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The chatbot revolution: Companies and consumers in a new digital age

Abstract

Chatbots are seen as something of a magic wand for both companies and consumers. They may enable companies to improve customer service and gather vast amounts of accurate data, while giving consumers a better experience as they engage with brands in a customised way. Chatbots can understand everyday language and respond by imitating human-to-human conversations. These anthropomorphic attributes, along with other advances in AI sophistication, have accelerated the commercialisation and prevalence of chatbots. This chapter explores chatbots as a form of evolving technology, provides a comprehensive understanding of their role in digital marketing, and sets out the academic theories associated with their use. It then theorises that machine learning processes are similar to those of humans, before exploring the big data being generated. After discussing the remaining challenges and obstacles to their wider use, conclusions are drawn about the likely future course of e-agents, with the intention of guiding researchers and practitioners into the next generation of AI advances.

1. Introduction to chatbots

Chatbots have undergone rapid evolution since the first software was developed in the 1960s (Weizenbaum, 1966). Seen as sophisticated commercial devices used in increasing numbers by corporations and consumers. Thus, the boundaries between human and artificial intelligence have diminished and the field of human-machine interaction has captured the attention of practitioners, investors and academics. As machines are mediating the digital world this reconstructs the cognitive sphere between humans and androids. Chatbots are a thought-provoking area within human-machine interactions, as they are built to hold conversations that feel natural (Rossmann et al., 2020). This section explores their definition, evolution, different types, characteristics, advantages and disadvantages.

1.1 Definition

The definition of chatbots has changed to reflect developments in technology. Early computer software employed a text-based dialogue process to imitate natural conversation (Weizenbaum, 1966; Colby, 1975; Mauldin, 1994; Wallace, 2009; Zumstein and Hundertmark, 2017). Shawar and Atwell (2005) defined chatbots as "machine conversation system[s] [that] interact with human users via natural conversational language" (p. 489). Tintarev et al. (2016) described them as computerised software that can aid users in decision making. Subsequently, the notion of machine singularity has emerged to reflect the higher capabilities of the latest AI chatbots. Singularity involves the hypothesis that empowering a machine with artificial intelligence that may exceed human intelligence has the potential to generate unprecedented developments in technology and intelligence (Kraikivski, 2019; Chalmers, 2009). Sheehan et al. (2020) discussed the 'chatbots ecosystem' developed by combining IPAs and text-based agents with wider borders. This led to a definition of chatbots as autonomous agents with abilities to understand and hold natural-sounding conversations with users (Smutny and Schreiberova, 2020; Sheehan et al., 2020).

The chatbot was introduced by Mauldin (1994), who combined 'chatter' and 'robot' to describe this new technology. Chatbots, also known as talkbots, chatterbots, bots and intelligent virtual assistants (IVAs), are continuing to expand their conversational skills through their competence in natural language processing (NLP) (Følstad et al., 2018b). NLP refers to chatbots' ability to recognise, evaluate and react to a human conversation (Dale, 2016).

1.2 Evolution

While chatbots are categorised as a subdivision of artificial intelligence, their roots can be traced back to Turing (1950) explorative question "Can machines think?" (p. 433) (Copeland et al., 2017; Hill et al., 2015). The technology was developed to explore whether chatbots could manipulate users into believing they were holding a conversation with a real person, which was proved to be possible (Colby et al., 1972). However, the mass use of chatbots was delayed for several decades by the prevalence of other technologies such as AI and social media (Gaia et al., 2019).

Some of the major chatbots break-throughs in the second half of the 19th century continue to influence AI progress. Following Turing (1950) conceptualisation of machines that could think, the chatbot pioneer Eliza was introduced in the late 1960s by Joseph Weizenbaum being part of the MIT lab. Designed to mimic a psychotherapist, it interacted with users on the basis of manually written scripts (Weizenbaum, 1966). Its search skills enabled it to provide suitable pre-prepared responses using pattern matching and merged answers to sound intelligent (Shum et al., 2018). Its shortfalls included its inability to actually understand conversations, its limited range of knowledge, and the fact that its interactions were confined to people within the same domain. Nevertheless, Eliza had the ability to deceive people into believing it was a real human (Weizenbaum, 1976). Inspired by Turing and determined to build on Eliza's early success, many researchers and engineers have sought to advance the simulation of human conversation (Colby, 1975; Wallace, 2009; Shieber, 1994).

Parry[1] was another key development in the evolving chain of chatbots. Developed by Kenneth Colby in 1971 to imitate a paranoid individual, Parry could show different negative emotions ranging from hostile to very angry (Shum et al., 2018; Colby et al., 1972). As a technology, it has been developed to explore whether chatbots could manipulate users to believe that the conversation is going with a real human (Colby et al., 1972). It became the first bot in history to pass a Turing test, and held its conversations by drawing on complex models of predictions, attributions and emotional answers driven by shifting weights allocated to verbal input (Colby, 1975). Parry was followed in the 1980s by a conversational bot with an opposite character, Jabberwacky, which impersonated a humorous personality.

Another primary chatbot that made a significant contribution to evolution was Alice (Artificial Linguistic Internet Computer Entity), which enabled users to tailor their own chatbots (Shawar and Atwell, 2002). Pioneered by Richard Wallace in 1995, Alice had the ability to employ an experiential pattern matcher, which simplifies the conversation (Wallace, 2009; Sharma et al., 2017). Alice won a number of prizes, including for the most human-like system (Shah, 2006). However, it failed to pass the Turing test because artificial intelligence markup language (AIML) meant it was unable to maintain a conversation for a long period (Wallace, 2009; Henderson, 2007).

Not all chatbots are created for conversation. Others are task-orientated, designed with a specific purpose in mind (Rudnicky et al., 1999; Wang et al., 2011). As chatbots with practical capabilities started to emerge, they captured commercial interest, leading to the introduction of SmartChild in 2001, followed by IBM's ground-breaking Watson[2]. This era has unlocked a new phase in chatbot development, as it integrates machine learning and NLP, commercialisation and consumer behaviour (Dale, 2019; 2017).

[1] See https://www.chatbots.org/chatbot/parry/
[2] See https://www.ibm.com/watson/about

Subsequently, the tech giant Apple pioneered the use of personal assistants in mobile phones with the introduction in 2011 of Siri,[3] considered a milestone in the introduction of intelligent personal assistants (IPAs) (Shum et al., 2018). Since the advent of Siri, IPAs have gained popularity among users and developers, with Microsoft's Cortana, Amazon's Alexa and Google Assistant joining the field. These companies hold a tremendous amount of consumer data, enabling them to invest in IPAs that provide customers with a unique experience (Rossmann et al., 2020; Adam et al., 2020). IPAs provide integration between different devices, delivering information as diverse as location, time, eye movements, skin temperature, heart rate and movement, while having access to users' details such as contacts, calendar, emails, watch lists and social profiles. These computerised assistants can therefore provide users with a wide range of services, and even if they are unable to answer a request directly, they can redirect a question to different sources as part of a learning process to provide the most relevant answer.

The period that witnessed the rise of IPAs also saw the emergence of social chatbots. Drawing on digital profiling, algorithms, social media and advances in technology (Følstad et al., 2018a), social chatbots are designed to create an emotional attachment with users by expressing various emotions during the conversation. They can also complete multiple tasks for users, generating informal conversations similar to seller-buyer "side-chats" while providing a service or processing a purchase, may even suggest topics to discuss (Xu et al., 2017). This marks them out dramatically from chatbots and IPAs, which are task-orientated systems that complete a task with a minimum conversation. Xiaoice, introduced by Microsoft in 2014, became the most frequently used social chatbot (Weitz, 2014). Its interpersonal and emotional conversations included offering encouragement, supporting people and guiding

[3] Siri was introduced in 2011 as beta version in iPhone 4s.

them through a process as if it were a real human friend (Zhou et al., 2020). Following the growth of social media platforms and commercialisation opportunities, businesses realised in 2015 that chatbots could be another tool to convert service into sales, leading to the deployment of chatbot messengers (Sheehan et al., 2020).

The creation of an emotional attachment topic has been surging by increasing the interest in emotional artificial intelligence (McStay, 2018). The introduction of Soul Machines'[4] "Digital People", which merge chatbots with emotional AI, highlighted the opportunities for businesses to use chatbots as frontline customer service agents to enhance consumer experience (Yuan and Dennis, 2019). In 2018, Google provided another advance by creating Duplex,[5] the first IPA that can handle real-life tasks such as restaurant bookings and more complicated issues in human-like conversations. Duplex works in parallel with Google Assistant, enabling users and businesses to maximise their time by providing natural conversations (Leviathan and Matias, 2018).

The timeline of the development of all these pioneers chatbots and their key features are set out in detail is shown in table 1.

[4] See https://www.soulmachines.com/
[5] See https://ai.googleblog.com/2018/05/duplex-ai-system-for-natural-conversation.html

Table 1 Summary of chatbot evolution

Chatbot name / Metric	Eliza	Parry	Alice	DARPA Communicator Program	Siri (Apple)	Xiaoice (Microsoft Asia)	Cortana (Microsoft) Alexa (Amazon) Messenger bots	Google Assistant	Soul Machines	Google Duplex
Date	1966	1972	1995	2000	2011	2014	2015	2016	2016	2018
Scalability	None	None	Customisable scripts	Limited	Scalable	Scalable	Scalable	Scalable	Scalable	Scalable
Key features	Mimicking human behaviour in conversation	Generating emotional (angry) responses	Easy customisation of scripts (via AIML)	Language understanding and dialogue management; goal-orientated	Providing personal digital assistance	Building emotional attachments to users based on emotional computing; scalable skill set for user assistance	Providing personal assistance related to shopping behaviour	Providing personal assistance and home integration	Real-time emotional reactions between customers and chatbots	Real-world tasks
Accomplishment	First chitchat bot	Passing Turing test	Won Loebner prize three times	Understood natural language requests and could perform tasks	First widely deployed intelligent personal assistant (IPA)	First widely developed "teen" social chatbot; 100m users; published poetry book;[6] hosted TV programmes	Shopping experience homegrown voice assistance; development of 10k skills	Integrated with Google Home creating a different user experience	Patented digital brain, digital people; won Academy Awards	First VA to carry out real tasks
Modality	Text only	Text only	Text only	Text and voice	Text, image, voice	Text, image, voice	Text, image, voice	Text, image, voice	Text, image, voice	Text, image, voice
Modelling	Rule-based	Rule-based	Rule-based	Learning-based	Learning-based	Learning-based	Learning-based	Learning-based	Learning-based	Learning-based
Domain	Constrained domain	Constrained domain	Constrained domain	Constrained domain	Open domain	Open domain	Open domain	Open domain	Open domain	Open domain

[6] See Zhu H, Liu Q, Yuan NJ, et al. (2018) Xiaoice band: A melody and arrangement generation framework for pop music. *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining.* 2837-2846.

Key technical break-through	Using scripts, keyword-based pattern matching, rule-based response	Adding personality characteristics into responses	Using AIML and recursion for pattern matching; multiple patterns can be mapped into the same response	Using statistical models for spoken language understanding and dialogue management	Providing both reactive and proactive digital assistances by covering a wide range of domains	Emotional intelligence model for establishing emotional attachments with users	Linking shopping experience with home experience	Integrating personal assistance and home assistance	Provide intelligent emotional-customer service agents	Natural conversation with real agents
Key technical limitation	Limited domain of knowledge	Limited domain of knowledge	Size of scripts can be huge	Only works in domains with well-defined schemas	Lack of emotional engagement with users	Inconsistent personality and responses in a long dialogue	Connectivity issues	Connectivity problems with other devices, e.g. homes or mobiles; limited ability to respond to multi-commands	In development progress because of customisation according to the client	Limited scenarios, e.g. bookings
Intelligence type	Mechanical	Mechanical	Analytical	Analytical-intuitive	Analytical-intuitive-empathetic	Analytical-intuitive-empathetic	Analytical-intuitive-empathetic	Analytical-intuitive-empathetic	Analytical-intuitive-empathetic	Analytical-intuitive-empathetic

Source: Adopted from Shum et al. (2018)

1.2 Types of Chatbots

Chatbots are used by firms for different purposes with varying intelligence levels depending on the tasks chatbots are required to perform (Hildebrand and Bergner, 2019). Most can be categorised as either rule-based chatbots (R-CBs) or AI-based chatbots (AI-CBs), although there is considerable ambiguity in the way these terms are used in practice. In simple terms, R-CB technology is built on enormous servers and is often industry-orientated, while AI-CBs such as Alexa, Siri and Cortana are more flexible and have software designed with a user focus. AI-CBs include IPAs, IVAs and emotionally based AI systems such as Soul Machines' Digital People. In all cases, chatbots differ from bots in that the former are dynamic systems built to enhance human-machine engagement, while the latter are developed for particular tasks, usually repetitive in nature, and cannot provide modified answers or perform unpredictable decisions. The differences between R-CBs and AI-CBs include their intelligence level, language skills, the tasks they can perform and the technology used to build them. These areas are explored in more depth in the following sub-sections.

1.2.1 Intelligence level

R-CBs use systematic technology based on a specific set of questions or statements known as 'a single-turn exchange' (de Rijke, 2019; Efraim et al., 2017). If the chatbot faces questions beyond the scenarios it has learnt, it cannot provide the answers. In general, chatbots are built using text-based programmes; however, technology developments have enhanced their ability to understand video and audio. In essence, they provide an FAQ service that enhances service levels and consumer experience (Okuda and Shoda, 2018).

AI-CBs, on the other hand, have more complex interactive artificial intelligence (Adam et al., 2020). They can interpret conversational language and understand meanings according to the context of a conversation. They can learn, adapt and develop their own responses, resulting in significant levels of unpredictable behaviour (Crosby, 2020). AI-CBs manage more

prolonged and sophisticated human-machine interactions, and can execute certain complicated tasks (Pillai and Sivathanu, 2020). Additionally, they provide reactive and proactive assistance to users in order to complete different types of tasks (Sarikaya, 2017). Reactive actions are taken in response to commands from the user (e.g. telling the time or booking a minicab), while proactive assistance is generated by the e-agent itself on the basis of previous specific situations (e.g. meeting reminders, ordering low-stock shopping or providing recommendations). Proactive responses are usually activated by previous user performance and improve over time through human-machine interactions (Antje et al., 2020). Integration between compatible devices also improves the user experience: for example, Apple Watch, iPhone, Apple TV all activate Siri, while Alexa Echo and Alexa Auto interact with Alexa mobile application (Shum et al., 2018).

1.2.2 Language skills

R-CBs have limited language processing abilities that rely on pre-programmed scripts along with searches and trend matching. Their inability to respond to unforeseen or different language means they fail to maintain complicated dialogue, sometimes leading to them looping back to a programmed start point such as “How can I help you today?”.

AI-CBs use much more advanced types of machine learning (see sections 1.2.4 & 4). Their primary focus is on NLP, including natural language understanding and interpretation (Semaan, 2012). NLP enhances their ability to comprehend situations and deal with complicated conversations (Yampolskiy, 2013). While AI-CBs may still sometimes fail to understand complex exchanges, they are more able to understand slang and dialects (Wilson et al., 2020) and to analyse the sentiments behind conversations (Mohammad and Turney, 2013). Robust NLP also enhances their “chatting” features, making conversations seem more natural and human.

1.2.3 Tasks

R-CBs operate on the basis of algorithms suitable for the task at hand. They usually perform simple rule-based operations relating to customer service or repurchasing. Currently, many frequent customer service tasks are handled by chatbots (Rossmann et al., 2020).

By contrast, AI-CBs can handle a wide range of tasks such as answering simple inquiries about the weather, checking stock prices, providing reminders, booking appointments or filing complaints (Zhou et al., 2020). The ability to help customers with product comparisons or recommendations elevates this type of chatbot to a sales machine. Other tasks involve entertainment, including telling jokes and playing music, as well as controlling home tasks. AI-CBs can adapt and learn from their previous experiences and can be personalised on the basis of an individual user's interactions with them.

1.2.4 Types of machine learning technology

R-CBs use machine learning models that are normally either generative or discriminative in type. Generative modelling can handle more complicated situations, using many levels of information, which each user query is run through to provide the most relevant answer (Lasserre et al., 2006). Discriminative modelling operates according to a ranking tree by ranking information according to a user's previous experience: the chatbots work their way through responses in order to deliver the best match (Satorras et al., 2019). Developers mainly use structured data to train these bots, making them a more affordable option for many businesses.

AI-CBs, on the other hand, employ artificial neural networks to learn from different situations and previous experiences. These networks are used to identify, classify and predict on the basis of data analysis (Livingstone, 2008). The use of application programming interface technology enhances the quality of responses, making them appear more natural, and enables two applications to communicate with each other. For example, every time Alexa receives a

command, it uses this technology to send the data back to the servers. These servers retrieve the data, interpret it, take the necessary action and send it back to the user (Surendran et al., 2020).

1.3 Characteristics of chatbots

Whether operating as service agents in a business context or as personal assistants to individual users, chatbots have several characteristics that mark them out from other autonomous technology. According to Stojanov (2019), there are six key characteristics: personalisation, capacity, accessibility, flexibility, adaptability, accuracy and anthropomorphism. These are explored in more detail in the rest of this section.

Personalisation: The direct conversations that take place between users and AI-agents enable the service to be customised to each customer (Chung et al., 2020). Chatbots provide reasonable certainty that service quality can be tailored to consumers' preferences (Stojanov, 2019). IVAs such as Siri and Alexa can perform user-focused tasks because of the personalised algorithms that are used (Cui et al., 2017). Chatbots can also perform the role of sales agents or consultants by making recommendations and promoting them subliminally to users (Przegalinska et al., 2019; Hildebrand and Bergner, 2019). This personalisation may seem helpful to some consumers, while for many others, it may raise serious concerns over data security and privacy (McStay, 2017).

Capacity: Chatbots draw their functionality from a huge number of servers, which complete multiple tasks in real-time, connect to other servers or machines, and provide fast and accurate responses to questions (Stojanov, 2019). This ability to respond swiftly and accurately, reducing costs and effort, has led to predictions that the use of e-agents will grow by 37% between 2017 and 2023 (Valtolina et al., 2018). Recognising "chatbots' capacity to perform certain functions may help companies reallocate their human assets to more valuable tasks or

cover out-of-office hours and staff breaks (Nawaz and Gomes, 2019; Haahr and Holm, 2018). In other words, elevate human value by elevating technology. The quality of customer service could also be enhanced by chatbots' ability to interpret, analyse and respond in real time (Stojanov, 2019; Smutny and Schreiberova, 2020). On the other hand, increasing the number of tasks performed by chatbots may threaten certain types of occupations, leading to the rejection of technology by society (Nawaz and Gomes, 2019).

According to their social nature, chatbots are progressively participating in the organisation's social configurations as part of their Customer Relationship Management (CRM) staffing capacity (DiSilvestro, 2018; Murtarelli et al., 2020). Stojanov (2019) discussed the chatbots according to their position within a firm by considering them as 'digital labour' that contribute to the firm's customer service process internally (employees) and externally (clients). As an example, Alexa, Siri, and Google Assistant are flourishing in the domains of human-machine interactions and customer service (Marr, 2018). In today's organisations business model, chatbots are performing human's tasks such as complaints handling, search queries and technical assistance to staff and clients (Stojanov, 2019). Moreover, Sands et al. (2020) argued that AI-agents could replace human-agent in the service market and deliver service that achieves customer satisfaction.

Accessibility: Human agents usually work during office hours and not all firms provide 24/7 customer service (Stojanov, 2019). Moreover, organisations frequently face shortages of customer service agents, influencing productivity and service quality (Huang and Rust, 2017). Chatbots can help fill these gaps because of their round-the-clock operation and global accessibility to internet users. For example, Facebook Messenger,[7] with 1.3 billion users, is one of the most widely used chatbots owing to its ease of use and accessibility as messenger

[7] See http://bit.ly/3pNJpj8

chatbots have wide acceptability and a large convergence rate (Smutny and Schreiberova (2020). The ability to access company services is key to building and maintaining long-term relationships and enhancing customer loyalty (Følstad et al., 2018b; Chung et al., 2020; Sands et al., 2020).

Flexibility: Chatbots can show flexibility during conversations, and can provide short or detailed answers according to user needs in a way similar to a human approach (Stojanov, 2019). Chatbots can also handle different inquiries simultaneously; however, they become overloaded, they will minimise their answers and reply only to relevant questions. Providing answers that match users' inquiries increases the acceptance of chatbots and the engagement rate (Kurachi et al., 2018).

Adaptability: AI-agents can redirect customers to real agents if they are failing to maintain the required level of information or if the customer requests it (Kreutzer and Sirrenberg, 2020). Chatbots' adaptability enables them to fit into many contexts, while their lack of emotions enables them to handle different – and difficult – customer situations. However, there is a risk of allowing these machines to engage in unsupervised learning, as firms may lose control over the input or output of data (Kuligowska, 2015). For example, Microsoft experienced a disastrous public relations episode on Twitter in 2016 after introducing the chatbot Tay to promote recent AI developments (Kreutzer and Sirrenberg, 2020: 113). The more the chatbot engaged with users, the more its data became biased, until it began tweeting racist comments and opposing social causes because its behaviour and opinions had been shaped by its interactions (Wakefield, 2016; Dewey, 2016).

Accuracy: In the near future, chatbots will control about 85% of customer service interactions (Sands et al., 2020). Answers provided by chatbots have higher accuracy than information from human agents as a result of their programmatic nature, their inability to become tired, and the

layers of information that they can access to provide the optimum solution (Cui et al., 2017), which achieve a higher level of accuracy immediately (Kurachi et al., 2018). However, chatbots may provide inaccurate information in situations of misinterpretation or data bias (Stojanov, 2019). The intelligence level of chatbots has yet not reached its full potential; therefore, there is a gap between what users expect and what they actually receive (Ransbotham et al., 2017).

Anthropomorphism: The primary function of chatbots is to appear human by engaging users in natural conversation. Regardless of whether this dialogue takes place via text or voice, chatbots simulate human behaviour; therefore, we anthropomorphise them (Sheehan et al., 2020). These human-like features can create social acceptance (Adam et al., 2020) and brand attachment (Przegalinska et al., 2019). Anthropomorphism theory is explored in more detail in Section 3.1.

1.4 Advantages and disadvantages of chatbots

Chatbots were initially used by companies to perform dull tasks such as operations and as back-office agents (Davenport and Ronanki, 2018). However, they have moved to the frontline of sales and customer service, performing a diverse range of tasks such as helping customers find cheap airline routes, buy flight tickets, book theatres and find advice on the best local restaurants (Adam et al., 2020). The advantages offered by this progress, along with the disadvantages of using chatbots, are explored in detail in the next sections.

1.5.1 Advantages

Cost-effective: E-agents are generally less expensive than their peers in the technology industries and provide an acceptable return on investment (Davenport and Ronanki, 2018). Moreover, they provide an acceptable quality of customer service (Sands et al., 2020). Chatbots can therefore reduce labour costs by replacing certain jobs, enabling companies to invest the savings in more skilful and cognitive jobs (Rossmann et al., 2020; Nawaz and Gomes, 2019). For instance, the pressure of funding large projects at NASA led to the automation of 86% of

HR duties (Davenport and Ronanki, 2018). Similar moves in banking have led to many transactions taking place through automated processes via ATMs or e-banking services. Different chatbots are available to fit budgets of various sizes. Some use technology such as robotic process automation, which is the least expensive and intelligent but capable of improvement with investment (Aguirre and Rodriguez, 2017; Van der Aalst et al., 2018).

Enhanced communication: The ability to store and recall users' data can enhance customer-brand communication (Zumstein and Hundertmark, 2017) and tailor consumer experience (Khan and Das, 2018). Human-machine interactions often have fewer errors than human-human contact (Sands et al., 2020). Furthermore, chatbots can handle multiple inquiries simultaneously (Chung et al., 2020), provide less biased recommendations (Parise et al., 2016) and interact with acceptable manners (Allen and Wallach, 2009).

Better customer relationships: Chatbots are available at any time and can be accessed from any online location, enabling customers to use a service in their preferred setting (Sands et al., 2020). They provide a management tool for tracking requests, queries, complaints and performance. In other words, they work as a one-stopshop for customers (Zumstein and Hundertmark, 2017; Davenport and Ronanki, 2018). Therefore, Chatbots shift efforts towards the attributes that significantly affect user experience (Kaczorowska-Spychalska, 2019).

1.5.2 Disadvantages

Not all aspects of the use of chatbots are positive, and firms need to consider the disadvantages when deciding whether and how to deploy them.

Acceptance: Regardless of the widespread use of chatbots, some people have concerns about the notion of machine autonomation (Indurkhya, 2019). This is especially true when the computerisation process replaces humans. The nature of the transaction is a determining factor in consumers' acceptance of chatbots. Some people may even feel more comfortable talking

about certain subjects with chatbots, because they feel they will not be judged (Sanny et al., 2020). However, users may feel that discussing other topics with chatbots poses significant financial or material loss risks.

Data and privacy issues: Many internet users have concerns about collecting, processing, and using their personal data. This may add to a reluctance to accept e-agents (Meuter et al., 2003). Revelations about the 2016 US election and Facebook's data-scraping practices only added to these concerns. Some policies have been initiated to create strict rules about privacy and the use of personal data, such as the European Union's General Data Protection Regulation (Goddard, 2017). Chatbots and other devices such as virtual assistants, mobile phones and laptops are capable of listening to conversations (Khan and Das, 2018). Particular concerns have been raised about whether command-activated devices such as Alexa and Siri have the potential to "spy" on users. Clear and transparent data protection policies may increase consumers' levels of trust and acceptance (van Ooijen and Vrabec, 2019).

Risk of bias: Chatbots function by using not only consumers' information but data inputted by developers or users. This can lead to issues such as the Microsoft Tay incident (Kreutzer and Sirrenberg, 2020). If the data is biased, the chatbot's behaviour will also be biased, which could influence a company's reputation and consumers' opinions, including by creating echo chambers or filter bubbles (Burbach et al., 2019; Pariser, 2011). The result can be misinformation, quality variance and customer dissatisfaction.

Perception disruption: The variance between what humans expect from a chatbot and what they experience may cause reality disruption, which causes rejection. This issue will be discussed further in Section 3.2, which deals with uncanny valley theory. Consumers expect AI-agents to perform as humans, and hold the same level of natural conversation they see in films such as iRobot. However, in reality, chatbots have not yet reached this stage of fluency:

they cannot reach human levels of understanding, language and interaction. This may affect users' psychological ties with them (Sands et al., 2020). Humanising autonomous machines is the subject of intense ongoing research by scholars and AI engineers (Howard and Muntean, 2017; Howard and Muntean, 2016; Indurkhya, 2019; Awad et al., 2018).

2. The role of chatbots in marketing

Chatbots present unprecedented opportunities for generating conversations that feel natural with users, with great capabilities in areas such as sales conversions, customer service and customer relationship management. They also generate invaluable data, enabling firms to enhance their communication strategies on the basis of real-time feedback, and can integrate with brand personalities or develop their own personalities, depending on their level of intelligence. These factors have led to increasing numbers of firms integrating virtual customer assistants or other chatbot devices into their customer service operations. In particular, their increasingly social nature means they are progressively forming part of organisations' customer relationship management staffing capacity (DiSilvestro, 2018; Murtarelli et al., 2020). Stojanov (2019) characterised chatbots as "digital labour", contributing to customer service processes internally (employees) and externally (clients). For example, Alexa, Siri and Google Assistant are flourishing in the domains of human-machine interactions and customer service (Marr, 2018). In business models, chatbots are performing human tasks such as handling complaints, dealing with search queries and providing technical assistance to staff and clients (Stojanov, 2019). Some researchers suggest that AI agents could ultimately replace human agents in the service market and achieve customer satisfaction (Sands et al., 2020).

A trend towards increased investment in customer experience technology is also being witnessed (Moore, 2018). According to Allied Market Research, the global chatbot market in banking, financial services and insurance alone was estimated at around US$495 million in

2019, and is anticipated to reach $3.4 billion by 2027 on the basis of a forecast compound annual growth rate of 27.3% (Goswami et al., 2020).

After reviewing chatbots in the literature, this section explores in more detail chatbots' role in digital marketing, as a business and branding opportunity, and as a key way to manage the changed business landscape during the COVID-19 pandemic.

2.1 Overview of chatbots in the literature

The digital marketing literature explores both the practical and theoretical aspects of the use of chatbots. Chatbots have moved from a narrow frame of reference, in which they were viewed simply as software, to a multi-aspect branding concept, with systems such as Siri, Alexa and Google Assistant generating sales and helping with customer relations. The increasing popularity of AI-based applications provides a fertile landscape for unique customer service experiences (Murtarelli et al., 2020). Marketing communications approaches are in continuous development to keep pace with changes in the technological landscape (Popescu, 2020). Practices have progressed from email marketing, social media and mobile apps to the increasingly prevalent use of chatbots.

Brands engage in an ongoing process of testing markets, communication vehicles and culture (Carah, 2017), mixing technological and calculative activities with cultural fundamentals in a process based on perceptions, initiatives and creativity. In a digitally mediated world, the fusion of brands, technology and consumer behaviour has led to the concept of brand machines. While machines are AI-enabled platforms that aim to help a brand perform a specific task (Belk, 2019), brand machines are applications, devices or platforms that analyse, facilitate and gather data, and establish communication with existing brand configurations with the aim of creating engagement, attraction and motivation within individuals' relationships with the brand (Brodmerkel and Carah, 2016).

Brands have moved from cultural configuration to involvement in daily activities, decisions and regulations, and from delivering symbolic experiences to affecting fundamental behaviours that result in audience action. This requires a dynamic relationship between the product, customer and medium, so they employ media platforms to organise ongoing circles of motivation, implementation and engagement with customers. Consequently, business success is measured not only in profit margins but in the volume of data held and the knowledge of how to use it. To generate this rich data, firms need robust and consistent communication tools.

2.2 Chatbots in digital marketing

Marketers are likely to be drawn to tools with the potential to help them achieve their targets. Chatbots tick this box by providing a communications tool with benefits to customer service and customer relationship management. At the same time, the social media landscape has enabled the integration of e-agents as part of a comprehensive digital experience. As digital marketing tools, chatbots offer many significant benefits. They can enhance emotional attachment and personalise the customer journey while simultaneously generating vast amounts of customer data from application-based or device-based use. For example, the Lark Health application, which can be linked to users' iPhones, iWatches and iMacs, can monitor the number of hours people are asleep, their emotional status and their daily activities, enabling the provision of tailored responses that can out-perform program-based services. As technology is an essential element of a firm's services, chatbots may influence customers' perception of the organisation itself (Larivière et al., 2017).

Sproutsocial (2020) reported Facebook's insights into the value of chatbots. For example, two billion messages were exchanged between individuals and businesses every month; 56% of customers preferred to text rather than telephone customer services, and 53% of people favoured brands they could message. Drift (2018) reported that 37% of users expected chatbots to provide a quick response in an emergency situation, and 35% predicted that they would be

able to resolve problems or complaints. This consumer preference is reflected in the mass spread of chatbots.

2.3 Chatbots as a business and branding opportunity

Chatbots play a key role in the integration of technology and business. Some firms have developed them beyond the simple rule-based systems such as those found at self-checkout counters in supermarkets. For example, Amazon took customer experience in the grocery category to a different level by introducing Amazon Go to the firm's digital marketplace. It used cutting-edge technology to enhance the customer experience by putting customers at the forefront of their priorities and taking advantage of consumers' digitalised lives (Polacco and Backes, 2018). This technology reduces time and stress for customers while benefiting Amazon by enhancing the customer journey, satisfaction, and loyalty and generating more accurate data about consumer behaviour by integrating the insights generated from the grocery experience with Alexa. It provides Amazon with a 360-degree view of the customer, enabling the firm to provide consumers with more tailored offerings.

Other examples can be found in the communications industry. Vodafone has been at the forefront of a number of innovations. In 2018, Vodafone Romania identified a communications gap among 14-18-year-olds: consumer insights showed they spent most of their time online chatting, were less exposed to offline advertising tools and television, and distanced themselves from online adverts. In response, Vodafone introduced a digital agent called Future Chatbot, which could discuss the evolution of technology, matching the theme of a wider campaign. In the first month, Future Chatbot generated 450,000 messages and interactions with 10,000 users. The analysis showed that 60% of users spread word-of-mouth, with an average conversation time of three minutes but some exchanges lasting an hour (Rotariu, 2018).

The financial sector has also demonstrated how chatbots can be deployed innovatively to enhance the customer experience. Capital One created Eno,[8] an AI-empowered chatbot designed to understand consumer abbreviations in texting to make exchanges sound more human, such as using "bal" for balance and using emojis such as thumbs up to confirm and thumbs down to cancel. Eno insights showed that 50% of users used the thumbs-up sign to proceed with transactions. The name Eno ('one' backwards) was chosen as it did not convey an age, race or gender to avoid unconscious bias (Andreasyan, 2017).

Chatbots enable firms across all sectors to integrate technology with personal and corporate branding, to give consumers a unique experience. This quest to create brand attachment can result in diverse projects far beyond simple customer assistance. For example, in 2018, Amazon carried out a joke-telling collaboration in the US with Tonight Show host Jimmy Fallon. Users who asked Alexa to tell them a joke would hear the reply "My friend Jimmy will tell you a joke", followed by a joke from Jimmy.

2.4 Chatbots and COVID-19

The COVID-19 pandemic had a significant influence on the use of chatbots as organisations sought to adapt to the new business landscape. In some countries, the lockdowns and restrictions made physical interaction with consumers impossible in certain service sectors, including banking and parts of the retail industry. Service providers had to find a quick and effective way to maintain high-quality customer service, which chatbots were able to fulfil in many cases.

Chatbots were also used to raise awareness about COVID-19 (Laranjo et al., 2018), as organisations, including the World Health Organization (WHO), sought innovative ways to fight the disease (WHO, 2020). Miner et al. (2020) note that effectively designed chatbots "may

[8] See Eno https://www.capitalone.com/learn-grow/money-management/eno-chatbot-banking-conversations-next-level/

help prevent misinformation, aid in symptom detection, engender infection-limiting behaviours and lessen the mental health burden of pandemic response" (p. 3).

3. Theories relating to chatbots

This section provides a review of the academic theories related to virtual assistant technology and the interplay between theory and practice. The most common theory used to explain the engagement between customers and chatbots is that of anthropomorphism. However, some customers tend to reject virtual assistant technology, which is explained by the uncanny valley theory.

3.1 Theory of anthropomorphism

Anthropomorphism refers to the process of ascribing human traits, behaviours or emotions to non-human agents (Guthrie, 1993; Epley et al., 2007). It affects people's perceptions of non-human identities by enabling them to assign an object attributes beyond its existing features (Hart et al., 2013), driven by a human tendency to seek to understand the behaviour of unknown entities by using anthropocentric knowledge (Epley et al., 2007; Pfeuffer et al., 2019). Chatbots can imitate human conversations through text, images, voice (Reshmi and Balakrishnan, 2018) and emotions (McStay, 2018). They can also behave autonomously, demonstrating acceptable human manners (Awad et al., 2018; Rahwan et al., 2019) and have the potential to simulate cognitive processes (Kelly III and Hamm, 2013). Users understand that they are not real people, but use their names and attribute human characteristics and behaviours to them. This process of anthropomorphism is spontaneous (Guthrie, 1993; Mithen and Boyer, 1996), as people automatically assign a human form to an object after encountering human characteristics through their senses, whether by hearing and/or seeing (Yuan and Dennis, 2019).

The chatbots used by brands can communicate using natural language, expressing answers in the same way as a member of staff might do (Popescu, 2020). Customer-brand-

machine interactions initiate a relationship of trust (Akash et al., 2017; Adam et al., 2020), and automata may even be trusted more than humans in some scenarios, since users believe that machines are more polite, rational and less judgmental than people (Przegalinska et al., 2019). However, the physical interaction is currently available when using chatbots as e-service agents may constrain attachment, engagement and familiarity (Sands et al., 2020).

Familiarity plays an important role in achieving user engagement, while elements such as disruption and cognition can alter users' perceptions over the longer term (Lemaignan et al. (2014: 2) The idea behind giving objects anthropomorphic attributes is to increase positive sentiments. However, imitations that are too realistic can lead to the opposite outcome (Sheehan et al., 2020). These theories are discussed in more depth in the section on uncanny valley theory. Misselhorn (2009) proposed that rejection could be avoided by introducing an idea to the user's mind and perception. Brahnam (2009) suggested that chatbot engineers should teach their creations a human ethos (morals and virtues) to create trust and credibility by enforcing an acceptable code of conduct.

Soul Machines holds a senior position in the chatbot hierarchy by providing what the firm calls "Digital People", which draw on a patented "Digital Brain" to create human-like interactions and enhance customer brand experience. It is technology has been used in a wide variety of settings, including banking (ANZ's Jamie), airlines (AirNZ's Sophie), cosmetics (SK-II's Yumi), healthcare (the WHO's Florence, created in partnership with Amazon Web Services and Google to help people stop smoking), and higher education (Maryville University's Emma and Mya). Organisations that use technology of this outstanding level of human likeness are unlocking opportunities to flourish by enhancing customer service, especially during the COVID-19 pandemic.

3.2 Uncanny valley theory

When humans encounter humanoid robots or software that generates a human face, voice or behaviour, they may find it disturbing. People have particular concerns about machines that can make autonomous decisions, even though they play some part in our daily lives. The psychological reasons for this may be the cognitive dissonance that arises from the gap between people's expectations of how human-like robots should look and how they actually look (Berberich and Diepold, 2018). The uncanny valley concept developed by Mori (1970) explains that, when it comes to acceptance, people develop defensive behaviour toward machines when they look like humans but do not fully respond like humans.

Different chatbots can simulate human responses with varying degrees of authenticity, including how they sound (Jenkins et al., 2007), act and appear (MacDorman et al., 2005). Uncanny valley theory sheds light on people's unfavourable response when communicating with non-human objects that have human-like features. These agents elicit uncanny feelings of revulsion or eeriness in observers (Mori, 1970), whose acceptance level of the robot is influenced by how closely it imitates human behaviour (MacDorman and Chattopadhyay, 2016). Mori's model was built mainly on the relationship between likeness and familiarity, and is not limited to machines' appearance but includes their human-like behaviour (MacDorman and Ishiguro, 2006). It hypothesises that individuals develop an unconscious repugnance towards androids when they look like humans but not completely. There are examples related to this phenomenon in robots, chatbots, virtual reality, augmented reality, games and animation (Tinwell, 2014).

According to Mori (1970) the uncanny valley theory has almost no effects on the left side of the graph, including industrial robots or Henry vacuum cleaners. The intelligence level of these machines is mechanical and consistent with their appearance and function. On the other hand, perception disruption takes place when intelligence is elevated to the artificial or

emotional level, cognitive skills become more autonomous, and machine learning enables the chatbots to simulate human cognition, behaviour and ethics (Berberich and Diepold, 2018).

Given the current and potential involvement of chatbots in daily activities such as work, shopping and home tasks, it is vital to diminish the negative effects of the uncanny valley, as this could lead to undesirable outcomes and negatively impact customer experience. For example, some customers become frustrated with Alexa or Siri if they cannot be understood, and ask to be moved to humans – leaving a real agent to handle frustrated customers. Chatbots that are not suited to their task, along with those that have major design flaws or use their autonomy in inappropriate ways, not only have a negative influence on reputation but can also cause financial losses. Engineers and researchers have to develop human-like autonomous cognitive systems to reduce this discrepancy and enhance people's acceptance of robots (Wallach and Allen, 2008; Allen and Wallach, 2012; Belk, 2019; Govindarajulu et al., 2019; Murtarelli et al., 2020).

4. Chatbot learning processes

The human-to-machine engagement between customers and virtual assistants enables chatbots to develop their skills and understanding. This section explores the similarities between machine and human learning processes, and discusses how this affects marketing decisions.

Moral learning is an important part of these processes. Academic theories regard morals as a group of conducts that gradually mature in a way that is rational and complies with societal norms (Aronfreed, 1976). In human learning processes, the methods involved in this progression include verbal guidance and actions that can be observed by other people (Bukatko and Daehler, 2012). Machines learn in a similar way, with three distinct approaches used to advance their knowledge: supervised learning, unsupervised learning and reinforcement learning. Supervised learning involves teaching algorithms on how to complete a task under

supervision, with full control of the input of labelled datasets and judgement of the output of these data. This approach is helpful in tasks such as classification or regression problems (Putatunda, 2019). Unsupervised learning is a process in which algorithms can model learning on the basis of their own experience. Developers can participate in the input but have no control of the output, Machine learning algorithms here can draw a conclusion based on unlabelled data. Unsupervised machine learning can be useful in tasks such as clustering, anomaly detection, association and autoencoders (Love, 2002; Maheshwari et al., 2019). Finally, reinforcement learning does not require labelled input or output, or actions to be overtly corrected; instead, it emphasises finding a balance between exploration and exploitation (Kaelbling et al., 1996). It decodes many sophisticated decision-making tasks that were previously unapproachable. The new application has been used in domains such as healthcare, robotics and finance (François-Lavet et al., 2018). All three of these approaches involve exposing algorithms to a set of actions, text classifications and behaviours of humans (Rahwan et al., 2019). Algorithms are trained to augment precision learning on the basis of particular datasets that are categorised by humans. The selection and qualities of the datasets can significantly influence the algorithms' behaviours (Buolamwini and Gebru, 2018).

5. Live data usage

Digitalised forms of customer-brand engagement – in other words, the three-way conversations between humans, machines and brands – have generated an enormous amount of data, known as big data. This is used in different forms to enhance business decisions, in-depth understanding of consumer behaviours and effective marketing budget planning (Heidrich et al., 2016; Kobayashi et al., 2018). Big data also enables the use of multiple practices such as sentiment analysis, text mining, topic modelling, pattern behaviour and behaviour forecasting. Big data analytics allows the analysis of diverse sets of data, i.e., structured, semi-structured and unstructured. This analysis enables brands, data scientists and researchers to gain insights

into chatbots' conversations, and usually requires specific analytics skills and software such as R, Python, Hadoop and Spark.

As the data generated by chatbots are complex, and of a vast scale, standard data processing procedures may be inadequate. Some chatbots not only gather their own data, but draw on data from social media and devices such as mobile phones, computers and smart watches, or from other cloud servers, in a process built on machine-to-machine trust (Liu et al., 2016; Loper and Swenson, 2017). The insights gained by analysing this data lead to more accurate information on market trends, better-personalised offerings, sales growth, enhanced customer care and a better competitive edge.

6. Challengesand Future Directions

This section highlights the challenges that virtual assistant technology faces as a digital marketing tool and sheds light on the concerns and negative aspects of the use of chatbots.

Challenges

Technical problems: Some chatbots have been shut down after a successful launch, mainly after user complaints that they had gone rogue. For example, Microsoft's Tay made socially unacceptable comments (Kreutzer and Sirrenberg, 2020), and IBM's $62 million Watson oncology project was shut down after providing unsafe advice (Strickland, 2019).

Lack of contribution: Some critics argue that chatbots, especially rule-based types, merely duplicate web searches or Q&A but in a different form. However, the authors argue that even rule-based chatbots can provide more personalised and direct responses than web searches.

Complexity: One of the concerns raised around chatbots is their ability to understand complex dialogue. However, advanced AI-empowered chatbots are enabled by an artificial neural network which enables them to handle multiple requests and complicated conversation.

Data bias: While concerns about data bias extend to all autonomous androids, chatbots – as a real-time conversational tool – could pose the greatest risks of harm. For example, in addition to the example of Microsoft's Tay, Amazon's AI recruitment system was found to prefer white men because its designers had used data drawn from current employees, gaining the system a negative reputation as sexist (Oppenheim, 2018).

Machine Ethics: Ethical concerns exist about all autonomous systems involved in daily tasks, given the need for them to operate according to acceptable social standards (Wallach and Allen, 2008; Allen and Wallach, 2009). Some scholars argued the role of culture as an essential factor in determining the level of acceptance (Awad et al., 2018; Rahwan et al., 2019), while others argue that machines should not learn according to human morals since these change over time and differ between cultures and societies; rather it is argued that machines should learn human virtues that are more grounded and unchangeable (Govindarajulu et al., 2019; Berberich and Diepold, 2018).

Chatbots of the future

As technology advances, chatbots of the future will be blended mixed reality as front-end (Park and Jeong, 2019). Mixed reality refers to the merger between virtual reality, augmented reality, machine learning and chatbots. While in the backend, if the use of chatbots in everyday life is to continue expanding, these machines have to interact with an acceptable code of conduct, especially as they are becoming autonomous. Studies have proposed that machines may be able to behave in line with moral codes in the future (Awad et al., 2018; Rahwan, 2020; Ishowo-Oloko et al., 2019).

Despite these advances in chatbots' ability to operate to socially acceptable standards, two main issues need to be highlighted. Firstly, social standards vary across cultural contexts: what may be acceptable in one society may be unacceptable elsewhere. Secondly, conversation between chatbots and humans remains under development, and certain responses by chatbots

can be perceived as unfriendly or even offensive. For example, chatbots that can deal appropriately with users' questions about beauty can hold more natural, friendly conversations and could even enhance consumers' self-esteem, in turn boosting their preferences for that device. This area could lead to a new sphere in marketing which chatbots' "personalities" could affect brand personality, image and identity.

For example, if a user called

"Siri, you're beautiful."

Siri answers "OK."

which can be perceived as a vulgar answer as we humans tend to answer more politely to nice compliments. Following the user's conversation "why you being rude?", Siri answers "hmm... I don't have an answer for that, is there anything else I can help you with?".

While we tried the same sentence with Alexa,

the user "Alexa, you're beautiful.",

Alexa replied, "Thanks! You too. You're beautiful. You're beautiful, it's true."

Chatbots have unlimited opportunities to develop as an industry and commercial product, and in literature as an underdeveloped concept related to multidisciplinary literature. Future researchers are encouraged to expand their investigation to understand how chatbots enhance brand equity, loyalty, image; and how it influences the purchase decisions and brand usage.

Furthermore, COVID-19 has also facilitated and increased the acceptance of the idea of chatbots. There has been a significant demand for personal and corporate use. However, a concern may arise, which need further research and investigation, will chatbots be mainly concerned with developed countries or higher social classes only?.

In conclusion, the machine learning behind chatbots continues to evolve. Machines can be considered as being at a child's level of development. The learning capabilities that they will evolve in future years will reduce perceptions of disruption and unlock unimaginable further opportunities for chatbots in commercial and non-commercial life as well as research.

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Chapter 21: the chatbot revolution: companies and consumers in a new digital age

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