Q&A, Scheduling, Payments	Availability, Scalability, Customer Support, Fast Resolution, Time Savings	"*For the chocolate shop, one thing we built for the owner was an e-commerce bot. The e-commerce site was taking orders and accepting payments…So there is also a tailor suit company and what they had a problem with was the workflow. So we had it so, at the front-end, orders are made, and the chatbot actually filters them and sends it over to their system*." (Vendor B) "*It integrates with our sales team's calendars to book in slots. Booking happens within the bot where customers are linked to a salesperson's calendar so they can click a date they want and the available times. Then they get an email confirmation. The salesperson also gets a confirmation that includes a link to our webinar room.*" (SaaS B)
Process Facilitation (process-oriented)	Integration Coordination Documentation, Reminders, Execution, Informational, Guidance	Time Savings C&C Awareness, Fast Resolution, Problem Surfacing, Confidence, Monetary gains	"*It handholds you through the entire process of starting and managing an incident. If you're a commander, someone who leads the incident, or if you're a participant, it will sort of just guide you along the way*." (SaaS A) "*If an issue was caused by a deploy[ment], maybe it takes up to 30 mins to an hour to resolve, whereas previously it might have been an hour and a half to two hours*." (E-Commerce A)

warped image of AI-related technology among the public, negatively impacting organisations use of CA. "*There're obviously people that don't want to see bots ever and think that AI is going to take over the world. Unfortunately, they've seen too many Hollywood movies. Hollywood definitely has not done us any favours in this area.*" (Product Owner, Bank A)

Project Management

Project management practices such as developing a strategic development roadmap and methodology were identified as enablers of CA usage. Having a strategic development roadmap was positive, especially in Bank A and Airline A. Both organisations had long and short-term plans for their CAs. The organisations had step by step plans on how they wanted to expand their current use cases and apply CAs to new areas. These organisations have intentions to roll out new functionalities and incorporate new technologies for the CAs. Bank A current use of its CA is limited to only answering basic customer questions, but it has plans to increase the CA usage by adding emotional intelligence functionalities and ultimately turning the CA into a personal assistant for customers. Airline A's roadmap involves slowly raising the visibility of its CA on its website and incrementally deploying it on different pages and their mobile app while adding new content and functionalities to it. "*So when he (CA) started, he was just having a hundred conversations a day, and he was hidden quite far into the website on the help and contact page, just down in the footer. But now he's in a prominent space he's always on display no matter where you are on the website, and we have him heroed for certain different processes that we particularly want you to engage him in*." (Airline A)

The development methodology used when developing a CA was also found to enable CA implementation in organisations. While not explicitly stating its methodology, Bank A mentioned that it took a piloting approach to develop and implement its CA. At the time of the interview with the product owner, Bank A had just rolled out its CA to the public in a pilot phase. The goal of piloting was to see what the CA could do and what reaction it would get from users. It is a watch and learn approach to see how the use of the CA could be improved. *"A part of what we do is in pilot mode because we are discovering: one, did we get it right, and two, how do people interact with her, and what do they prefer. So with that, we are developing all the time new stuff and new content*." (Innovation Manager, Bank A)

Airline A adopted an agile methodology to develop its CA. At the start of development, they took a prototyping approach to create simple prototypes of the CA to identify areas where they were wrong and what customers wanted from the CA. Having been a year since its release, Airline A's development team is continuously enabling its usage by swiftly responding to customer demands through a continuous delivery pipeline. This development approach allows Airline A to identify new areas of use and content for its CA, enabling further usage. "*We run a Kanban board, and we release most days into production, sometimes twice a day into production. We have to be quite responsive. We're constantly iterating him, which is why we have such a big team to support him and constantly refine and polish what he does*." (Product Owner, Airline A)

DISCUSSION

Strategic Applications of CAs in Routine Capabilities

Responding to the first research question, "What strategic rationale stands behind the business application of CAs in organisational capabilities?", we present a provisional typology of CA strategic applications. We find that the use of CAs can go beyond serving the fundamental need of business operations, including information processing and business process management. CAs can also facilitate value co-creation through enhanced collaborative efforts as well as ensuring a rich customer experience. In other words, the business value is created at the blur boundaries of the digital and human world (Saunila et al., 2019) when the relationship between CAs and users is forged. While less common, the relation-oriented strategic application should be carefully considered when building a business case. The findings echo the customer demands in the "feeling economy" (Huang et al., 2019) and employees' needs for social and relational support in the digital workplace characterised by Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA) (Parker & Grote, 2020).

Our findings also reveal that organisations use CAs internally and externally. Customer-facing CAs automate processes, capture customer information, disseminate information, and provide new CX channels, whereas employee-facing CAs support internal operations such as collaboration, training, and process facilitation. This finding is consistent with previous studies, showing that CAs can be used for team creation (Feng & Buxmann, 2020), task facilitation, problem-solving and ideation in collaborative environments (Bittner & Shoury, 2019) and education and training (Meyer von Wolff et al., 2020).

The transferability of CA applications needs to be considered when looking at the relationship between CAs in customer-facing roles and internal operations roles. Four of the applications were applied in customer-facing routine capabilities, while three were applied to internal operations. This does not present a conclusive link that the applications are exclusive to either a customer-facing or internal operations role. It instead suggests that CAs use can be transferred across contexts. For instance, it is possible to use CAs for process facilitation in both customer-facing and internal processes. The Amtrak CA application found in the literature review provides an example of how organisations can implement CAs to guide customer-specific processes. Similarly, use cases such as information dissemination and CX Channel, which were prevalent in customer-facing roles, could be used internally, as in the case of Bupa's application of a CA for employee support. This is in line with previous research that found that CAs or chatbots can support employees, automate internal processes and tasks, capture and retrieve information (Feng & Buxmann, 2020; Meyer von Wolff et al., 2020).

It should be noted that the malleability of CAs allows organisations to use a CAs' routine capability for transforming different business purposes. For instance, SaaS B and Airline A both implemented CAs to capture information, but for very different purposes. SaaS B used its CA for lead generation, while Airline A used its CA to identify customer problems. Even though the outcomes of these uses are different, they both essentially followed a similar process of capturing information through users' conversations with the CAs. Therefore, the findings suggest that even though organisations implement CAs for different purposes and outcomes, the use of CAs does not have to be bound to a specific application.

The findings also show that the value generated by the implementation of CAs was inherently tied to the type of routine capability they enabled and the contexts in which the CAs were used. The context of use is important as organisations use CAs for different purposes and have different outcomes in mind. Hence, two organisations using CAs for the same purpose are unlikely to realise the same benefits. For instance, SaaS B and Airline A both used CAs to capture customer information; however, since their objectives and goals for implementing the CAs were different, the benefits that these organisations realised were also different. SaaS B was able to generate high-quality sales leads, while Airline A gained visibility and insights into the problems that customers were having and how they interacted with the organisation. In some instances, organisations may realise similar benefits despite different contexts and goals for implementing CAs.

The benefits realised from the *collaboration* application were primarily around improvements in communication, collaboration, and coordination. The findings show that organisations use CAs as an intermediary when individuals and teams communicate with each other. Organisations were able to improve the efficiency and effectiveness of coordination and promote collaboration, with the extra benefit of raising awareness of issues. Using CAs for collaboration and problem-solving scenarios has previously been found to significantly lead to better task outcomes and a high degree of collaboration quality (Bogg et al., 2020).

Organisations using CAs as *CX channels* can improve customer engagement and interactions by creating new avenues through which internal personnel and customers can interact. Using CAs to *capture information* helps organisations continually gain insights into internal and external users' activities and needs. *Information dissemination* increases the spread of information to users by providing users with access to information 24/7, anywhere, which is one of the key objectives of implementing chatbots (Meyer von Wolff et al., 2020). The capacity of CAs also allowed for scalability in information dissemination by removing the limits of how many users' information can be distributed to. Organisations that used CAs for *process automation* were able to automate processes and tasks, and benefits realised include more efficient and stable processes. *Process facilitation* enables organisations to assist and guide users through a process from the start to the end, which increases user confidence in executing the process-related activities and reduces the time it takes to complete them. Reducing the time spent on an activity has been shown to be one of the objectives of implementing chatbots (Meyer von Wolff et al., 2020). Regarding the application of CAs for *training*, CAs provide organisations with an isolated environment that could be used to train users or allow users to practice certain processes or scenarios. Benefits of using CAs for training include the confidence boost and preparedness afforded to users when transitioning to actual scenarios.

Enablers and Challenges for Implementing CAs

The second research question aimed to identify the enablers and challenges that impact the implementation of CAs. The findings discovered two types of enablers: *technology and project management* related enablers. *Technology related enablers* include KB simplicity, deployment platform, and integration capability. Simple knowledge rules were easily transferred to a CA, making it easier to implement. Deploying CAs on widely adopted platforms enables CA usage because of network effects as a substantial number of targeted users are present on and familiar with the platform. An organisation's integration capability also enables the implementation as it allows organisations to integrate CAs with existing systems to make workflows and processes seamless. *Project management related enablers* identified include development roadmaps and methodology, which are critical success factors for information systems (IS) implementations (Avison & Fitzgerald, 2007). Having a development roadmap helps organisations understand their short- and long-term plans for implementing CAs in different routine capabilities over time and how to fully utilise them. The methodology, on the other hand, considers how CAs are developed and implemented. The organisations we studied usually opted for agile or pilot approaches. These approaches allow organisations to trial and explore CAs in certain use cases, assess the effectiveness of CAs in those use scenarios and identify areas for improvement.

Technology challenges such as NLP and KB insufficiencies proved to be problematic for maintaining a fully functioning CA. The NLP engine of an organisation's CA may not always understand the intent or context of what users are saying. Creating a KB that is both specific and broad also proved challenging for the case organisations. An effective KB requires the right content to cover the different types of conversations users would have with the CA. However, it is often difficult for organisations to create and maintain KBs that allow CAs to handle the variety and complexity of user requests (Kvale et al., 2019). Implementation challenges also arise due to *users*' perception of CAs and their ability to use CAs, which ultimately impact the adoption and use of CAs. These challenges illustrate that when organisations implement CAs in specific routine capabilities, numerous factors can prevent them and the users from utilising a CA to its maximum potential. If organisations are not effectively using CAs, then benefits may not fully be realised.

Implications

This study sheds light on the use of CAs from the organisational perspective and presents implications for organisations already using CAs and those that plan to implement CAs. This study offers a typology of CA strategic applications that organisations can use to identify the scenarios in which they could apply CAs. Notably, we highlight three types of higher-level routine capabilities that can be enabled by CAs. The embeddedness of CAs in information-oriented routine capabilities create value by capturing, disseminating, and presenting information. In process-oriented routine capabilities, CAs are used to make internal business operations and external service processes faster, cheaper, and better. Relation-oriented routine capabilities demonstrate the unique value that CAs can deliver where their affordances can step up and build relationships with users. The typology can guide academics and practitioners when considering business value generated from CAs.

For practitioners, this study also provides useful insights into different situations in which CAs can be applied and the benefits organisations may expect to realise. The previous literature suggests the benefits of building a business case to gain organisational support (Jang et al., 2021; Nielsen & Persson, 2017). Organisations planning to adopt CAs, can identify what routine capabilities they aim to digitise and transform, consider the needs and challenges of their existing environment, and then evaluate what gain can be achieved using CAs. For those organisations already using CAs, the typology presents alternative modes to use CAs. It presents an opportunity for organisations to expand their CA usage to other application areas, such as employee IT / HR self-service, as a medium for providing relevant information that employees need. Organisations can also use the typology we have presented to identify areas of improvement in their current CAs.

This study sheds lights on the specific enablers and challenges of CAs. In addition to the crucial role of NLP and KBs, as emphasised in the previous literature (Castro et al., 2018; Clark et al., 2019; Jang et al., 2021), the ability to integrate CAs into the existing business processes is essential. Additionally, the deployment of CAs on the same platform is suggested to enhance synergies across different usage contexts and reduce maintenance costs. Practitioners need to be aware that the deployment platform, integration of CAs with existing systems, and the type of KB can impact CAs usage. Our research further contributes to the user factor in the context of CA use, which has received limited attention. Practitioners need to consider the perceptions and abilities of the target users as these can negatively affect how CAs are used.

The current literature barely investigates the choice of implementation approach. Our study suggests that, when developing CAs, organisations benefit from having a roadmap in place for CAs and using agile or pilot development and implementation approaches to better explore and experiment with CAs use cases in different scenarios. This finding suggests that future inquiries should examine the appropriate balance between the planning perspective involved in developing a roadmap versus the adaptive perspective involved in agile approaches to the development and implementation of CAs. In that regard, the literature on paradoxes (e.g., Robey & Boudreau, 1999) could help highlight how this tension is managed by managers, developers, and users, and thus further refine our modelling of the interactions between the implementation considerations we identified.

Limitations

Inherent to the nature of case study research, the findings have contextual boundaries that can limit their generalisation. While eight case organisations were used, each case had different contextual factors that affected why and how the CAs were implemented, how they were used, and the types of benefits gained. However, the value of exploratory case study research resides in its ability to develop novel notions and models that can be validated and extended via further empirical inquiry. The typology identified involve seven high-level CA applications that could be transferred to different scenarios. Nevertheless, it is still important to be aware of the different contexts and situations from which these use cases were derived. For example, most organisations included in this study possess abundant resources, including IT and finance. Therefore, future research may consider the organisation with limited resources and investigate if they hold similar implementation considerations. Furthermore, because future empirical inquiries are likely to identify further variations in applications and contexts, the typology should not be considered as exhaustive or final but as a provisional theoretical model that can be used as a platform.

Another limitation concerns the cross-sectional nature of this study. Interviews were conducted just once with each case organisation, making the study's findings only indicative of how the organisations used CAs at the time of data collection. It is possible that after data collection was completed, organisations may have changed how they used CAs, identifying new use cases and benefits. Alternatively, organisations may have discontinued the use of CAs due to failure or other factors. Future work could benefit from longitudinal data collection to see if organisations change their CA usage over time.

While the current research design serves the purpose of building a foundational understanding of the CA landscape, future work could complement these findings through a quantitative lens. Although a rich interpretive approach provides a detailed contextual outlook of the field, it often limits the ability to examine causal relationships (Shadish et al., 2002). Perhaps, future studies could investigate scenarios where CA's within an organisational implementation did not prove to be a success. Such "negative" cases (Merchant & Stede, 2006) could strengthen the typology of applications and implementation considerations by unearthing factors that remain hidden in successful implementation.

The final limitation relates to the diversity of interviewees. We interviewed one key informant, who is a key player in development and implementation from each case organisation. We believe that their views are of value, particularly considering this research aims to offer implementation insights. However, we acknowledge that stakeholders may have different perspectives, especially for realised benefits. Future research can consider investigating multiple stakeholders' perceptions of organisational use of CAs.

CONCLUSION

While conversational agents (CAs) have become ubiquitous in the consumer space, they still haven't made significant inroads into organisations. Yet, this emerging technology promises significant value from the transformation of organisational practices by augmenting and substituting human labour for AI-powered technology. Via the examination of eight organisations that have embedded CAs in a range of routine capabilities, this paper provides a framework that systematises the types of strategic applications that generate business value. These applications can support both operational and service innovations, and we found that they rely on a mix of information-oriented, process-oriented, and relation-oriented capabilities. A thorough understanding of the challenges and enablers of this new technology's implementation is needed to unleash this value. This paper identified implementation considerations that complement the past literature on CA design and adoption in particular and on digital innovation implementation in general. The core technology of conversational agents involves machine learning, deep learning, knowledge bases, and natural language processing, which are fundamentally different from the transactional and collaborative technologies of the past. While some implementation considerations, such as the need to involve users and develop their competence, remain the same, this technological shift highlights the importance of attention to project management practices such as road-mapping and experimental approaches in order to learn how they can be applied and generate value. For organisations to maximise the value derived from CAs, these factors need to be considered to avoid pitfalls. Ultimately, this study's findings serve to guide organisations in their planning for and implementation of CAs.

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REFERENCES

Abu Shawar, B. A., & Atwell, E. S. (2007). Chatbots: Are they really useful? *Journal for Language Technology and Computational Linguistics*, *22*(1), 29–49.

Avison, D. E., & Fitzgerald, G. (2007). *Information systems development: Methodologies, techniques and tools* (4th ed.). McGraw-Hill.

Bank of America. (2021). *Meet Erica, Your Financial Digital Assistant From Bank of America*. https://promo.bankofamerica.com/erica/

Barki, H., & Hartwick, J. (1994). Measuring user participation, user involvement, and user attitude. *Management Information Systems Quarterly*, *18*(1), 59–82. doi:10.2307/249610

Bavaresco, R., Silveira, D., Reis, E., Barbosa, J., Righi, R., Costa, C., Antunes, R., Gomes, M., Gatti, C., Vanzin, M., Junior, S. C., Silva, E., & Moreira, C. (2020). Conversational agents in business: A systematic literature review and future research directions. *Computer Science Review*, *36*, 100239. doi:10.1016/j.cosrev.2020.100239

Berry, P. M., Gervasio, M., Peintner, B., & Yorke-Smith, N. (2011). PTIME: Personalized assistance for calendaring. *ACM Transactions on Intelligent Systems and Technology*, *2*(4), 1–22. doi:10.1145/1989734.1989744

Bittner, E., & Shoury, O. (2019). Designing automated facilitation for design thinking: A chatbot for supporting teams in the empathy map method. *Proceedings of the 52nd Hawaii International Conference on System Sciences*.

Bogg, A., Birrell, S., Bromfield, M. A., & Parkes, A. M. (2020). Can we talk? How a talking agent can improve human autonomy team performance. *Theoretical Issues in Ergonomics Science*, 1-22. doi:10.24251/HICSS.2019.029

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, (57), 1–16.

Castro, F., Tedesco, P., Alves, H., Quintino, J. P., Steffen, J., Oliveira, F., Soares, R., Santos, A. L., & da Silva, F. Q. (2018). Developing a corporate chatbot for a customer engagement program: A roadmap. *International Conference on Intelligent Computing*.

Chakrabarti, C., & Luger, G. F. (2015). Artificial conversations for customer service chatter bots: Architecture, algorithms, and evaluation metrics. *Expert Systems with Applications*, *42*(20), 6878–6897.

Chowdhury, G. (2005). Natural language processing. *Annual Review of Information Science & Technology*, *37*(1), 51–89. doi:10.1002/aris.1440370103

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2018). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*. Advance online publication. doi:10.1016/j.jbusres.2018.10.004

Ciechanowski, L., Przegalinska, A., Magnuski, M., & Gloor, P. (2018). In the shades of the uncanny valley: An experimental study of human–chatbot interaction. *Future Generation Computer Systems*, *92*, 539–548. doi:10.1016/j.future.2018.01.055

Clark, L., Pantidi, N., Cooney, O., Doyle, P., Garaialde, D., Edwards, J., Spillane, B., Gilmartin, E., Murad, C., & Munteanu, C. (2019). What makes a good conversation? Challenges in designing truly conversational agents. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*.

Collier, M., & Jeory, M. (2019). *Special Study Artificial Intelligence in Action: Chatbots*. https://aiforum.org.nz/wp-content/uploads/2019/10/Ambit-Case-Study.pdf

Coram, A. (2017). Bank Of America's Digital Banking Chief On Chatbot Erica And Being Mobile-First. *Investor's Business Daily*. https://www.investors.com/news/bank-of-americas-digital-banking-chief-on-chatbot-erica-and-being-mobile-first/

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, *96*(1), 108–116.

de Barcelos Silva, A., Gomes, M. M., da Costa, C. A., da Rosa Righi, R., Barbosa, J. L. V., Pessin, G., De Doncker, G., & Federizzi, G. (2020). Intelligent personal assistants: A systematic literature review. *Expert Systems with Applications*, *147*, 113193. doi:10.1016/j.eswa.2020.113193

Deng, L. (2014). Deep Learning: Methods and Applications. *Foundations and Trends in Signal Processing*, *7*(3-4), 197–387. doi:10.1561/2000000039

Devaney, E. (2016). *Infographic: Rise of the Chatbots*. https://chatbotsmagazine.com/infographic-rise-of-the-chatbots-1e2c086aece4

El Sawy, O. A., & Pavlou, P. A. (2008). IT-enabled business capabilities for turbulent environments. *MIS Quarterly Executive*, *7*(3), 139–150.

Feng, S., & Buxmann, P. (2020). My Virtual Colleague: A State-of-the-Art Analysis of Conversational Agents for the Workplace. *Proceedings of the 53rd Hawaii International Conference on System Sciences*.

Fereday, J., & Muir-Cochrane, E. (2006). Demonstrating rigor using thematic analysis: A hybrid approach of inductive and deductive coding and theme development. *International Journal of Qualitative Methods*, *5*(1), 80–92.

Fichman, R. G. (2004). Going beyond the dominant paradigm for information technology innovation research: Emerging concepts and methods. *Journal of the Association for Information Systems*, *5*(8), 11. doi:10.17705/1jais.00054

Ghandeharioun, A., McDuff, D., Czerwinski, M., & Rowan, K. (2019). Emma: An emotion-aware wellbeing chatbot. *2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII)*.

Grand View Research Centre. (2017). *Chatbot Market Size And Share Analysis | Industry Report, 2014 - 2025*. https://www.grandviewresearch.com/industry-analysis/chatbot-market#:~:text=The%20global%20chatbot%20market%20was,order%20to%20reduce%20operating%20costs

Hallam, S. (2017). *5 Outstanding Chatbots: the business of digital conversations*. https://www.hallaminternet.com/5-outstanding-chatbots-conversational-digital-business-applications/

Hao, K. (2018). Amazon Echo's dominance in the smart-speaker market is a lesson on the virtue of being first. *Quartz*. https://www.nextgov.com/emerging-tech/2018/01/amazon-echos-dominance-smart-speaker-market-lesson-virtue-being-first/145034/

Henfridsson, O., Nandhakumar, J., Scarbrough, H., & Panourgias, N. (2018). Recombination in the open-ended value landscape of digital innovation. *Information and Organization*, *28*(2), 89–100. doi:10.1016/j.infoandorg.2018.03.001

Huang, M.-H., Rust, R., & Maksimovic, V. (2019). The feeling economy: Managing in the next generation of artificial intelligence (AI). *California Management Review*, *61*(4), 43–65. doi:10.1177/0008125619863436

Huang, M.-H., & Rust, R. T. (2021). Engaged to a robot? The role of AI in service. *Journal of Service Research*, *24*(1), 30–41. doi:10.1177/1094670520902266

Hudson, C. (2018). Bank of America rolls out AI assistant Erica to all mobile customers. *Charlotte Business Journal*. https://www.bizjournals.com/bizwomen/news/latest-news/2018/05/bofa-rolls-out-ai-assistant-erica-to-all-mobile.html?page=all

Io, H. N., & Lee, C. B. (2017). Chatbots and conversational agents: A bibliometric analysis. *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*.

Jain, A., Kulkarni, G., & Shah, V. (2018). Natural Language Processing. *International Journal on Computer Science and Engineering*, 161–167.

Jang, M., Jung, Y., & Kim, S. (2021). Investigating managers' understanding of chatbots in the Korean financial industry. *Computers in Human Behavior*, *120*, 106747. doi:10.1016/j.chb.2021.106747

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25. doi:10.1016/j.bushor.2018.08.004

Kvale, K., Sell, O. A., Hodnebrog, S., & Følstad, A. (2019). Improving Conversations: Lessons Learnt from Manual Analysis of Chatbot Dialogues. *International Workshop on Chatbot Research and Design.*

Lucas, H. C. Jr, Swanson, E. B., & Zmud, R. (2008). Implementation, innovation, and related themes over the years in information systems research. *Journal of the Association for Information Systems*, *8*(4), 8.

Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., Hinz, O., Morana, S., & Söllner, M. (2019). AI-based digital assistants. *Business & Information Systems Engineering*, *61*(4), 535–544. doi:10.1007/s12599-019-00600-8

Marblestone, A. H., Wayne, G., & Kording, K. P. (2016). Toward an Integration of Deep Learning and Neuroscience. *Frontiers in Computational Neuroscience*, *10*. Advance online publication. doi:10.3389/fncom.2016.00094 PMID:27683554

Markus, M. L., & Mao, J.-Y. (2004). Participation in development and implementation-updating an old, tired concept for today's IS contexts. *Journal of the Association for Information Systems*, *5*(11), 14. doi:10.17705/1jais.00057

Mayo Clinic. (2019). *Sensely and mayo clinic: Advancing digital healthcare solutions*. https://www.sensely.com/wp-content/uploads/2019/07/SenselyMayo.pdf

McManus, B. (2017). *Marriott International Launches Careers Chatbot for Facebook Messenger*. https://hospitalitytech.com/marriott-international-launches-careers-chatbot-facebook-messenger

Merchant, K. A., & Stede, W. A. V. (2006). Field-based research in accounting: Accomplishments and prospects. *Behavioral Research in Accounting*, *18*(1), 117–134. doi:10.2308/bria.2006.18.1.117

Meyer von Wolff, R., Hobert, S., Masuch, K., & Schumann, M. (2020). Chatbots at Digital Workplaces–A Grounded-Theory Approach for Surveying Application Areas and Objectives. *Pacific Asia Journal of the Association for Information Systems*, *12*(2), 3.

Mimoun, M. S. B., Poncin, I., & Garnier, M. (2012). Case study—Embodied virtual agents: An analysis on reasons for failure. *Journal of Retailing and Consumer Services*, *19*(6), 605–612. doi:10.1016/j.jretconser.2012.07.006

Murphy, K. P. (2014). *Machine Learning: A Probabilistic Perspective*. MIT Press.

Nadarzynski, T., Miles, O., Cowie, A., & Ridge, D. (2019). Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: A mixed-methods study. *Digital Health*, *5*, 1–12. doi:10.1177/2055207619871808 PMID:31467682

Neff, G. (2016). Talking to bots: Symbiotic agency and the case of Tay. *International Journal of Communication*, *10*, 4915–4931.

NEXT IT. (2016). *Enterprise Chatbot Use Case: "Ask Julie" Amtrak's Virtual Travel Assistant*. https://www.youtube.com/watch?v=sDj2shuxFMM&feature=emb_logo

Nielsen, P. A., & Persson, J. S. (2017). Useful business cases: Value creation in IS projects. *European Journal of Information Systems*, *26*(1), 66–83. doi:10.1057/s41303-016-0026-x

Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Administration and Policy in Mental Health*, *42*(5), 533–544. doi:10.1007/s10488-013-0528-y PMID:24193818

Parker, S. K., & Grote, G. (2020). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. *Applied Psychology*, 1–45. doi:10.1111/apps.12241

Peffers, K., & Santos, B. L. D. (2013). Research opportunities in information technology funding and system justification. *European Journal of Information Systems*, *22*(2), 131–138. doi:10.1057/ejis.2012.60

Power, B. (2017). *How AI is Streamlining Marketing and Sales*. https://hbr.org/2017/06/how-ai-is-streamlining-marketing-and-sales

Radziwill, N. M., & Benton, M. C. (2017). Evaluating Quality of Chatbots and Intelligent Conversational Agents. *Software Quality Professional*, *19*(3), 25–36.

Riccardi, G. (2014). Towards healthcare personal agents. *Proceedings of the 2014 Workshop on Roadmapping the Future of Multimodal Interaction Research including Business Opportunities and Challenges.*

Robert, L. P., Pierce, C., Marquis, L., Kim, S., & Alahmad, R. (2020). Designing fair AI for managing employees in organizations: A review, critique, and design agenda. *Human-Computer Interaction*, *35*(5-6), 545–575.

Roberts, N., Galluch, P. S., Dinger, M., & Grover, V. (2012). Absorptive capacity and information systems research: Review, synthesis, and directions for future research. *Management Information Systems Quarterly*, *36*(2), 625–648. doi:10.2307/41703470

Robey, D., & Boudreau, M.-C. (1999). Accounting for the contradictory organizational consequences of information technology: Theoretical directions and methodological implications. *Information Systems Research*, *10*(2), 167–185. doi:10.1287/isre.10.2.167

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. *Management Information Systems Quarterly*, *27*(2), 237–263. doi:10.2307/30036530

Saunila, M., Ukko, J., & Rantala, T. (2019). Value co-creation through digital service capabilities: The role of human factors. *Information Technology & People*, *32*(3), 627–645. doi:10.1108/ITP-10-2016-0224

Serban, I. V., Sankar, C., Germain, M., Zhang, S., Lin, Z., Subramanian, S., Kim, T., Pieper, M., Chandar, S., Ke, N. R., Rajeshwar, S., de Brebisson, A., Sotelo, J. M. R., Suhubdy, D., Michalski, V., Nguyen, A., Pineau, J., & Bengio, Y. (2017). A Deep Reinforcement Learning Chatbot. *arXiv:1709.02349 [cs, stat].*

Sestino, A., & De Mauro, A. (2021). Leveraging Artificial Intelligence in Business: Implications, Applications and Methods. *Technology Analysis and Strategic Management*, 1–14. doi:10.1080/09537325.2021.1883583

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Houghton, Mifflin and Company.

Shankar, V. (2018). How artificial intelligence (AI) is reshaping retailing. *Journal of Retailing*, *94*(4), vi–xi. doi:10.1016/S0022-4359(18)30076-9

Sharma, R., & Yetton, P. (2003). The contingent effects of management support and task interdependence on successful information systems implementation. *Management Information Systems Quarterly*, *27*(4), 533–556. doi:10.2307/30036548

Sheehan, B., Jin, H. S., & Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption. *Journal of Business Research*, *115*, 14–24. doi:10.1016/j.jbusres.2020.04.030

Sheth, A., Yip, H. Y., Shekarpour, S., & Sheth, A. (2019). Extending patient-chatbot experience with internet-of-things and background knowledge: Case studies with healthcare applications. *IEEE Intelligent Systems*, *34*(4), 24–30. doi:10.1109/MIS.2019.2905748

Shin, D. (2020). How do users interact with algorithm recommender systems? The interaction of users, algorithms, and performance. *Computers in Human Behavior*, *109*, 106344. doi:10.1016/j.chb.2020.106344

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551. doi:10.1016/j.ijhcs.2020.102551

Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. *Computers in Human Behavior*, *98*, 277–284. doi:10.1016/j.chb.2019.04.019

Shin, D., Zhong, B., & Biocca, F. A. (2020). Beyond user experience: What constitutes algorithmic experiences? *International Journal of Information Management*, *52*, 102061. doi:10.1016/j.ijinfomgt.2019.102061

Shum, H.-Y., He, X., & Li, D. (2018). From Eliza to XiaoIce: Challenges and opportunities with social chatbots. *Frontiers of Information Technology & Electronic Engineering*, *19*(1), 10–26. doi:10.1631/FITEE.1700826

Siddike, M., Kalam, A., Spohrer, J., Demirkan, H., & Kohda, Y. (2018). People's interactions with cognitive assistants for enhanced performances. *Proceedings of the 51st Hawaii international conference on system sciences*.

Sinatra, A. M., Pollard, K. A., Files, B. T., Oiknine, A. H., Ericson, M., & Khooshabeh, P. (2021). Social fidelity in virtual agents: Impacts on presence and learning. *Computers in Human Behavior*, *114*, 106562.

Sjödén, B., Silvervarg, A., Haake, M., & Gulz, A. (2011). Extending an Educational Math Game with a Pedagogical Conversational Agent: Facing Design Challenges. In *Interdisciplinary Approaches to Adaptive Learning. A Look at the Neighbours* (pp. 116–130). Springer. doi:10.1007/978-3-642-20074-8_10

Skjuve, M., Følstad, A., Fostervold, K. I., & Brandtzaeg, P. B. (2021). My Chatbot Companion-a Study of Human-Chatbot Relationships. *International Journal of Human-Computer Studies*, *149*, 102601. doi:10.1016/j.ijhcs.2021.102601

Swanson, E. B. (2019). Technology as routine capability. *Management Information Systems Quarterly*, *43*(3), 1007–1024. doi:10.25300/MISQ/2019/14653

Tangoworks. (2018). Chatbot Case Study: Bupa, an International Healthcare Company. *Tangowork: Chatbots for Internal Communications*. https://tangowork.com/chatbots-case-study-bupa-healthcare/

Tarafdar, M., Beath, C. M., & Ross, J. W. (2019, Summer). Using AI to enhance business operations. *MIT Sloan Management Review*, 37–44.

Tarau, P., & Figa, E. (2004). Knowledge-based Conversational Agents and Virtual Storytelling. SAC ’04 *the 2004 ACM Symposium on Applied Computing*.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533.

Viswanathan, V. (2017). *How To Make A Chatbot Intelligent?* https://chatbotsmagazine.com/how-to-make-a-chatbot-intelligent-a232dc367aed

Wang, H., Czerminski, R., & Jamieson, A. C. (2021). Neural networks and deep learning. In *The Machine Age of Customer Insight*. Emerald Publishing Limited. doi:10.1108/978-1-83909-694-520211010

Weizenbaum, J. (1966). ELIZA—A computer program for the study of natural language communication between man and machine. *Communications of the ACM*, *9*(1), 36–45. doi:10.1145/365153.365168

Youn, S., & Jin, S. V. (2021). In AI we trust?” The effects of parasocial interaction and technopian versus luddite ideological views on chatbot-based customer relationship management in the emerging feeling economy. *Computers in Human Behavior, 119*, 106721.

ENDNOTE

[1] We focused on ‘realised benefits’ rather than ‘expected benefits’ because the CAs under study have already been implemented.

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