A systematic framework for analysis available on the market **AI conversational systems** with a view to implementing them in **e-commerce** to improve **customer experience.**

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Abstract

These days after the global post-pandemic shift of the customer`s behavior to online shopping, e-commerce is still adapting to the new reality. E-commerce consumers are starting to have higher expectations from the online shopping experience, becoming more conscious of the brand choice. Thus, e-commerce businesses need to strengthen their positions on the market, enhancing the customer experience with new solutions. With last technological breakthroughs AI conversational systems in e-commerce have become extremely in demand, delivering better customer experience with quick responses, personal and friendly assistance and availability 24/7.

Whereas there are a lot of turnkey solutions on the market of AI conversational technologies and applications, many e-commerce businesses take a wait-and-see approach, postponing the adoption of the technologies until more information about appropriate AI conversational strategies is known. But the popular sources online fail to provide reliable and accurate information on opportunities and potential of particular AI conversational type implementation.

This way, in the first phase of the research, while approaching the exploration of the AI conversational applications` wide market and the potential of these types of systems application in e-commerce, the faceted taxonomy of AI conversational systems was formed. In the following phase of the research, this taxonomy was considered as a basis for further close investigation of every particular conversational model type as a variable component of any AI conversational system. This allowed the formation of an ontology of AI conversational systems in order to make more meaning with the data linking and achieve a higher level of awareness regarding AI conversational system implementation to enhance the customer experience in the context of e-commerce.

Contents

Contents

Introduction

Today when online purchases are expected to reach 24.5 percent of total global retail sales(by 2025)(eMarketer) after the global post-pandemic shift of the customers behavior to online shopping, e-commerce is still adapting to the new reality. E-commerce consumers are starting to have higher expectations from the online shopping experience, becoming more conscious of the brand choice. According Stackla (2022) 72% of online consumers are more likely to purchase from a brand that percieve their clients as individuals and creates a personalized experience for them. Thus, e-commerce businesses need to strengthen their positions on the market, improving the customer experience as consumers will be quick to move on to the competitors if they are not satisfied with the service they are getting.

New technologies timely application to business models and value proposition models has become a strong factor determining the precedence and success of the brands on the competitive market. With last technological breakthroughs in big data, machine learning, deep learning, and natural language understanding AI technologies have become extremely in demand. Investment in AI applications is expected to grow exponentially. Globally it is projected that approximately 70 % of businesses will use AI by 2030 (Bughin et
[1] al., 2018). In particular, the market of e-commerce recommendation engines is expected to grow to $ 15.13 billon in revenue by 2026 (Mordor Intelligence). Apart from AI technologies ensuring personal recommendations, numerous e-commerce market researchers refer to AI conversational technologies as another potent tool enable to enhance customer experience and increase customer engagement and loyalty. According recent researches over 60% of e-commerce shoppers will leave a web site if they can’t quickly find what they’re looking for or access help and over 50% of customers expect a business to be available 24/7(Juniper). Thanks to AI-powered conversational technologies and applications, businesses can overcome these challenges, delivering better customer experience with quick responses, personal and friendly assistance and availability 24/7.

Among additional benefits that AI conversational technologies could bring to business are: boost sales and conversions, build brand awareness and engage, gather customer data. What is more the business strategy of AI conversational technologies and applications implementation provides the opportunity of operational costs cutting of the business in long perspective. According to projections from Juniper Research, the total cost savings from deploying chatbots will reach $11 billion by 2023.

However, despite a number of the AI conversational technologies and applications beneficial opportunities listed above still not many e-commerce businesses actually use the opportunities and continue to take a wait-and-see approach, postponing the adoption of the technologies until more information about appropriate AI conversational strategies is known. Chatbots are used by less than 19% of the businesses according the TIDIO survey(2022). So what does hold the e-commerce businesses from AI conversational technologies adoption after all?

Whereas there are a lot of turnkey solutions on the market of AI conversational technologies and applications, a number of issues that arise above businesses still remain. Some of them: **What types of AI conversational applications have proven to be effective in e-commerce and which will revolutionize customer experience in the near future? How to choose the appropriate type of conversational AI for strengthening customer experience? What difficulties can be faced when implementing conversational AI in e-commerce? How will the introduction of AI conversational applications in e-commerce affect the customer experience?**
Although most of these questions should be considered according to the **specific industry context and user journey. An overview of the broad market for conversational AI applications and a systematic approach to the implementation process of a particular conversational system can be beneficial to both businesses and designers in the early stages of development.**

The research gap and objective

Based on this investigation a lack of systematic approach could be defined. Namely, a lack of systematic approach to modern AI conversational systems implementation in fields of e-commerce that enable to improve CX.

Thus, the purpose of this research is to study the broad market of AI conversational systems to identify an approach to the analysis of each type of system's strengths and weaknesses in relation to the customer experience in e-commerce and as a result - create a systematic framework for investigation available on the market AI conversational systems with a view to implementing them in e-commerce to improve customer experience. The insights from particular research could bring value for both, designers and businesses in the early phases of development and implementation of this kind of technologies.

The research gap and objective

In order to achieve the main objective, the following steps should be fulfilled:

1. Understanding the concept of AI conversational systems and core terminology.
2. Exploration the technologies available on the market.
3. Create a methodology for analyzing the potential of application available on the market AI conversational systems in e-commerce to enhance CX.

The rest of the paper is organized as follows. In Sect. 3 the research of all available typologies and classifications of AI conversational applications with focus on principal parameters relevant for customer experience will be reported. After that, in Sect.4, the taxonomy of AI conversational models in context of their implementation in e-commerce for enhancing customer experience will be framed. Next, in Sect. 5, each model`s potential in context of customer experience in e-commerce will be explored. In Sect. 6, A step from Taxonomy to Ontology of AI conversational models in context of customer experience in e-commerce will be made to make more meaning with data linking.

1. Introduction to conversational AI

1.1 What is Conversational AI?

In recent years, thanks to the growing hype around, AI conversational technologies and applications are highly referenced in the literature by numerous sources, including research articles, industry documentations, and internet blogs. However the inconsistency in terms and mixture of concepts of **conversational AI technologies and applications** are still common throughout different recourses especially on the Internet. Therefore, the aim of this chapter is to improve clarity, by providing definitions for the main relevant concepts currently in use.

Boost.ai - one of the providers of conversational AI technologies on the market suggests to think of conversational AI as the 'brain' that powers a virtual agent or chatbot. It encompasses a variety of technologies that work together to enable efficient, automated communication via text and speech by understanding customer intent, deciphering language and context, and responding in a human-like manner.

According Interactions - another AI conversational technologies provider, conversational AI is the set of technologies behind automated messaging and speech-enabled applications that offer human-like interactions between computers and humans.

According to one of the leaders in the industry of software providers - IBM, Conversational artificial intelligence (AI) refers to technologies, like chatbots or virtual agents, which users can talk to. They use large volumes of data, machine learning, and natural language processing to help imitate human interactions, recognizing speech and text inputs and translating their meanings across various languages.

Based on the research published in International Journal of Information Management (2022), conversational AI could be defined as an interactive class of software applications that engage in dialogue with their users by
[2] utilising natural language (Dale, 2019). Conversational AI can have a voice- or text-based interface and can be used by organisations externally to support customers or internally to support employees.

[3] At the same time in IEEE research publication(2022)an Artificial Intelligence (AI) program that originated to imitate human conversations using spoken or written natural language over the Internet is described as conversational

agent. And many other alternative terms are used for conversational agents in different sources. Earlier, dialogue system, this term was popular. But nowadays, chatbots, smart bots, intelligent agents, intelligent virtual assistants/agents, interactive agents, digital assistants, and relational agents are used alternatively in research articles.

We can see that under the term of **conversational AI** could be meant both, the particular applications or software that carry out communication processes with human user and also a range of technologies that power this applications. Thus, to avoid misunderstandings, in this thesis work will be used a term of **conversational AI applications or systems** referring to a generic term for a set of software applications that enable computer to interact with human in manner really close to natural, human-human way. This range of applications could be also called in different academic papers: AI Conversational Agents
[4] (Nicolescu, Tudorache 2022), intelligent or interactive agents, digital or virtual assistants, Artificial conversation entities and etc.

All of these applications are realized with use of different combinations of components - **conversational AI technologies** which would be studied closely in the following chapters which range from more simple like text analysis (TA) to more complex like machine learning (ML) systems that can detect and interpret a much wider range of vocal and nonvocal **inputs such as written text, emojis, spoken words, tone of voice, sentiments, accents, dialects and different languages.** A well-designed and appropriate combination of technologies has unique opportunities and enable to detect, recognise, understand, memorize, interpret, proceed the input and depending on the task to give a propriate output as a respond, recommendation, a task performing and etc and carry on quite complex conversations with humans in order to assist them in their problems solving. The interaction may be served to the user through messaging channels (e.g. Facebook Messenger, Whatsapp and Skype), through dedicated phone or web applications, integrated into a website, or shipped as part of an operating system. Conversational AI applications have many names depending on their capabilities, domain, and level of embodiment. These terms include automatic agent, virtual agent,
[5] conversational agent, chatbot. (Elayne Ruane et al., 2019). But to better understand the core difference between different types of applications and reach the objectives of this research, the overview of basic components and technologies that power each type of AI conversational application is needed.

1.2 Development of the technologies that power Conversational AI

The idea of conversational technologies is not new. Since the first computers emerged to facilitate the human operations an issue of the most efficient way to interact with a machine arose and has remained relevant for decades up to our days. At the same time another burning question has been occupying the minds of the computer scientist - the issues of anthropomorphising the machine or attempts to investigate how intelligent and close to human way of thinking and acting the machine could be in order to communicate with human in a regular, natural for him way. These two basic questions have become a start point for a number of findings in the field of computer science and computer-human interactions and have triggered the emergence of breakthrough technologies that determine the quality of human communication with machine nowadays.

Artificial intelligence(AI) algorithms including **Machine learning(ML)** and **Deep Learning(DL)** mechanisms appeared on a basis of sciences, theories and techniques (including mathematical logic, statistics, probabilities, computational neurobiology, computer science) that aimed to imitate the cognitive abilities of a human being and even surpass them in computational power (computer storage and processing speed). In early 1950 in famous paper “Computing Machinery and Intelligence” Alan Turing suggested that humans use available information as well as reason in order to solve problems and make decisions, so why can’t machines do the same thing? Moreover, these algorythms could potentially proceed massive amounts of data much more easier, making required decisions faster. Thus, a long journey of technologies improvement inspired by Turing and developed by different groups of scientists all over the world has led to startling current opportunities of AI to predict, recognize/categorize, cluster/profile, recommend, understand/interpret, communicate, generate, optimize, navigate. This resulted inevitably with AI technology application in science, technology, banking, marketing and entertainment to facilitate and fasten large amount of operational and communication processes and bring the quality of computer-human interaction to a new level.

That way, conversational technologies also made a shift from programed responses and prescribed conversations to intelligent, dynamic and non-linear conversations based on large amounts of data continuously collected and processed. Thanks to the ability of AI powered conversational technologies to know, remember and learn the meanings of many words and understand them in many combinations, to understand the context, intentions of the interlocutor and to learn his behavior and preferences, AI powered conversational technologies have become a promising tool for a variety e-commerce platforms, where the communication between machine and human got the opportunity to become more effective and goal achieving for both - customers and business.

Natural Language Processing (NLP) technologies appeared at the intersection of linguistics and computer science, starting from a revolution in linguistic concepts based on the sentence structure by Chomsky (1957). This concepts formed the basis for teaching machines to understand human language. NLP technologies attempted to close the gap between human and computer communication by providing computers the ability to convert instructions from human`s natural language in both written and spoken forms to computer language and then to return the information again in natural language after processing. Even if natural language processing technology is still in its infancy, it`s modern capabilities allow its successful application in search engines to provide relevant results faster, as well as in academic, research, or healthcare settings NLP technologies have become indispensable to quickly process text and extract the most important information with text summarization or topic modeling feature. The NLP ability of text analysis on the sentiments, intention, urgency was recognised by businesses, marketers and market researchers as essential in order to sort a large amount of unstructured data from any variety of text or customer communication and understand the nuances and emotions in human voices and text, giving organizations valuable insights.

Natural language understanding(NLU) is just that algorithm that converts the unstructured data provided by the user to structured or meaningful information. Text entity extraction also known as **Named Entity Extraction (NER)** is that technique that is used to add structure to text by labeling its elements with certain meanings. During voice recognition process, the system should have an implemented **Acoustic Model (AM)** trained from a speech database and a **Linguistic Model (LM)** that determines the possible sequence of words/sentences. Speech-based conversational AI have to be able to distinguish between different accents, voice rates and pitches as well as abstract from any ambient sounds. After this, audio segmentation steps in to divide it into short consistent pieces that are later converted into text. “The software breaks your speech down into tiny, recognizable parts called phonemes — there are only 44 of them in the English language. It's the order, combination and context of these phonemes that allows the sophisticated audio analysis software to figure out what exactly you're saying. For words that are pronounced the same way, such as eight and ate, the software analyzes the context and syntax of the sentence to figure out the best text match for the word you spoke. In its database, the software then matches the analyzed words with the text that best matches the words you spoke,"Scienceline says.

Natural Language Generation (NLG) mechanism in its turn after understanding the input and proceeding the information recieved, generates output in natural languages text or speech that humans can understand.

Dialog management systems (DMS) are another NLP components responsible for interpreting and contextualizing human-like conversations that become important in context of dialog between chatbots or any voice assistants with any live users. Context and state awareness provided with DMS make possible a fluid conversation without unnatural for human repetitions. The state depends on the information collected before while the follow-up actions depend on the context. Jain et al. (2018) illustrate the state as intent and entities - goal and its variables. For example, if the user says: "I want to order Coca- Cola," the intent is to order a drink and the entity is Coca-Cola. The chatbot answers: "Ok, anything else?" whereas the user replies: "Make it large and add ice." Thus, the context is still ordering the drink, while large and add ice can be related to Coca-Cola. Without the context, large and add ice are new entities without intent. NLP technologies development have brought unique opportunities for conversational technologies to deliver a communication with a high level of accuracy in understanding and responding in both voice and text formats that allowed to improve the entire user experience by providing close to natural, habitual for human communication format. These opportunities have found a use in e-commerce, intended to bring limited in some ways e-commerce experience closer to engaging and immersive in store experience.

Combinations of these core algorithms that were mentioned briefly with variations of their numerous components such as **Automatic Semantic Understanding(ASU)** mechanisms, **Text Analysis(TA)**, **Speech-to-text**, **Text-To-Speech (TTS)**, **Value extraction**, **Computer Vision** and etc. have brought to market a wide range of AI conversational applications that are considered now as a powerful business tool affordable for e-commerce. Since this research does not pursue a goal to study deeply the technical characteristics, but only clarify crucial distinctions in the principles of work of different types of AI conversational applications, exploring the cases of their successful application in e-commerce, we will not study here all the components in details. And instead, with understanding of presence of different components, will explore more closely the typology of AI conversational applications available on the market in following chapters.

1.3 Chronology and milestones of AI Conversational applications development

So It was Alan Turing who in 1950 raised the bar with the test named after him Turing test. The test aimed to determine the degree of intelligence or human-likeness of conversational application. The concept of Turing Test is quite simple: if a machine can hold a conversation in written form in a limited time period with a human being that is indistinguishable from a conversation with another human, then the machine can be said to be intelligent. Though, the universality and reliability of Turing test has come under criticism from time to time for instance by Hugh Loebner, who created another extended version of Turing test and in 1990 set an annual competition in artificial intelligence, the Turing test remains the most widely used method for testing artificial intelligence. It also remains an important indicator of the level of perfection of the conversational technology that human is able to accept and could trust. On the one hand, this aspect seems to be important regarding the objectives of the particular research. Since the conversational application that is human-like could potentially win more trust and loyalty from the clients side and excel in their experience improvement more efficiently. As the degree of trust a conversational application gains from its use depends on factors related to its behavior, appearance, privacy protection, the level of likeness of human, its personality, its efficiency to handle human language
[6] and its emotional awareness(Adamopoulou, Moussiades, 2020). But on the other hand for now there are only single cases in history of any conversational application`s successful passing the Turing test with a numerous cases of successful and beneficial implementations of the conversational AI applications in business, that will be described in a current research. This fact is illustrative to give a statement that weighted and accurate application of the available technologies matter, rather than its perfection from the point of view of resemblance to humans. This concept could be supported by Cathy Pearl, Google’s Head of Conversation Design

Outreach as she mentioned in one of the interviews :“ [...] AI is this buzzword and everybody thinks you have to have AI to have a successful conversational system, which [...] is certainly something to strive for [...] But I think some people forget that you can have a very effective, important conversational systems without a lot of AI.” (Crowley 2019).

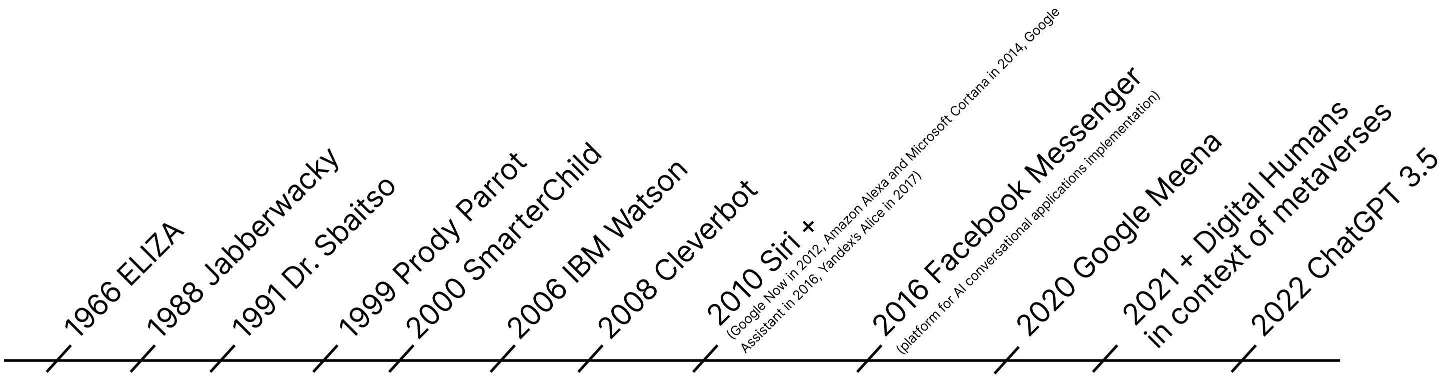


Fig.1 Chronology and milestones in field of AI conversational applications development remarkable for this particular research

The first milestone in the history of conversational applications bears no relation to AI but is really instructive to illustrate the successful implementation of the right technology to the right field and industry, drawing on the final users specifics and particular needs. It is also an iconic example in computer science which gave the name to a well known AI phenomenon called Eliza Effect - the tendency to unconsciously assume computer behaviors are analogous to human behaviors or tendency to “project own complexity onto the undeserving object” (1997: Trust and
[7] Decision Making in Turing's Imitation Game)

The rule based chatbot called **ELIZA** was constructed in the Artificial Intelligence Laboratory of MIT, between 1964-1966. The script that powered ELIZA was relatively simple and was using one of the several rules and early NLP mechanisms. The algorithms of ELIZA were able to simulate a psychotherapist’s operation, returning written user’s inputs - sentences in the
[8] interrogative form Weizenbaum (1966). It was not able to understand real intends of the users. However, the simple mechanism of “mirroring” allowed to create an illusion of empathy, and understanding which are essential in this type of therapy and allowed to enhance the real trust and loyalty from the users side. Thus ELIZA`s ability to communicate was limited, the tests results were astounding. People during the experiment started to

anthropomorphised ELIZA and attributed human feelings to the machine. Some even got attached to it and refused to believe it was a machine developing increasingly intimate relations with her. The case of ELIZA is instructive for understanding any technology orientation on serving particular needs of the user. And it was a source of inspiration for the further
[9] development of other conversational applications (Klopfenstein et al., 2017).

Artificial Intelligence was firstly used in the domain of the conversational applications with the construction of **Jabberwacky** in 1988 which has become an important step to further technological growth. Created by British programmer Rollo Carpenter, it attempted to simulate natural human conversations in an entertaining, interesting and humorous manner, using the AI technique called ‘contextual pattern matching’ and mechanisms of dynamic learning. Every time a user is writing something to Jabberwacky, Jabberwacky learns it and then tries to match it with something a user and previous users have said before. It has no simple programmed tricks used by other bots, and does not use keyword match. Jabberwacky doesn’t really work with words themselves. Instead a central string similarity algorithm compares whole lines with each other – millions of times over for every reply it gives. Existor.com consider from the user’s side of the conversation to be nearly 100% reliable. In other words, given the context of all the previous lines, the user’s response to that context is almost always a reliable human response, though they can make no claims for its intelligence. The same could be attributed to the bot. The purpose of the Jabberwacky it was created for was entertaining and passing the Turing Test. Thus the only function of this chatbot was mimic human conversations and nothing more. Carpenter imagined Jabberwacky as an entertainer and a companion. It can be made a part of smart objects around the house, like robot pets, but not a smart assistant solving the problems. However Jabberwacky was released on the internet only in 1997. Carpenter went on to create a number of different personalities, or avatars, for Jabberwacky such as George, Joan, and others. The George chatbot appeared in 2003 and in 2005 it won the Loebner Prize.

The updated female version of the George, Joan was launched in 2005 and went on to win the Loebner prize in 2006. The new version was taught to answer questions about herself, the technology behind her and she was having much more full database of conversational interactions.
In 2008 Jabberwacky was transformed to **Cleverbot** that powers now the

popular websites like Cleverbot, Evie and Boibot. Cleverbot is now available for conversation online and in the form of mobile applications available on Android Play Store and Apple App Store. Since starting to learn online in 1997 Cleverbot has had 7 or 8 billion total interactions(2015). It speaks many languages, in countless styles and on every possible topic. Cleverbot data is considered now as the largest source of machine-human conversational interaction available anywhere and the entire experience starting from 1988 has brought a valuable insights for all the conversational AI software industry.

Dr. Sbaitso (Sound Blaster Artificial Intelligent Text to Speech Operator) is meaningful to mention considering the first attempts to voice-based conversational technologies development and Dr. Sbaitso became the first chatbot that utilized text-to-speech functioning. However it was not really a chatbot as we understand them now. Creative Labs, the developers of Dr. Sbaitso, were the leading sound card manufacturer of the time, and they released Dr. Sbaitso at the end of 1991 along with their latest product to demonstrate the sound production capabilities of Creative Labs' sound cards. Dr. Sbaitso was able to converse with the users like a psychologist, but only in rudimentary manner. Instead of problem solving or at least replying intelligently to the user, most of the time, Dr. Sbaitso used the same reply, " Why do you feel that way?" And if he didn't understand the the input, he replied with, "That's not my problem". One of the best abilities of the program it was designed for was an ability to pronounce a written sentence if the user added the word "say" at the start of a sentence. It was a weird digitized voice that sounded not at all human, however did a remarkable job of speaking with correct inflection and grammar.

Later in 1999 Dr. Sbaitso was improved by Creative Labs and a version of the program for Windows 95, Windows 98, and Windows ME known as **Prody Parrot** emerged. It was presented in a parrot avatar that flew around the screen of a computer and offered its services when it felt the user needed them. Prody Parrot could be considered as the Microsoft's first attempt at anything resembling a true chatbot and virtual assistant. As it was an application that combined advanced artificial intelligence technologies and natural language processing technologies in order to help PC users to perform their work tasks such as navigate the web, manage their schedule and mailbox, reach out to different applications and also to entertain in between with games and prompted conversations. The application was so good that has gone beyond the working spaces and began to users to perform their work tasks such as navigate the web, manage their schedule and mailbox, reach out to different applications and also to entertain in between with games and prompted conversations. The application was so good that has gone beyond the working spaces and began to be used on personal computers as well. Users were able to access the parrot by clicking on it, using a keyboard shortcut, hot word input, or using voice commands. Moreover, the advanced at this time voice activating mechanisms were not the only novelties. Machine learning technologies allowed to introduce the users unique opportunities for personalisation with mouse gesture recognition - that enabled users to teach the assistant what kind of gesture should represent a command. Thus, Prody Parrot could learn new skills according to the user`s needs, as well as obtain knowledges from the Internet. Through speech recognition and speech synthesis technology, Prody Parrot could understand spoken commands and responses, and respond using natural language. However, both Prody Parrot and Dr. Sbaitso were discontinued by Microsoft after 2004.

In 2000, there was a breakthrough in conversational AI applications development with ActiveBuddy, Inc. release of **SmarterChild**, which was available on Messengers like America Online (AOL), Microsoft (MSN) and Yahoo Messenger. The concept for conversational instant messaging bots was new with added written natural language comprehension functionality to the increasingly popular instant messaging applications. It could be considered as a cross between a chatbot and an early Virtual Assistant that was able to help people with their daily tasks as it could pick up information from databases about movie times, sports scores, stock prices, news, and weather, as well as various tools like personal assistant, translator, calculators, etc. Later the application was positioned as first in history automated customer service agents for large companies and the SmarterChild chatbot got a lot of popularity in the targeted market. It had a lineup of marketing-oriented bots for firms like Radiohead, Austin Powers, Keebler, The Sporting News, Intel, and many more. A concept of natural language processing being incorporated into an AIM instant messaging application with the abilities mentioned above have brought a significant development in both the machine intelligence and human–computer interaction trajectories as information systems could be accessed through discussion with a chatbot.

The next phase of revolution started with **IBM Watson** release that forced the next generation of AI conversational applications that began to interact with users through speech only. Originally, IBM Watson was a computer program that combined artificial intelligence (AI) and sophisticated analytical software for optimal performance as a "question answering" machine. In comparison with all previous technologies it was doing a remarkable job of understanding a tricky question and finding the best answer. This result was obtained thanks to a completely different approach. The IBM developers didn`t intend to simulate the human`s way of thinking as all the other developers did. According to David Ferrucci, the IBM researcher “The goal was to build a computer that can be more effective in understanding and interacting in natural language, but not necessarily the same way humans do it.” As search engines of the computers don’t answer a question–they only compare and match keywords and deliver the search results as an answer. While the exact answer is not likely to be written somewhere, but involves pieces of information from different sources put together. Watson algorithms were able to analyse the question in different ways and find many different possible answers that were ranked than with a score according the number of evidences that may support or refute that answer. The highest-ranking answer becomes the answer. This approach allowed the program to understand difficult for the machines subtlety, puns and wordplay in questions that allowed it to beat all current AI conversational technologies in more accurate understanding of natural human language. Healthcare was one of the first industries to which Watson technology was applied. The first commercial implementation of Watson came in 2013 when the Memorial Sloan Kettering Cancer Center began to use the system to recommend treatment options for patients. Years later, Watson enabled businesses to create better virtual assistants. However, a drawback of Watson is that it supports only English.

Next logical step to make for the development of AI conversational applications was creation of personal smart voice assistants, which could enter every house, understand voice commands, respond by digital voices, and handle routine tasks like monitoring home automated devices, calendars, email and other. What is more with the rapid development of smartphones after the first decade of 21st century, Conversational AI assistants got a chance to become portable and attendant.
Released in 2010 after the first iPhone(2007), **Siri** pioneered the way for personal AI conversational assistants employing both voice and textual

interaction modalities. It could be powered as an app of iOS on smartphone with just voice command and was able to respond to user`s requests with real human voice while providing relevant recommendations, based on users searches and desires learned from previous interactions. This became possible thanks to NLP software that was using the AI subsets of machine and deep learning, along with large datasets of real human voices, to make the system recognize the complexities of tone, accent, and intent in human language. However, the system was not without weaknesses. There were many languages that Siri didn`t support, it was having difficulties hearing
[10] the interlocutor, who had a heavy accent or in the presence of noise (Soffar, 2019). Also the first version of Siri and all the further versions where requiring an internet connection to perform even non-Internet requests right up to 2022 when iOS 15 was released. But being able to interpret efficiently human language and support this way user`s daily tasks was a major steppingstone in the development of effective personal digital assistants for consumer use. And following this direction another applications with the same core functions were continuously appearing and still appear on the market. Google Now in 2012, Amazon Alexa and Microsoft Cortana in 2014, Google Assistant in 2016, Yandex's Alice and Samsung Bixby in 2017, are the most popular among them. Furthermore, the systems that power AI conversational applications listed above, provide the technical basis for many other stand-alone applications and are implementing both for personal use in smartphones, smart home devices and car smart systems, and also in customer service in fields of marketing, education, healthcare, entertainment and etc.

Another revolution that should be mentioned occurred not only in technological field but also in the field of culture. With first early signs in 1980th, Instant massagers` and later Social media platforms` rapid expansion during the beginning of 2000th have changed forever the way people interact with each other and opened up new ways for conversational AI development. The opportunity to catch the attention of the audience, strengthen relations with them and provide relevant services through these touchpoints could not be missed by companies in spheres of marketing, services, entertainment, education and etc. Businesses have started to require developers to create chatbots for their brand or service to enable customers to perform specific daily actions within these platforms and applications.

In 2016 **Facebook** launched a **messenger** platform which allowed developers to create conversational bots that were able to interact with Facebook users. At the end of 2016, 34.000 chatbots covered a wide range of uses in wide range of industries. Being able to respond FAQs, recommend relevant products and provide unique services online 24/7, AI conversational applications are continuously forcing the customer experience to a new level.

Recently in 2020, Google has launched the most state-of the-art AI text-based chatbot called **Meena**, a 2.6 billion parameter end-to-end trained neural conversational model. What is noteworthy, Meena can hold sensible conversations that are more specific than existing best-performing chatbots
[11] (Adiwardana et al. 2020). Since, all current open-domain chatbots, according Google researches, have a critical flaw — they often don't make sense. And sometimes say things that are inconsistent with what has been said so far, or lack common sense and basic knowledge about the world. Moreover, chatbots often give responses that are not specific to the current context. For example, "I don't know," is a sensible response to any question, but it's not specific. Current chatbots do this much more often than people because it covers many possible user inputs. Meena showed the great 79% in Sensibleness and Specificity Average (SSA), metric specially designed by Google researchers for human evaluation. In comparison Cleverbot showed 56% and 86% showed human. And this success could be considered as only first step of Meena to the wide market.

By the way, the evolution of the internet still leads to opening new directions for AI conversational applications development. Though we are now at the very beginning of the global transformations, the emerging tendency already has shaken the industry of AI conversational applications development. The **concept of Metaverse and "digital humans"** is not totally new as the first time the term "metaverse" appeared in author Neal Stephenson's 1992 science-fiction novel Snowcrash which describes a future where millions of people use virtual avatars to participate in a cyberspace realm. Later the concept of network of shared, immersive virtual worlds where people can connect with each other, create and play games, travel and attend virtual events was developing on the cross of science-fiction, video games and video simulators. But 2021 could be mentioned as the year when the idea of metaverse blew the minds of larger public after the Facebook's rebrand to Meta and the concept of their Metaverse announcement. And according GARTNER By 2026, 25% of people will spend at least one hour a day in the metaverse for work, shopping, education, social and/ or entertainment(2022). Hence, many companies also started a series of initiatives to promote this technology and to be the first to occupy the new virtual reality spaces, meeting their audience there. For instance there already could be found Zara, the textile giant that has chosen Zepeto as the metaverse to launch its first collection of virtual garments. It is a South Korean metaverse for smartphones, with 3D avatars and more than 2 million daily users, which has made it one of the fastest-growing virtual environments. Zara has launched a collection that is also sold in selected stores in the real world. But it is not the only company joining the virtual fashion boom, as Dolce & Gabbana, Gucci, Adidas, or Nike are already reinventing their lines in metaverses. Since this metaverse allows the purchase of digital and also physical items through its own currency and provides interaction with millions of users around the world, the metaverse inevitably would need virtual assistants. Considering the current opportunities of AI conversational technologies some of the experts predict that in the nearest future advanced speech based AI conversational technology would just be the tip of the iceberg in terms of communicative capabilities of these conversational applications that could be considered more like “digital humans”. Naturally interacting virtual characters with human facial expressions, body language, emotions, and physical interactions in addition to speaking would deliver more compelling digital experiences for users inside metaverse.

The development of the new AI conversational technologies and approaches is rapidly evolving. In the days when this particular work is processing, a new AI technology by Open AI is blowing the participial community and wide public. A new Chatbot is called **ChatGPT** (Chat Generative Pre-trained Transformer) and it is able to answer follow-up questions, admit its mistakes, challenge incorrect
[12] premises, and reject inappropriate requests. According to Shanahan(2022) the advent of large language models (LLMs) such as Bert and GPT2 was a game-changer for artificial intelligence. Artificial intelligence and machine learning experts like Ali Chaudhry from Oxylabs speak about LLM as technology that will define AI. ChatGPT3 is a chatbot built on top of OpenAI's GPT-3 family of large language models and is fine-tuned with both supervised and reinforcement learning techniques. What sets LLM apart is its scale, with a training set size of hundreds of billions of parameters, as well as training on hundreds of terabytes of textual data, such as pages of material in a particular language. As a result, these networks are sensitive to contextual relationships between the elements of that language (words, phrases, etc). Search Engine

Journal reports that GPT-3.5 was trained on massive amounts of data like information from the internet, including sources like Reddit discussions, to help ChatGPT learn dialogue and attain a human style of responding. ChatGPT was also trained using human feedback. This technique is called Reinforcement Learning with Human Feedback, so that the AI learned what humans expected when they asked a question. Training the LLM this way is revolutionary because it goes beyond simply training the LLM to predict the next word. ChatGPT3 is an open source and many users have already awed at its ability to provide human-quality responses, inspiring the feeling that it may eventually have the power to disrupt how humans interact with computers and change how information is retrieved. While some of the technologies mentioned seems like a perspective for now, at this moment there are already numerous available AI conversational solutions on the market ready to serve any specific purpose of different industries. As was discovered above, over the last 30 years, the AI conversational applications field has become so dynamically developing thanks to new opportunities arising from arrivals to the market of technical innovations and new approaches. And nowadays the exact boundaries of a particular type of AI conversational application has become quite subjective due to its specific technical characteristics that could bring closer one type to another blurring these boundaries. Moreover on public resources on the Internet there is a plenty of different terms referring sometimes to the same type and sometimes to different types of applications with different capabilities that leads to confusion. Regarding the objectives of this research a subgoal should be mentioned. As the main goal requires to define and differentiate properly the typology of AI conversational applications available on the market to explore the potentiality of each type implementation in e-commerce in order to improve customer experience. For this reason in next chapter a methodology applied to this research will be described in details.

2. Methodology for analyzing the potential of application available on the market AI conversational systems in e-commerce to enhance CX.

2.1.Research sub goal

As was discovered in previous chapters, the rapid development of AI conversational technologies and new approaches to this technologies immediate implementation to different industries evokes on public readily accessible sources online a large amount of hype around with predictions and guesses considering the potential of the particular technology or system adoption in other industries. The amount of academic studies researches and tests conducted is significantly inferior to them also in speed of appearance to a wide audience. Moreover a numerous different terms that are used on public and also scientific sources online regarding the particular type of conversational system and its capabilities considering the potential of application in any industry or business, creates a blurry picture of the real situation in this context. **Conversational agents, chatbots, intelligent or interactive agents, digital or virtual assistants, artificial conversational entities, voice assistants, voice bots, intelligent or smart voice assistants are only a part of the most commonly used terms that in many cases essentially does not determine the affiliation to a particular type of conversational AI system. And, therefore, fails to provide reliable and accurate information on opportunities and potential of its application.** This
[13] common confusion in terms was noted by some other researches(MOTGER et al.,2021)

Moreover, if to consider e-commerce industry **a lack of systematic approaches to AI conversational systems application in order to enhance customer experience could be mentioned.** According a systematic literature review that was focused specifically on parameters influencing AI
[14] conversational agents usage in e-commerce(Alnefaie et al., 2021) as a determining criteria forming the typology was outlined the style of interaction. And two types of AI **conversational models** were divided based on this criteria: text-based and voice-based. The majority of examined in this work studies (23 of 24) were focused on text-based models due to their popularity in the e-commerce and marketing discipline. At the same time, another approaches while forming the typology of conversational applications could be considered in other scientific papers. For instance, in conference paper “An Overview of Chatbot Technology” published online in 2020 as part of IFIP International Conference on Artificial Intelligence Applications and Innovations, chatbots were classified using following parameters: the knowledge domain(open domain and closed domain models), the service provided

(interpersonal, intrapersonal, inter-agent models), the goals(informative, chat based/conversational, task-based models), the input processing and response generation method(rule-based, retrieval-based, generative models), the amount of human-aid, and the build method(open-source platforms, closed platforms). **It's obvious that any particular conversational application does not exclusively belong to only one or another type of model, but always joins in the system several models in varying proportions. However, the taxonomy properly defined will allow us to examine more precisely any possible conversational system, exploring separately its every particular component - the conversational model and its capabilities regarding enhancing customer experience.** This way, while approaching to exploration the AI conversational applications` wide market and the potential of these type of systems application in ecommerce in order to enhance customer experience, a sub goal should be set. In particular, **framing a typology of all modern AI conversational applications available on the market based on their core parameters singled out by recent researchers, but what is more, selected and marked as relevant specifically for customer experience in e-commerce.** In the borders of this kind of typology the possibility to analyze the wide market of AI conversational systems through each system`s components - models, becomes more feasible to reach this research's objective, which is **exploring the potential of AI conversational systems applications in e-commerce to enhance customer experience.**

2.2.Procedure of the research

The first phase of research was based on available academic papers published online between 2018-2023, and involved an exploration of all available typologies and classifications of AI conversational applications with focus on principal parameters that allowed their grouping by type. This period was chosen in order not to repeat previous work done by other researches, and to give an up-to-date version of AI conversational applications evaluation methods. At the same time all these parameters were reviewed from the perspective of their relevance in the context of e-commerce and customer experience. The review aimed to reveal parameters that essentially affect capabilities of one or another type of conversational models in context of its implementation in e-commerce for enhancing customer experience. The opportunity to influence directly the customer experience was affirmed or disproved by numerous previous researches in fields of technology, computer-human interaction, customer relationships management and customer experience conducted and published online between 2018-2023 and available to public access on Google Scholar. **After that a new typology, based on set of relevant for customer experience in ecommerce principal parameters of AI conversational applications was proposed. These parameters allowed to define of a range of AI conversational models that in a variety of combinations specify any type of modern AI conversational system available on the market for exploitation in e-commerce.**

This way, in the following phase of the research this primary typology was considered as a basis or guideline for further close investigation of every particular conversational model type as a component of AI conversational system. The following research questions were stated on this phase:
RQ1 What are the general **benefits and drawbacks** of each of the **model**(for designers, developers, stakeholders and final users)**,** considering its implementation in a conversational system in e-commerce to enhance customer experience?
RQ2 What are **another factors or attributes** of each of the model that have to be considered by designers while implementing any particular model in a conversational system to enhance customer experience in e-commerce?
RQ3 What is the **potential of each of the model considered as a part of conversational system** implemented in ecommerce field in order to strengthen customer experience?
The results of this investigation aimed to guide designers and stakeholders by pointing on attributes of each of the model that have to be considered while implementing AI conversational system in e-commerce.

3. Exploration of all available typologies and classifications of AI conversational applications with focus on principal parameters relevant for customer experience.

The typology implies a system used for putting things into groups according to how they are similar. In other words, typology is the study of how things can be divided into different types(acc. The Britannica Dictionary). This part of the research aimed to discover the criteria able to divide all available AI conversational systems into types of conversational models each of which affects customer experience to a certain extent. The criteria were discovered while examining the general featured characteristics of modern AI conversational systems mentioned in academic papers. Though the specifics of each ecommerce industry could make adjustments to the degree of effect on customer experience, this investigation of the capabilities of different conversational models in the context of e-commerce will provide a conceptual framework for understanding how to approach any conversational system implementation.

3.1. Types of Chatbots according Adamopoulou & Moussiades(2020)

As was already mentioned in previous chapter, one of the broadest typology based on featured characteristics that determine principles of work of modern AI conversational systems(in particular AI chatbots), was provided by
[6] Adamopoulou & Moussiades as a part of IFIP International Conference on Artificial Intelligence Applications and Innovations(2020). It involves the following criteria: **the knowledge domain, the service provided, the goals, the input processing and response generation method, the amount of human-aid, and the build method.(Fig 2.)**

According this paper, typology based on the criteria of **knowledge domain** considered the knowledge that AI conversational application can access or the amount of data it is trained upon. In this context **open domain applications** obtain the ability to talk about general topics and respond appropriately, while **closed domain applications** are focused on a particular knowledge domain where they can show incredible awareness and at the same time fail to respond to general questions. This distinction should be mentioned as a key parameter determining the field of these types` potential of implementation in ecommerce for customers experience. Thus, some of the academic papers mention close domain type of applications as the only proven option in the field of customer experience in e-commerce as it will be able to consult

Exploration of available typologies and classifications

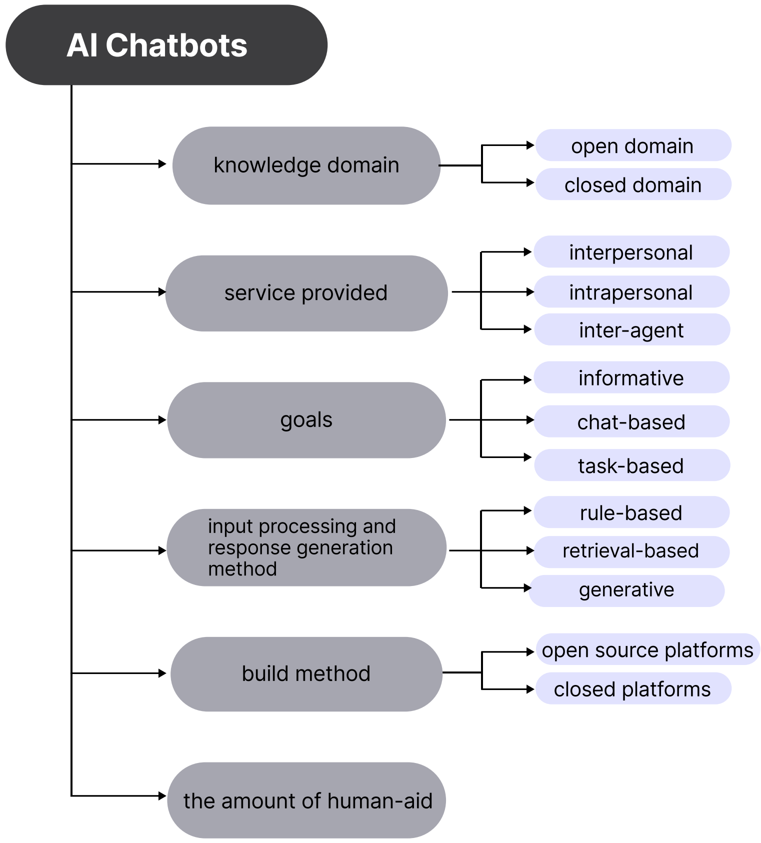


Fig.2 Typology of AI Chatbots according "An Overview of Chatbot Technology" published online in 2020 as part of IFIP International Conference on Artificial Intelligence Applications and Innovations

[15] customers in a specific area required by any particular business(Skrebeca et al., 2021), another researches do not exclude the opportunity of open domain [16] types in context of emerging conversational commerce.(Lim et al.,2022). The opportunities of both types for customer experience will be explored more precisely in next chapters.

The same general classification based on the **service provided** (Fig 2.) considered the sentimental proximity of the chatbot to the user, the amount of intimate interaction that takes place, and it is also dependent upon the task the chatbot is performing. As described in "An Overview of Chatbot Technology", **interpersonal** chatbots lie in the domain of communication and provide services such as Restaurant booking, Flight booking, and FAQ bots. They are not companions of the user, but they get information and pass them on to the user. They can have a personality, can be friendly, and will probably remember information about the user, but they are not obliged or expected to do so. **Intrapersonal** chatbots exist within the personal domain of the user, such as chat apps like Messenger, Slack, and WhatsApp. Managing calendar, storing the user's opinion etc. They are companions to the user and understand the user like a human does. **Inter-agent** chatbots become omnipresent while all chatbots will require some inter-chatbot communication possibilities. While a

bot cannot be completely inter-agent bot, but it can be a service that handles other bots or handles communication making it easier for developers and users to integrate different services in the conversational ecosystem. The need for protocols for inter-chatbot communication has already emerged. Alexa-Cortana integration is an example of inter-agent communication.
The potential of these types of AI conversational applications in ecommerce
[17] was studied in a wide range of works. For instance, Muangkammuen et al. (2018) proposed and explored a potential of interpersonal chatbot for e-commerce that automatically responds to FAQs by customers. The results of tests showed that the chatbot could process 86.36% of questions with 93.2% accuracy of correct answers.

[18] In another recent research (Illescas-Manzano et al., 2021) the approaches to implementation of Chatbot in e-commerce are studied from the perspective of AI conversational applications embodiment to social media channels such as Facebook Messenger service that allow to consider this type of applications as an intrapersonal type, relevant for e-commerce. Both these types` potential in context of e-commerce should be explored deeper in next chapters. Relevance of the inter-agent type could be considered in context of voice commerce that was studied regarding the concept of shopping-related voice assistants also
[19] by Alex Mari(2019). And numerous available successful and also failed cases emphasize the need of this type`s potential more close study.

General classification based on the **goals**(Fig 2) considers the primary goal chatbots aim to achieve. According to the paper provided by IFIP International Conference on Artificial Intelligence Applications and Innovationst, **informative** chatbots are designed to provide the user with information that is stored beforehand or is available from a fixed source, like FAQ chatbots. **Chat-based/ Conversational** chatbots talk to the user, like another human being, and their goal is to respond correctly to the sentence they have been given. **Task-based** chatbots perform a specific task such as booking a flight. At the same time, restaurant booking bots and FAQ chatbots are considered in the paper as examples of task-based chatbots, that blurs the borders of three types mentioned. Instead Motger et al. (2021)(Fig4.) present two major categories for
[13] classifying conversational agents based on their goals: **task-oriented** and **non-task-oriented**. Task-oriented agents are defined as short-conversation agents designed to execute a particular action from a known sub-set of pre-configured tasks triggered by the conversational process. An online shopping

chatbot designed to assist users in their shopping process searching products and solving order-related questions is an example of a task-oriented agent. Non-task-oriented agents aim to simulate a human-conversational process without a specific task or action as the main goal of the user interaction with the agent. Leisure or entertainment agents like Cleverbot fall into this category. While **conversational** agents match the definition of non-task-oriented, **informative** agents are defined as a type of non-task-oriented agents which do not pursue a specific activity or task to be executed, but the interaction and the conversational process has the purpose of collecting information. Q&A and service support chatbots fall into this category.

[20] This is classification provided first by Hussain et al.(2019) (Fig 3.).Based on goals, division involve: **task-oriented** and **Non-task-oriented** chatbots. According the paper, task-oriented chatbots are designed for a particular task and are set up to have short conversations, usually within a closed domain. Unlike task-oriented chatbots, non-task oriented chatbots can simulate a conversation with a person and seem to perform chit-chat for entertainment purpose in open domains. Non-task-oriented applications could be also considered as **Social** as was done in one of the topic related researches [21] (Chattaramana et al., 2018). In this particular research the potential of both task-oriented and social types of AI conversational applications in context of ecommerce were explored with focus on a particular target group - elderly(61-89 years). Social or non-task oriented goals in this case were implying informal and casual conversations that foster an exchange of social-emotional and affective information. They involved interactions such as customary greetings, small talk, emotional support, and positive expressions to achieve socioemotional goals. The results have not been conclusive, however allow to consider both types task-oriented and non-task-oriented(social) as relevant regarding the purpose of this particular research.

General classification based on the **input processing and response generation method** according to the paper provided by IFIP International Conference on Artificial Intelligence Applications and Innovations, implies three models used for conversational applications to produce the appropriate responses: **rule-based model, retrieval-based model, and generative model(Fig 2).** According to this paper, rule-based chatbot is a model that most of the first chatbots have been built with. The mechanisms choose the system response based on a fixed predefined set of rules, based on recognizing the lexical form of the input text without creating any new text answers. The

knowledge used in this chatbot type is humanly hand-coded and is organized
and presented with conversational patterns. A more comprehensive rule
database allows the chatbot to reply to more types of user input. However, this
type of model is not robust to spelling and grammatical mistakes in user input.
[13] This type could be also considered as deterministic(Motger et al., 2021) (Fig4.)
and doesn't imply the use of any AI components and hence is not relevant for
this particular research.

On the other hand, more recent strategies are exploring the potential of AI-
based strategies, which integrate the use of machine learning and deep
learning models to process user input and build output messages based on the
knowledge sources and training data. Mainly, there are two types of AI-based
[6] strategies: retrieval-based and generative-based. As defined by Adamopoulou
and Moussiades,(2020) retrieval-based systems use Machine Learning and
Deep Learning models and techniques to predict the most accurate response
from a closed set of responses using an output ranked list of possible answers.
On the other hand, generative-based systems focus on using Deep Learning
models to synthesize and build the reply to a specific user input, rather than
selecting it from a closed data-set of responses. These chatbots are more
[13] human-like, however, there are difficulties in building and training them(Motger
et al.,2021).

Some of the ample opportunities of retrieval-based systems in the field of
[22] ecommerce were studied in the following works by Majumder et al.(2018), or
[23] by Vakili Tahami et al.(2020) in context of its potential implementation in
customer support.

The implementation of generative models in context of ecommerce was
considered as quite challenging a little while, first and foremost because of its
[24] complexity in comparison with retrieval models (Kusuma Wardhana et al.,
2021). However, with recent technological development, generative models
with its pronounced ability to perform with inference, personalization,
empathy, and knowledge, have become studied more from the perspective of
[25] its usage in customer support including ecommerce(Meng Chen et al. 2020).
The application potential of both retrieval-based and generative models will be
studied deeply in next chapters.

Another general classification for chatbots according “An Overview of Chatbot
Technology” considers the **amount of human-aid** in their components(Fig. 2).

[13] As Motger et al. describe, human aid depicts the degree of autonomy in which
the conversational agent can be handled, whether it is designed as a **human-**
[6] **mediated** or an **autonomous agent**. As depicted by Adamopoulou and
Moussiades, human-mediated refers to agents which require from human
computation at some point in the conversational process to be
[26] operated(Kucherbaev et al., 2018). On the other hand, autonomous agents are
fully operated autonomously by users without human assistance in the loop.
The recent researches done in field of "hybrid Intelligence" that was defined by
[27] (Dellermann et al., 2019), as the ability to achieve complex goals by combining
human and artificial intelligence, thereby reaching superior results to those
each of them could have accomplished separately, and continuously improve
by learning from each other" reveal the strong potential of human-mediated
models implementation in business, ecommerce and customer experience. At
the same time a breakthrough in technologies allow to consider totally
autonomous systems as an equal player in the field of customer support
requiring, though, more detailed examination for instance considering the
[28] issues of service quality and trust(Trawniha et al., 2022).

Chatbots typology proposed in paper "An Overview of Chatbot Technology" assumes in addition the division according to chatbots **built method** or permissions provided by their development platform(Fig 2). Development platforms are considered in this case as an **open-source**, such as RASA, or can be of proprietary code such as development platforms typically offered by large companies such as Google or IBM. Open-source platforms provide the chatbot designer with the ability to intervene in most aspects of implementation. **Closed platforms**, typically act as black boxes, which may be a significant disadvantage depending on the project requirements. This criteria influence dramatically the process of development and training, that however has only indirect influence on customer experience that is finally affected by the level of accuracy of the model in understanding and producing natural speech while performing a task. Thus the chatbot built method as a formation parameter of the typology relevant for customer experience in ecommerce was not considered in this particular research.

3.2. Broad classification of Chatbots according Hussain et al.(2019)

Another research on conversational agents/chatbots general classification and
[20] design techniques conducted in 2019 by Hussain et al. (2019) among other
criteria already mentioned, pointed out one more important parameter relevant

for classification of modern AI conversational applications. Namely, its an **interact mode** that determines two principal types of AI conversational systems: **text-based and voice-based(Fig. 3).**

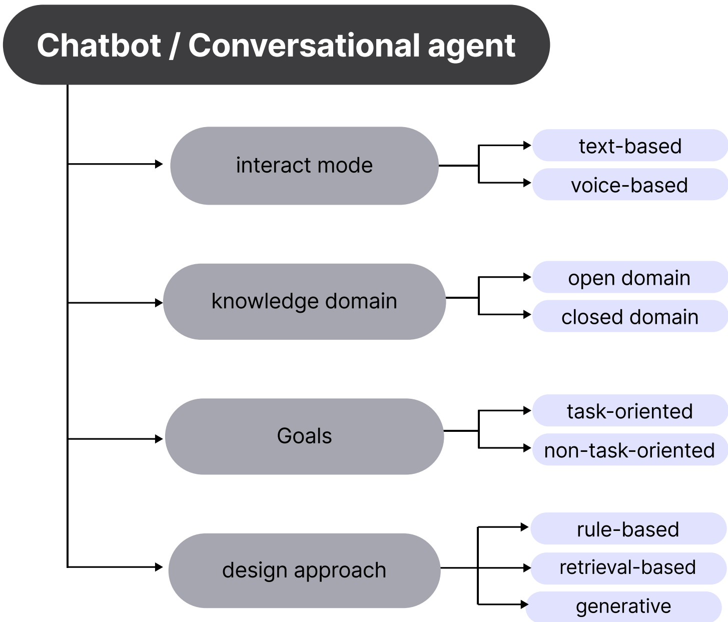


Fig.3 Broad classification of Chatbots according "A Survey on Conversational Agents/Chatbots Classification and Design Techniques" published online in 2019.

3.3. Conversational agents' design dimensions according Motger et al.(2021)

The same approach to classification by interact mode criteria was illustrated by Motger et al. in their "Conversational Agents in Software Engineering: Survey, Taxonomy and Challenges" published in 2021(Fig4.)**.** However, in this particular paper text-based and voice-based models are considered as subcategories of one of the types characterised by interact mode. And this type is based on general **natural language** processing mechanisms involving text or voice recognition or both of them. In addition, some studies introduce complementary interaction mediums to overcome the limitations of natural language using alternative data formats. For instance, Adamopoulou & Moussiades report **image** processing as a valuable mechanism for user interaction able to support and extend the limitations of natural language communication.

[13]

[6]

A numerous researches done in field of ecommerce, exploring for instance the

[29] consumers' trust and response to text-based chatbots (Cheng et al., 2022) or
the potential of text-based chatbots application to customers journey on the
[30] basis of Open Source platforms (Mamatha & Sudh, 2021) that prove the
interest and relevancy of text-based type of AI conversational applications for
ecommerce along with countless real cases of this category application in
different phases of customer journey. The particular opportunities will be
studied more precisely in the following chapter. As wel as voice-based models
[31] that are gaining popularity with raising voice shopping trend (Hu et al., 2022)
that reveal new opportunities for the customers but also new challenges like
gaining trust and development of such a trusted relationship that affect
[32] customers decisions in ecommerce(Mari & Algesheimer, 2021). Types of
applications that process both text and voice or also other alternative data
formats like images also find applications in ecommerce especially in beauty
sector. The proposal of the Chatbot that aims to recommend skin care
[33] products through Telegram chat Yi Kei (2021) is one of them.

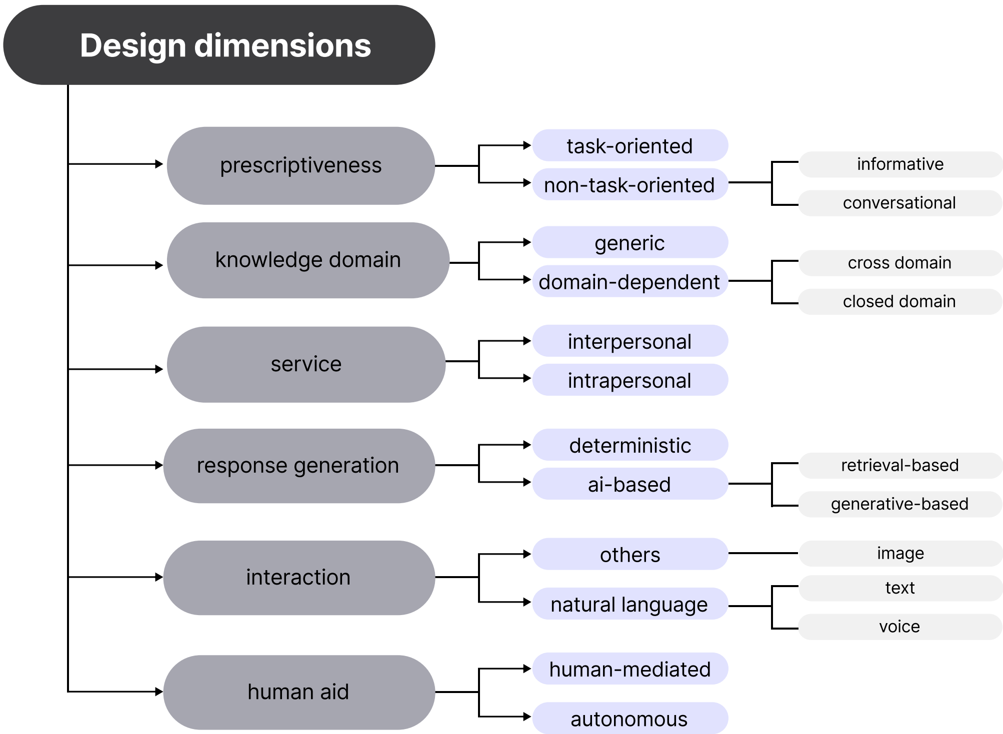


Fig.4 Broad classification of conversational agents according "Conversational Agents in Software Engineering: Survey, Taxonomy and Challenges" published in 2021.

3.4. Chatbot attributes according Wijaya & Sari(2021)

Beside general AI conversational applications classifications based on more technical approach that have been just reviewed, some recent studies in the field of customer relationship management pointed out another important parameters of conversational applications that proved to affect customer experience dramatically. For instance, the study of Heterogeneity in CRM in
[34] relation to chatbots (Wijaya & Sari (2021) suggested four basic attributes:

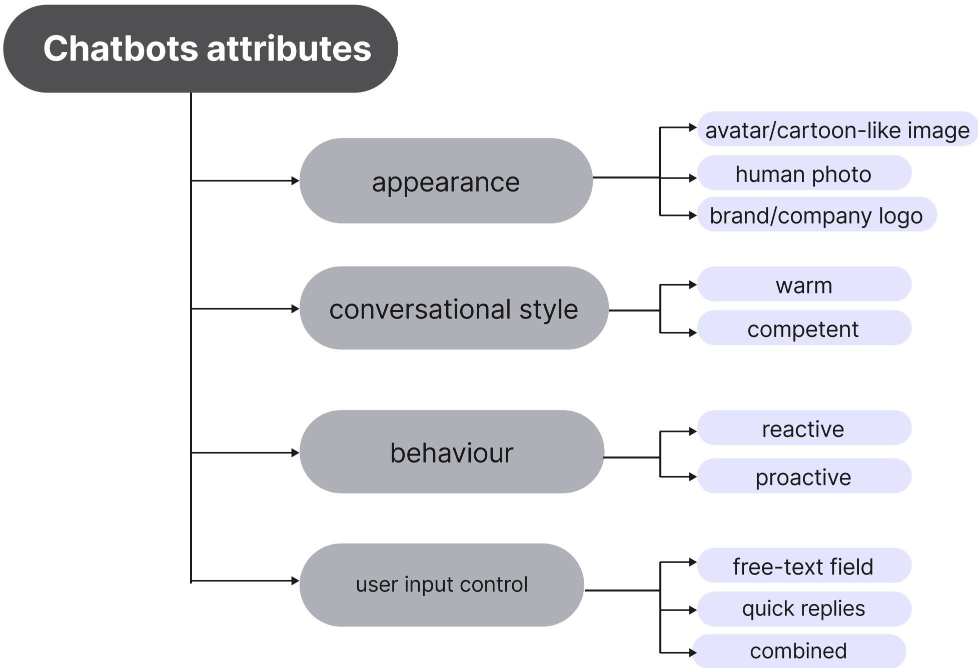


Fig.5 Typology based on chatbot attributes according the conference paper "Understanding Heterogeneity in CRM Chatbot User Preference" published in 2021.

appearance, conversation style, behavior and user input control. (Fig.5) that if considered as criteria, could form a typology relevant for objectives of this particular research. According Wijaya and Sari, chatbot **appearance** such as the use of avatar/cartoon-like image, human photo or brand/company logo and **conversational style** that was divided here in two types: warm style and competent style, with some descriptive variables such as demographics, personality and experience in using chatbot, influence the customer experience, in particular the level of customers` acceptance of conversational application. Moreover some early investigations showed an interaction between these two criteria. An example of a possible relation is the study of
[35] Mimoun et al.(2012). Their research explained that visual anthropomorphic characteristics can cause user`s false expectations and disappointment when

expectations of smart communication set by the anthropomorphic avatar are not met. However, more recent researches, that explored the chatbot acceptance in the context of customer service with focus on its appearance **(human avatar, robot avatar, logo)** and conversational style (**formal and informal)** (Raunio, 2021) noted some preferences from the user`s side, but these preferences did not show direct relation to their perceived ease of use, usefulness, helpfulness, competence, trust, or attitude towards using chatbots. Even though some studies in the field of online marketing proved the deployment of anthropomorphic chatbots to trigger favourable outcomes such as increased customer`s purchase intentions, willingness to reuse it and accept its recommendations (Sheehan, 2018),(Adam et al., 2020). Taking into account variable results directly dependent on the particular context, the criteria of appearance and conversational style will be studied more closely in this research in order to trace their possible impact on customer experience through real case studies in the following chapters.

[36]

[37],[38]

Another chatbots attribute mentioned by Wijaya and Sari(Fig.5) represents a chatbot **behaviour**. According the paper, chatbots could behave as **proactive** or **reactive** while interacting with user. In this context a proactive chatbot is programmed to take some initiatives in providing messages without being asked directly by the user. Meanwhile, reactive chatbots tend to deliver messages only based on what the user is asking or ordering.
Both approaches have been already studied considering its impact on users satisfaction by the customer service that chatbot provided(Følstad & Halvorsrud, 2020). According the research, on the one hand, proactive chatbots demonstrated their ability to provide relevant information to users, improving conversational efficiency, that led to a good impression of service. But on the other hand, a chatbot's proactive attitude could also give a bad impression in the cases when it was considered as disturbing for some people and intruding on one's privacy, thus proactive behavior should be designed with care. This way, the criteria of AI conversational application behaviour seems to be relevant to observe more precisely on the basis of real cases in next chapters.

[39],

The last chatbots attribute mentioned by Wijaya and Sari(Fig.5) is **user input control** that divide all modern AI conversational applications in tree categories. According the paper, users can enter messages through **free-text field** or **quick replies** or through a **combined method**.
The relevance of studying these methods in particular context of customer

experience was proved by some of the previous research, for instance Valério
[40] et al. (2020), who concluded that designers have to consider carefully the goal of their chatbot in making decisions on the best way to present them. While the early study of user input control as one of the attributes of chatbot in context of the service quality through the paradigm of Kano model
[41] (Meerschman & Verkeyn's, 2019) revealed use of quick replies as good addition, not a must-be. Anyway, nowadays this particular typology based on user input control seems to be not a full if to take into account growing popularity of using voice as an input. And in this particular research free-text field, quick replies and a combination of them as a type of input could be considered as subcategories of text-based type. And this is exactly the way, they would be explored through real case studies in this particular research. In this context the classification proposed by Smutny, Schreiberova(2020)(Fig. 6) illustrates a wider range of input types as the category was called by the researchers, but actually **button-based, keyword recognition-based, contextual, voice-enabled** types pretend to represent approaches to user input processing.

3.5. Chatbot classification according Smutny & Schreiberova(2020)

Exploring the wide typology of available on the market AI conversational applications, it is important to mention one more parameter described by
[42] Smutny, Schreiberova(2020) in their classification. In this research this parameter was defined as **messaging channels type** and implies the division of all chatbots into: **standalone applications(desktop or mobile), web-based service(integrated on the web or individual), integrated(to instant messaging apps or communication and collaboration platform).** Thus this typology was applied to chatbots in the field of education, its relevance for customer experience in context of ecommerce left no doubt. Numerous researches done explore different channels potential of Ai conversational applications implementation to improve customers experience in the context of ecommerce. The opportunities of chatbot implementation to website in order
[20] to answer frequently requested queries was studied by Hossain et al. (2022).
[43] The academic study by Sanchez(2019) illustrated the main chatbot potentialities and opportunities, highlighting how business can benefit from integrated models reducing the customer service costs at the same time growing revenues on the Facebook Messenger platform.

Exploration of available typologies and classifications

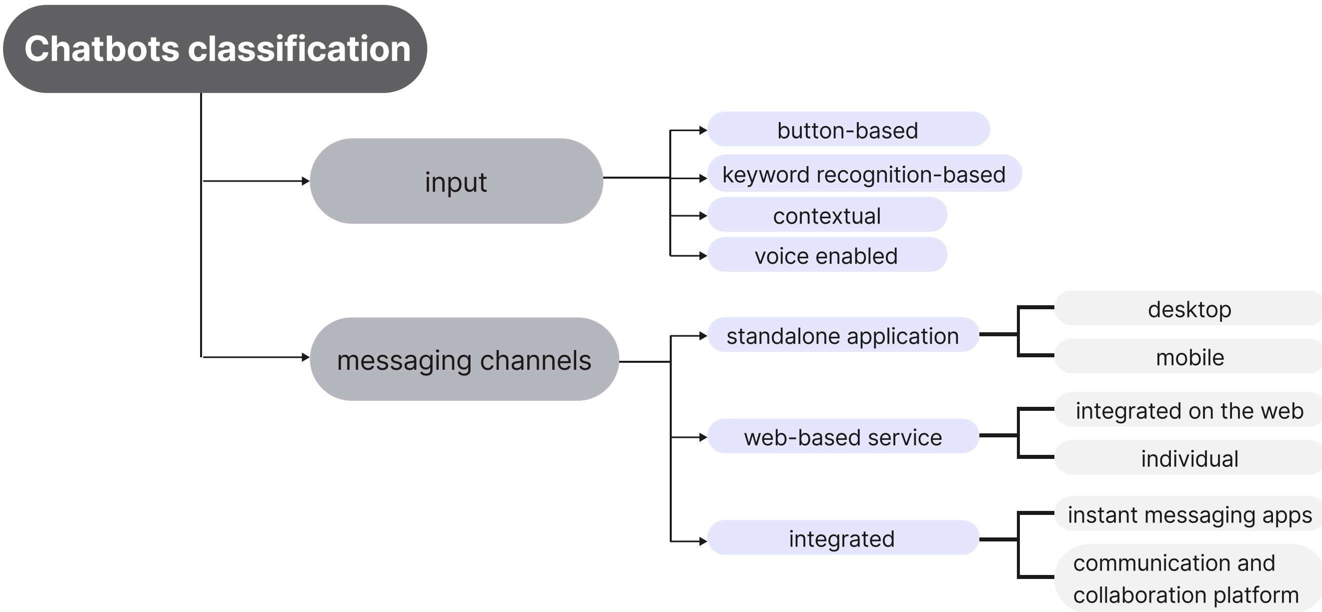


Fig.6 Chatbot classification according the research "Chatbots for learning: A review of educational chatbots for the Facebook Messenger" published in 2020.

That way, a wide range of AI conversational models types that were established on a basis of particular parameter or attribute were reviewed. In this way, based on the qualitative research done and parameters marked as determining customers experience, a taxonomy of modern AI conversational models regarding its potential of implementation in e-commerce for strengthening customer experience could be formed. This taxonomy will guide to analysis of a wide market of available AI conversational applications as systems of models, and describe each model`s opportunities regarding its effect on customer experience.

4. Faceted taxonomy of AI conversational systems in context of their implementation in ecommerce for enhancing customer experience.

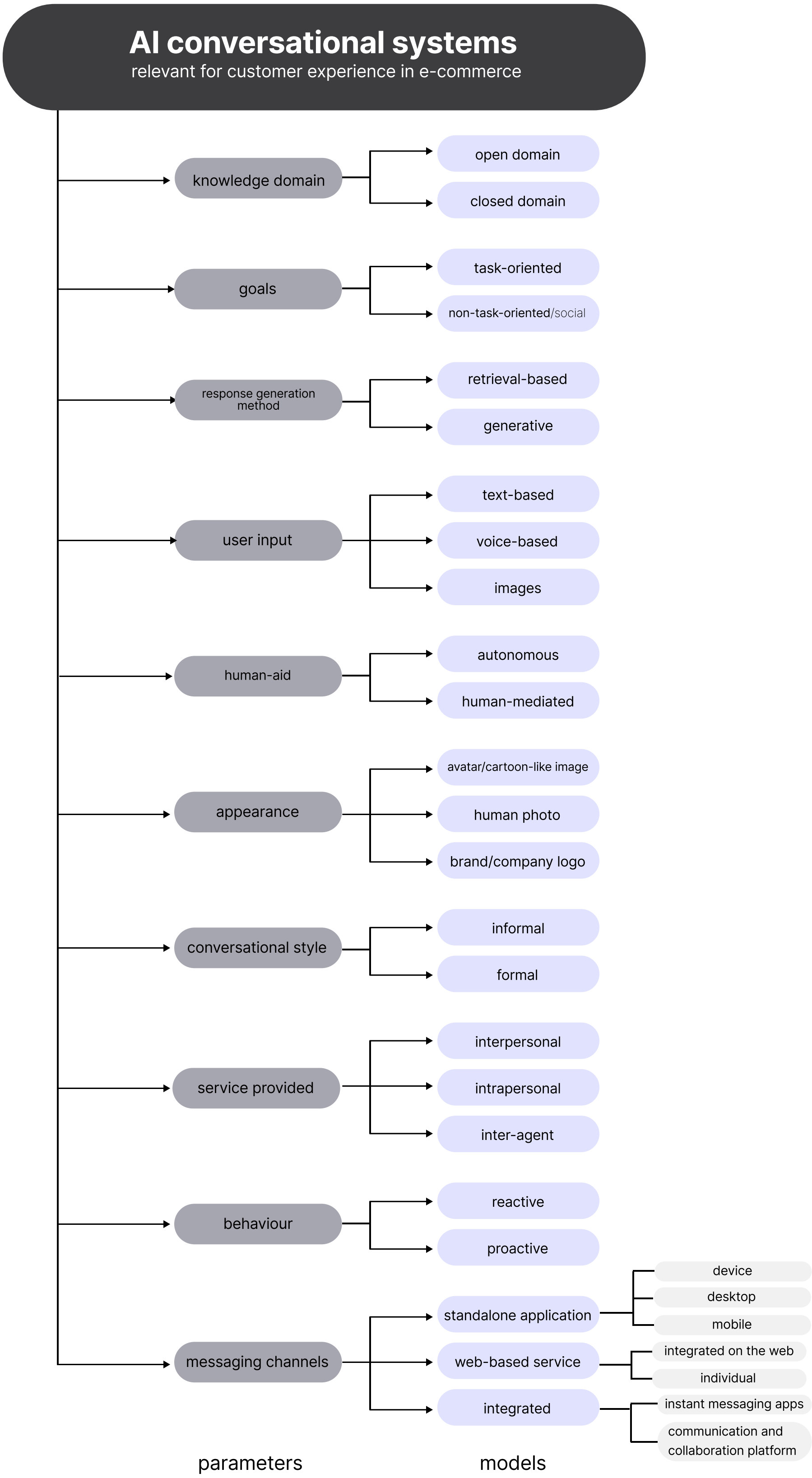


Fig.7 Faceted taxonomy of AI conversational applications available on the market and relevant for enhancing customer experience in e-commerce.

5. Exploration of the Taxonomy.

As a summary for the first phase of research, the faceted taxonomy of AI conversational systems, was formed. As the faceted taxonomy use semantically cohesive categories, which are called "models" in this particular work (Fig 7.) that could be combined as needed to create an expression of the concept(any AI conversational system), the faceted classification is not limited to already defined categories. The premise is that any conversational system could be analyzed into its component parts(models). But in this case the particular models defined were proved by numerous of recent researches collected in the field of CHI, technology and customer experience to have the capabilities to influence customer relationships. In particular, to influence how does the customers perceive the particular conversational model and the system at large(Chattaraman et al. 2019),(Mimoun et al. 2012), what does they expect(Meerschman and Verkeyn's (2019),(Alex Mari, René Algesheimer, 2021), the level of trust, loyalty, satisfaction and intend to use it again(Følstad& Halvorsrud, 2020),(Sheehan, 2018),(Adam et al., 2020).

[21], [35]
[41], [32],
[39]
[37], [38]

In the following phase of the research, this taxonomy would be considered as a basis or guideline for further close investigation of every particular conversational model type as a component of the conversational system. This way, the answers to the research questions stated would be found:
RQ1 What are the general **benefits and drawbacks** of each of the **model**(for designers, developers, stakeholders and final users)**,** considering its implementation in a conversational system in ecommerce to enhance customer experience?
RQ2 What are **another factors or attributes** of each of the model that have to be considered by designers while implementing any particular model in a conversational system to enhance customer experience in ecommerce?
RQ3 What is the **potential of each of the models considered as a part of conversational system** implemented in ecommerce field in order to strengthen customer experience?

Findings for this particular research phase were based on studies, researches and real case studies available online on the scholar portals such as: Researchgate, Sciencedirect, SpringerLink, ArXiv, Emerald insight, Politesi and etc.

5.1. Open-Domain VS Closed-domain. Knowledge domain.

[6] As was described previously in the paper by Adamopoulou et al. the selection of a particular **knowledge domain type** affects the ability of the AI conversational system to answer properly to questions in a specific domain(closed-domain) or understand and reply to any question in any domain(open-domain). Thus, closed-domain models are basically considered as dominant type in the field of ecommerce as it is **easier to develop and**
[15] **manage with focus on a specific domain** of a particular business(Skrebeca et al. 2021). However, some another researches do not exclude the opportunity of open domain types in context of emerging conversational commerce(Marc
[16], [44] Lim et. al.,2022) and changing or growing or needs of customers(Young et al., 2022). As such models generate the response based on the context and exhibit general chitchat ability, keeping the user engaged.
According to Symbl.ai one of the conversational technologies providers on the market, choosing between two types depend on the **scope and complexity of the conversation** the conversational system is expected to follow. When the scope is limited, a closed domain conversation understanding system (CUS) can get the job done. A closed domain model, also known as domain-specific, focuses on a particular set of topics and has limited responses based on the business
problem. But when the scope is unlimited, an open domain CUS is better equipped to capture the right context and use it to perform conversation understanding tasks (CUT). This free-flowing conversation has no defined objective or goal, so the responses need to adapt to whatever information provided by the customer.

Symbl.ai also pointed out two types of conversations **human to machine (H2M) or human to human (H2H**) for which a particular type of domain was well established practically. H2M conversations imply use cases in the phase of online experiences and personalized services as well as customer support with a fixed set of questions where closed-domain models could perform convincingly. In cases of H2H conversations, like in H2H meetings in customer support, open domain modes are able to assist human agent efficiently, performing well conversation understanding tasks like noting conclusions, action items, and follow-ups, pulling questions raised during the conversation, listing important information, like topics and open issues, automatically suggesting the next step. In this case open domain CUS perform efficiently for customer experience behind the line of visibility for the customer.
Thus, Symbl.ai mention the following **factors to conside**r while selecting the

appropriate AI conversational system and knowledge domain model in particular:

Time-to-market. Closed domain fits well cases with a specific problem to solve like personalised recommendations. But if several use cases are required, such as customer service and information management for instance, it's quicker to calibrate an open-domain CUS to specific tasks rather than build a new closed domain CUS for each one.

Specification and Generalization. Symbl.ai noted that the narrower the scope of the conversations, the easier it is to build. And short and straight-forward H2M conversations are prime closed domain territory. However, If understanding of general issues across different domains is required, an open-domain models will be easier to set than stuffing individual closed-domain models with tremendous amounts of domain-specific data.

Scalability. An open-domain model is much easier to scale since the same model across different use cases could be used. With a closed-domain model, juggling multiple AI systems for different domains and tasks will be probably required, which could become tedious and expensive in the long run.

[45] The research by Xu et al. in the field of open-domain chatbots(2021), pointed on another important factor to consider while selecting between open domain and closed domain model.

Safety from unpredictable outcome. While closed-domain models are trained on specifically prepared, not very large data sets, open-domain models have to be trained to understand general issues and mimic human-human conversations utilizing large pre-existing datasets. This way they are having a risk of learning undesirable features from this human-human data, such as the use of toxic or biased language. However in the particular research several strategies were proposed in order to make the process of training and subsequent interaction with customers safer, requiring however more time for implementation: unsafe utterance detection, safe utterance generation, sensitive topic avoidance, gender bias mitigation.

[46] **Consistency.** According Li et al.(2021) good open-domain chatbot should avoid presenting contradictory responses about facts or opinions in a
[47] conversational session, known as its consistency capacity. As Nie et al.(2020) mention, current open-domain chatbots hold a superiority in generating fluent,

engaging, and informative responses, but show the soft spot on consistency. However, considering the context of ecommerce **long-term dialogues** are not a common thing and could be viewed in specific circumstances.

If to consider the **quality of response** in configurations based on knowledge domain, the interrelation with **response generation method** should be mentioned that is able to form specific and appropriate to different context **answer`s model**(Fig. 10). These configurations will be described better while exploring models based on response generation method.

During the investigation it became obvious that the potential of models based on knowledge domain is strongly interrelated also with **goal parameter.** In other words, different combinations of models based on parameters of knowledge domain and goal allow to create configurations of systems that define the appropriate **form of communication** with client or specify the AI conversational system`s **social role** to perform during interaction(Fig. 8). Thus, the approach of building intelligent dialogue systems a little while has generally been established under two paradigms: task-oriented dialogue (TOD) systems, which perform task-specific functions in closed domain of a particular business, and open-domain dialogue (ODD) systems, which focus on non-
[44] task-oriented or social conversation.(Young et. al, 2022) Nowadays, there is a growing tendency of conversational commerce with digital assistants that are not restricted to task-oriented behaviour, but seek to build strong relationship with the customers through engaging human-like conversations. Recent
[48] researches(Balakrishnan et al. 2021) in this field focused on AI attributes like **perceived anthropomorphism, perceived intelligence, and perceived animacy**, confirming that perceived anthropomorphism plays the most significant role in building a positive attitude and purchase intention through
[44] digital assistants. In this way,(Young et. al, 2022) suggested a model when the task-oriented model was joined with the open domain model seamlessly in the same conversation, containing exchanges from both dialogue modes. It overcomes limitations of the task-oriented model such as the limit of conversational scenarios by fusing the two common forms of human conversations, i.e., casual open-ended conversations supported only by common sense, and task-oriented conversations supported by specific knowledge bases. Furthermore, it allows rich interactions between the two dialogue modes, which can not be modeled in either mode independently. Such ability is desirable in conversational agents, as the integration makes them more natural as **human-like consultants** in a brick-and-mortar store.

Knowledge domain

However, this perspective approach is not yet proven in the context of e-commerce. In reality, it could be quite expensive as requires a lot of manual creative effort while adjusting.

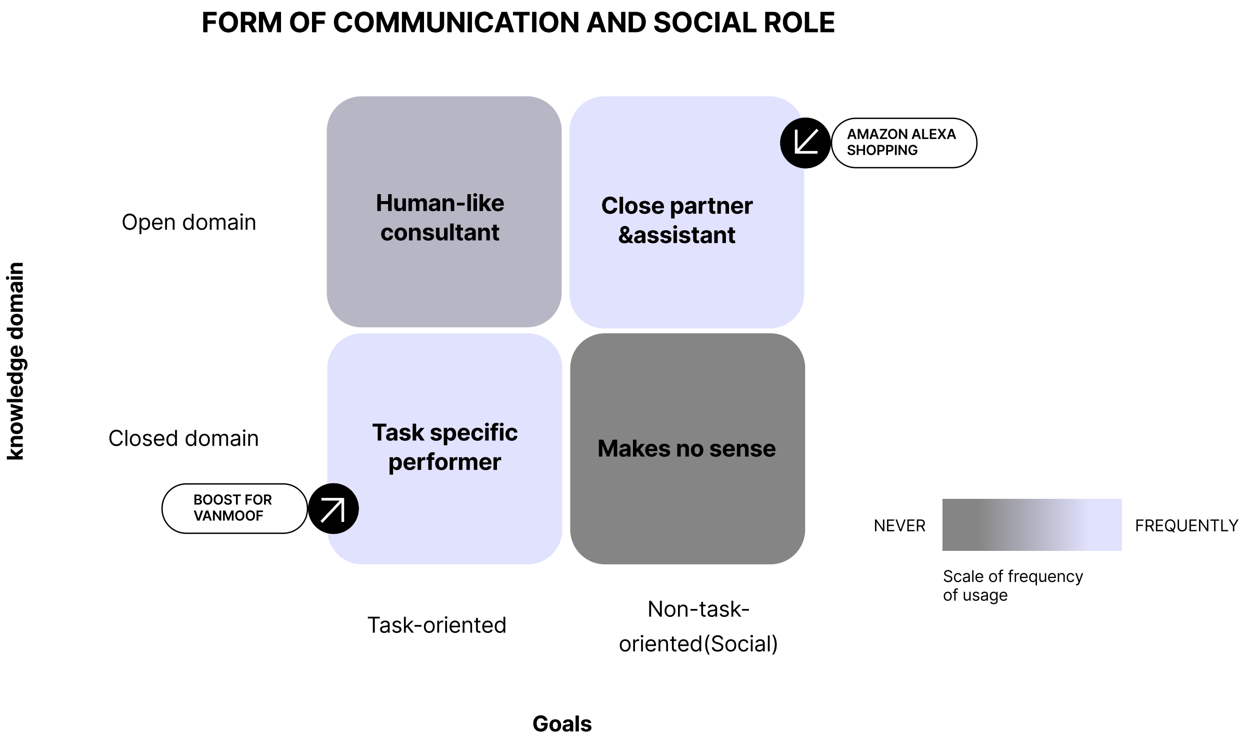
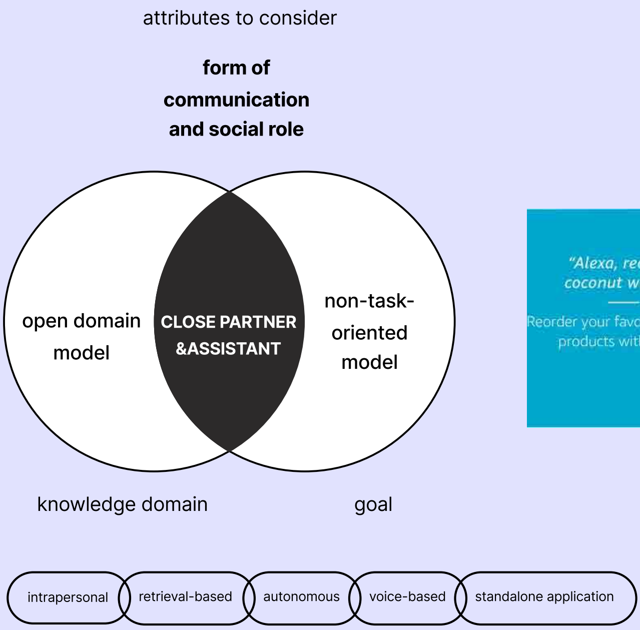


Fig.8 AI powered conversational system configurations based on type of domain and goal parameter and form of communication and social role as configuration-generating attributes

AMAZON ALEXA SHOPPING

configuration and models involved



configuration-generating attribute

form of communication and social role - **CLOSE PARTNER & ASSISTANT**

description of the configuration`s opportunities for CX improvement:

[50]
[49]

[51]

[52]

Particular configuration offers a qualitative **increase of socio-emotional and relational elements** such as the **humanness** in conversational systems. It stretches its role beyond a utilitarian communication tool to become the main actor that realises **intrapersonal communication**. Unlike conventional usage of conversational systems to increasing **performance and productivity** while performing daily tasks their roles extend to playing **a role of a close partner to consumers** (Mishra et al., 2021) in Computers are Social Actors (CASA) paradigm(Seymour et al., 2022). In this kind of relationships, **trust** becomes a determining factor that effects satisfaction, when consumers could be confident about recommendations and in the process that generated them (Gefen et al., 2003). Such a feeling of **confidence** towards an exchange partner incorporates elements of **honesty, benevolence and competence** in relationships between **assistant-partner** and customer, increasing the frequency of addressing. This configuration allow Alexa to become an actor in the **engagement process**, in the same manner that service staff or other consumers are part of the engagement process(McLean, 2021).

limitations

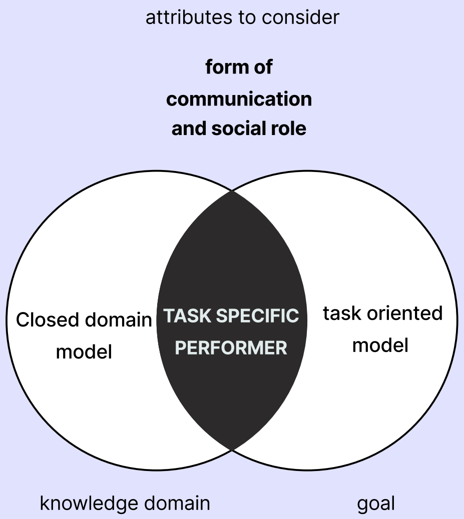
[53]

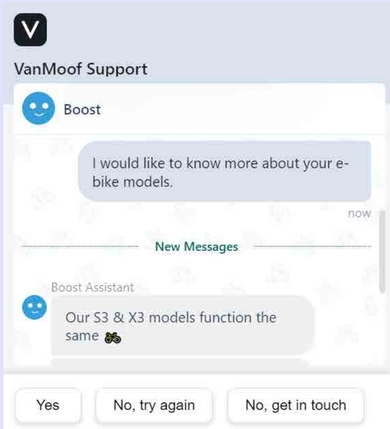
Concerns pertaining to the **negative psychological experience of anthropomorphism** by consumers in form of **mismatched expectations** or **unpredictable outcome.**

Interplay between data **privacy concerns** (Hew et al., 2018) and the autonomy associated with this type of conversational systems.

"BOOST" FOR VANMOOF

configuration and models involved





interpersonal | retrieval-based | human-mediated | text-based | web-based service | avatar

configuration-generating attribute

form of communication and social role - **TASK SPECIFIC PERFORMER**

description of the configuration`s opportunities for CX improvement:

After investing time and effort in using the technologies and services, users hope to obtain highly relevant information, and particular configuration recommended itself in a role of **task-specific performer, but without losing the personal touch.** Task-oriented model in closed domain that framed Boost`s approach to communication aimed to strengthen **performance** and **productivity,** providing deliberate services to customers **faster as it is straightforward to achieve a goal.** And the closed domain of the particular configuration have to obtain a high level of **competence** in frequently asked questions thanks to not very large and verified training data sets limited to specific scope that involve VanMoof`s products catalogue with principal characteristics of every particular model. However **Goal centric approach** of the system allows to delegate conversation management to human agent when Boost is unable to solve the problem on its own that improve entire **service quality.**

limitations

limit of conversational scenarios and responses

Insufficient training data set

Inability to understand the issue

Exploration of the taxonomy

Knowledge domain

Summary

	STRENGTHS	LIMITATIONS	ATTRIBUTES TO CONSIDER WHILE IMPLEMENTING
OPEN DOMAIN	more natural conversation no limits of scope of conversation easy to scale engaging content enhance perceived anthropomorphism, intelligence and animacy	inconsistency no well defined intention or goal unpredictable outcome	scope of conversation duration of conversation scalability time-to-market H2M or H2H model of conversation goal form of communication and social role response generation method variables: gender, age, experience with technologies.
CLOSED DOMAIN	easy to build and manage competence straightforward to achieve a goal	limit of conversational scenarios and responses lack of empathy dependence from correctness and completeness of training data set	

customer experience

deveopment

5.2.Task-oriented VS Social. Goals.

In the context of ecommerce task-oriented conversational models occupied a priority position thanks to their focus on efficient and prompt solving particular customer`s problems by providing short responses to FAQs or simple requests
[54] like processing orders (Fellows et al., 2021). They are also not too complicated to build and manage with the biggest issue comes from **size and correctness of the training dataset** that will be able to fulfill all the user requests based on
[55] the specific topic for which it was designed. And Hageman(2021) pointed out that training data for task-oriented dialogue systems are often **hard to collect, expensive to annotate, and time-consuming to gather** if businesses choose to develop their own system with collecting a specific database.

At the same time well trained task-oriented models have the ability to improve **efficiency** of customer`s interactions by guiding customers through any step of the process. The customers surveys conducted by Følstad &
[56] Brandtzaeg(2020) point out the efficiency and **accessibility** as positive attribute of conversational systems, primarily perceived by customers. As it can save customers time and effort, making overall experience more efficient and enjoyable.

[57] **Personalization.** In recent research Blümel&Jha(2023) stated that conversational AI need to build on customer knowledge and experiential data to meet the customer where they are and tailor the communication. Task-oriented models can gather information about customers preferences, purchase history and other relevant data to provide personalized recommendations and product suggestions. This can help customers find products they are looking for more easily, strengthening the entire experience.

Unlike task-oriented dialogue systems, which aim to complete specific tasks for user, non-task-oriented dialogue systems focus on conversing with human
[58] on open domains (Ritter 2011). This allow them to revolution consumers' consumption patterns (e.g., identifying needs, searching for information, purchasing, and interacting with firms, and becoming an **integral part of**
[59] **consumers' social lives in various aspects** (McLean and Osei-Frimpong, 2019). Consumers tend to engage with non-task-oriented models in like **manner as they would with other humans**. Moreover, it has been reported that consumers who use digital voice assistants for shopping transactions, that are exploiting non-task-oriented models are more **loyal** to the company that
[60] they engaged with earlier(Moriuchi, 2019).

However, many companies are jumping onto the bandwagon to deploy new conversational systems as part of their marketing efforts without understanding the orchestration of optimal configurations of conversational system that foster desirable shopping perception and customer retail
[60] experience (Moriuchi, 2019).

The introduction of **humanness** in AI conversational systems has been heralded as a game-changer for the industry and might radically alter human-computer interactions, which stretches its role beyond a utilitarian communication tool to become the main actor that realises **intrapersonal communication.** The identified humanlike attribute was in many ways
[56] associated with the social attribute Følstad & Brandtzaeg(2020). To explain, unlike conventional usage of technological devices, the role of non-task-oriented systems like digital voice assistants extends beyond increasing performance of tasks and productivity to facilitating personal social and
[50] hedonic tasks in one's private life (Mishra et al., 2021).

Engagement: Social dialogue systems can engage with customers in a more conversational and natural way, making the shopping experience more enjoyable and memorable. Overall, using a social-oriented communication style boosts customer satisfaction. Warmth perception of the chatbot mediates this effect, while chatbot’s anthropomorphised role (servant versus
[61] partner) moderates this effect(Ying Xu et al., 2021). These mechanisms can help build brand loyalty and increase customer satisfaction. Participants in
[56] Følstad & Brandtzaeg`s survey (2020) reported the entertainment value of chatbots typically referred to situations where they engaged in small talk with a chatbot. That is, they often did not have a particular task to be resolved but rather saw the chatbot as a means of involving themselves in a pleasing activity. Specifically, they reported that the chatbots’ ability to be funny and witty was a source of pleasure.

However, if to consider the evaluation metrics of task-oriented and non-task-
[54] oriented models regarding customer experience(Fellows Et al. 2021), beside the advantage of efficiency and reliability in case of task resolution, another factor affecting customer experience should be mentioned, namely **customer satisfaction** that is commonly considered as another performance metric. In this context, task-oriented models may be able to handle a high volume of customer inquiries efficiently, however they may **lack the human touch, empathy** and **flexibility** that could affect customers satisfaction. Some recent

researches point on perception of task-oriented models as cold and uncaring
[62] (Liu-Thompkins et al., 2022) At the same time, non-task-oriented models may **not be able to handle complex or nuanced customer inquiries** that require a human touch. Therefore, it is important to provide a way for customers to escalate issues to human agents when necessary, such as when inquiries are more complex or require a personal touch. In this context, the **level of human aid as a parameter to consider in order** to provide **service quality** to customer experience, should be mentioned(Fig.9). Though autonomous conversational systems(CS) seem more effective in the context of cost-cutting associated
[63] with customer service operations, such as staffing and training costs(Araujo et al., 2022). And the ability to handle a high volume of inquiries 24/7 without additional resources seems tempting. In some cases task-oriented models could be joined with human agents in operational processes to obtain the following improvements in customer experience. In Hybrid systems could be seen the **decrease of customers' frustration** when autonomous conversational systems are unable to provide appropriate service or increase customers satisfaction when they prefer to interact with human
[64] operators(Oshrat et al. 2022). **Reduce the time needed for handling of the request** by human agent and improve **service quality** in hybrid systems when conversational system assists human agent behind the line of visibility for the customer, performing well conversation understanding tasks like noting conclusions, listing important information, like topics and open issues, automatically suggesting the next step, minimizing the risk of human error(Symbl.ai). Social or non-task-oriented systems could increase the level of knowledge that organizations can have about consumers, as every interaction is logged, thus opening up opportunities for deeper changes in the ability to
[65] customize or **personalize the experience** for individual consumers (Meuter et al. 2000) But this way, the issue of defining the appropriate **form of communication** and **social role** is arising and goes back to the choice of the suitable for its objectives **knowledge domain** model. (Fig. 8) Which will determine the particular conversational system to act like an expert in a particular domain(Task-specific performer), well-informed companion(chat-based assistant), or human-like consultant like in a brick-and-mortar store. Moreover more before implementing task-oriented or non-task-oriented model in e-commerce strategy some other factors to consider should be reviewed:

Costs. Task-oriented systems may be less expensive to implement and maintain, while non-task-oriented systems may require more resources and ongoing maintenance. However, developing and implementing task-oriented

Exploration of the taxonomy

Goals

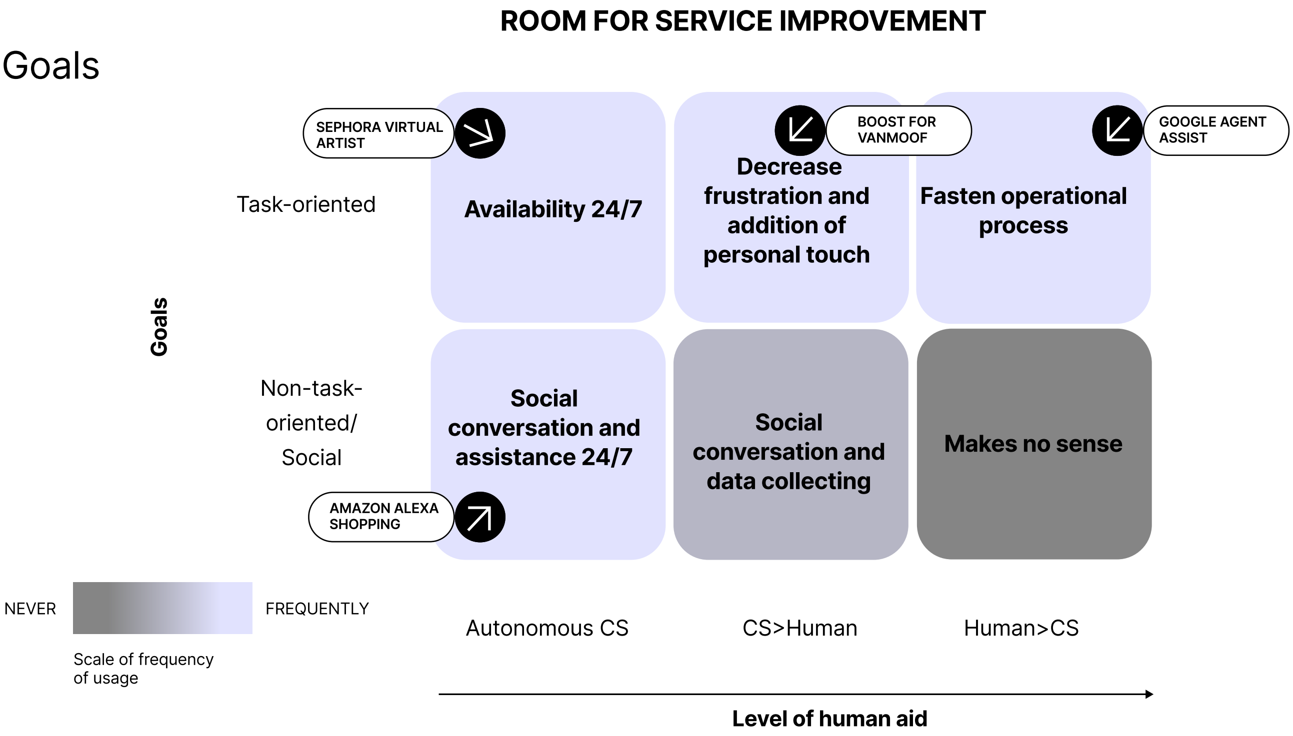


Fig.9 AI powered conversational system configurations based on goal parameter and level of human aid with room for service improvement as configuration-generating attribute

[55] models could be expensive especially if businesses choose to develop their own systems with collecting a specific database (Hageman, 2021). Thus, it is important to carefully consider the costs of developing and maintaining such systems, as well as the potential return on investments.

[21] [64] [56] **Customer preferences and needs.** Some customers categories may prefer to interact in more natural or social manner like older users, however those who are less experienced with Internet in general prefer using task-oriented chatbots.(Chattaraman et al., 2018) or rather prefer human agent to AI conversational system(Oshrat et al. 2022). While other categories could prefer self-service with straight-lined and time saving experience with task-oriented model(Følstad & Brandtzaeg, 2020). It is important to understand customer preferences and ensure that the system is designed to meet their needs and expectations.

[64] **Complexity of customer inquiries:** Consider the complexity of customer inquiries and whether they require a human touch(Oshrat et al. 2022). If customer inquiries are straightforward and can be resolved through a set of predefined rules and processes, a task-oriented system may be more appropriate. On the other hand, if customer inquiries are complex and require a more personalized and nuanced approach, a non-task-oriented system may be more appropriate.

Integration with existing systems. Task-oriented systems may require less advanced technology, while non-task-oriented systems may require more advanced technology and expertise. Task-oriented conversational model may need to integrate with existing e-commerce systems, such as inventory management or order processing systems. It is important to ensure that the system can be integrated seamlessly and that it does not disrupt existing business processes.(Crafter.ai)

Data privacy and security: Task-oriented dialogue systems may collect and store sensitive customer data, such as payment information or personal details. It is important to ensure that the system is secure and that customer data is protected.

Scalability and maintenance: Task-oriented models typically rely on components specifically developed for a single task or domain. This limits such systems in two different ways: If there is an update in the task domain, the dialogue system usually needs to be updated or completely retrained. It is also harder to extend such dialogue systems to different and multiple domains. Task-oriented dialogue systems may need to handle a large volume of customer inquiries and may require ongoing maintenance and updates. It is important to ensure that the system can scale to meet the needs of the business and that it can be maintained and updated efficiently.

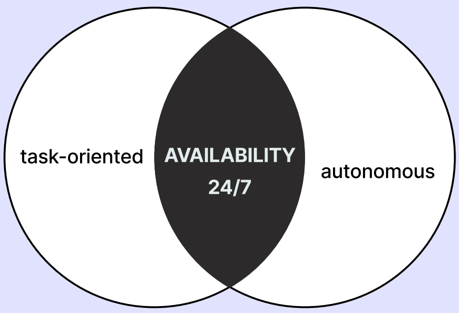
Business goals: The choice between task-oriented and non-task-oriented systems should align with the business goals of the organization. For example, if the goal is to provide quick and efficient customer service, a task-oriented system may be a better fit. On the other hand, if the goal is to create a more engaging and personalized customer experience, a non-task-oriented system may perform better.

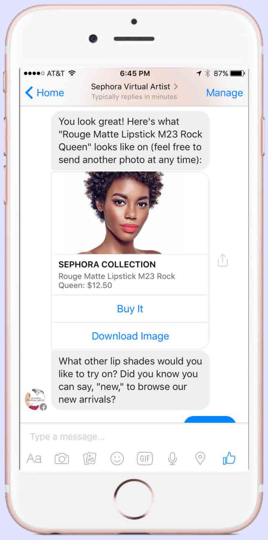
SEPHORA VIRTUAL ARTIST

attributes to consider

room for service improvement

configuration and models involved





goals level of human aid

retrieval-based | closed domain | text-based with image processing | intrapersonal | integrated | proactive | brand logo

configuration-generating attribute

room for service improvement - **AVAILABILITY 24/7**

description of the configuration`s relevance for CX

This configuration could be considered as on of the most widespread in the context of e-commerce as it is able to provide tangible benefits fo businesses such as operational costs-cutting and deliver a higher conversion rate. Sephora reported also the increase in sales, that mean that customer **engagement** increased also with the ability to efficiently **solve their problems distantly** at any **convenient** for the clients moment. 46 seconds is the average response time for a live chat request in 2022(chatlayer.ai), while autonomous conversational systems are able to **respond immediately.**

limitations

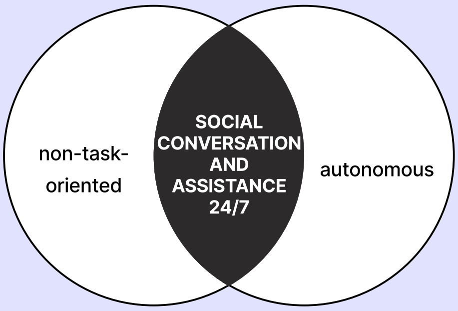
lack of human empathy

AMAZON ALEXA SHOPPING

attributes to consider

room for service improvement

configuration and models involved



goals level of human aid

open domain | retrieval-based | voice-based | standalone application | intrapersonal

configuration-generating attribute

room for service improvement - **SOCIAL CONVERSATION AND ASSISTANCE 24/7**

description of the configuration`s relevance for CX
[60]

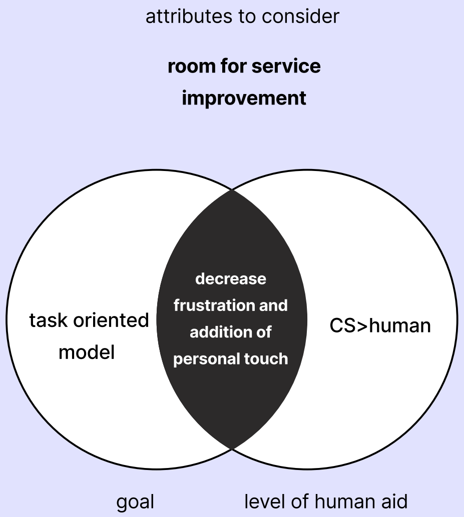
Autonomous non-task-oriented configuration for customer experience could provide social conversation and assistance at **any time requested**. Alexa`s non-formal conversational style simulates a conversation with a human or partner that was studied and proven to lead to **loyalty** from the customers' side(Moriuchi, 2019) and at the same time **strengthening relationships** with brands that **encourage new purchases**. The customer is more **engaged** to talk to the assistant in a **natural way** without extra operational processes and human intervention.

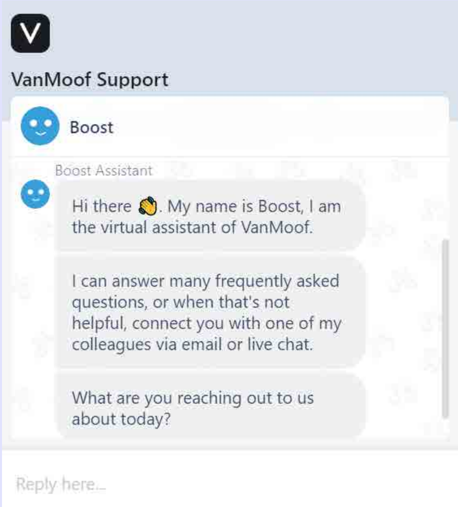
limitations

complex and nuanced customer`s inquiries

"BOOST" FOR VANMOOF

configuration and models involved





interpersonal | retrieval-based | closed domain | text-based | web-based service | avatar

configuration-generating attribute

added value - **DECREASE FRUSTRATION AND ADDITION OF PERSONAL TOUCH**

description of the configuration`s opportunities for CX improvement:

The company asserts that Boost can handle more than 70% of customer queries in **different languages**, and helps prevent many handovers to live chat agents. However, if the system is not able to solve the problem, as it showed during the testing, or the customer prefer talking to human from the beginning, the chatbot provides a **smooth transfer to an agent**. In this the case, the agent already has some information about the customer. This handover of information from the bot makes sure that the agents are already prepared when they start talking to a customer and can provide a **quicker answer with personal touch without a need of request repetition**. This helps to **decrease frustration** and **alleviate possible negative experience** with chatbot and brand at the end.

limitations

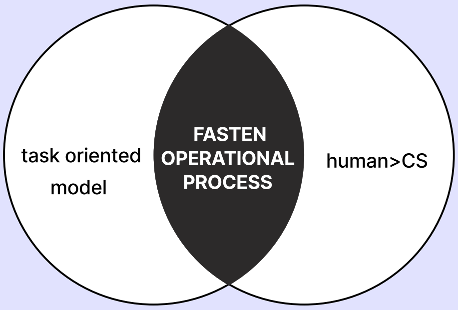
limited by human availability(time zone, languages, working hours)response time to chat with is 1h25 minutes. In case sending an email, within 6 working days.
not as immediate in problem solving as autonomous systems

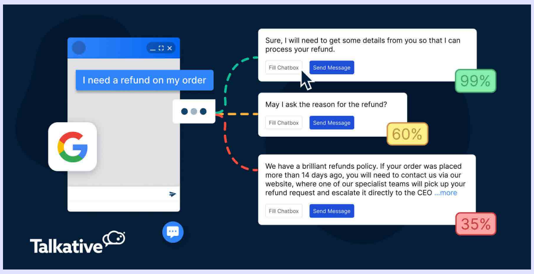
GOOGLE AGENT ASSIST

attributes to consider

room for service improvement

configuration and models involved





goal   level of human aid

retrieval-based | open domain | text-based | voice-based | proactive

configuration-generating attribute

added value - **FASTEN OPERATIONAL PROCESSES**

description of the configuration`s opportunities for CX improvement:

Google Agent Assist helps agents to perform to their best ability - leading to optimal contact center **efficiency** and **higher quality customer service**. Conversational system achieves this by analyzing customer conversations, case context, and customer data in real-time. This insight is used to provide contextual guidance, such as ready-to-send response recommendations and solutions to common problems. That allows to decrease the waiting time for the response. Agent Assist can extract content from the knowledge base documents, website, and FAQ database to help agents resolve customer issues and provide more **accurate information, minimizing the risk of human error.** Moreover, Agent Assist can help agents provide a **tailored experience and more accurate personalized recommendations(Talkative)**.

limitations

limited by human availability(time zone, languages, working hours)

not as immediate as autonomous systems

Exploration of the taxonomy

Goals

Summary

<table>
<tr><th></th><th>STRENGTHS</th><th>LIMITATIONS</th><th>ATTRIBUTES TO CONSIDER WHILE IMPLEMENTING</th></tr>
<tr><td>TASK ORIENTED</td><td>easy to build and manage
efficiency of interactions
personalisation of the experience</td><td>appropriate dataset is hard to collect, expensive to annotate, and time-consuming to gather
lack of human touch, empathy and flexibility</td><td rowspan="2">size and correctness of the training dataset
level of human aid
complexity of customer inquiries
form of communication and social role
costs
customers` preferences and needs
integration wth existing systems
data privacy and security
scalability and maintenance
business goals
knowledge domain</td></tr>
<tr><td>SOCIAL</td><td>perceived more anthropomorphic
new consumption patterns
interpersonal level of communication
enhancing loyalty
engagement</td><td>complex or nuanced customer inquiries</td></tr>
</table>

- customer experience
- deveopment
- business

5.3.Retrieval-based VS Generative-based. Response Generation method.

[6] As was defined by Adamopoulou and Moussiades, 2020 retrieval-based systems predict the most accurate response from a closed set of responses using an output ranked list of possible answers. Machine Learning and Deep Learning mechanisms and techniques are currently used as underlying [66] technology for this kind of model (Caldarini et al., 2022). These mechanisms ensure quite high **accuracy in responding** that in field of customer experience in e-commerce allow achieve consistency, affecting **trust and loyalty** from the customer`s side. On the other hand, generative-based systems focus on using Deep Learning models to synthesize and build the reply to a specific user input, rather than selecting it from a closed data-set of responses. These chatbots perform more **human-like** with the ability to improve accuracy over time. Generative systems can learn from customer interactions, which can lead to **improved accuracy and relevance of the generated responses,** however [13] there are difficulties in building and training them(Motger et al, 2021).

It is important to mention that the quality of response is strongly interrelated with **knowledge domain.** In other words, different combinations of models based on parameters of the knowledge
domain and response generation method allow to create different configurations of systems that will define specific and appropriate to different context **answer`s model**(Fig. 10). Retrieval-based model with closed domain is

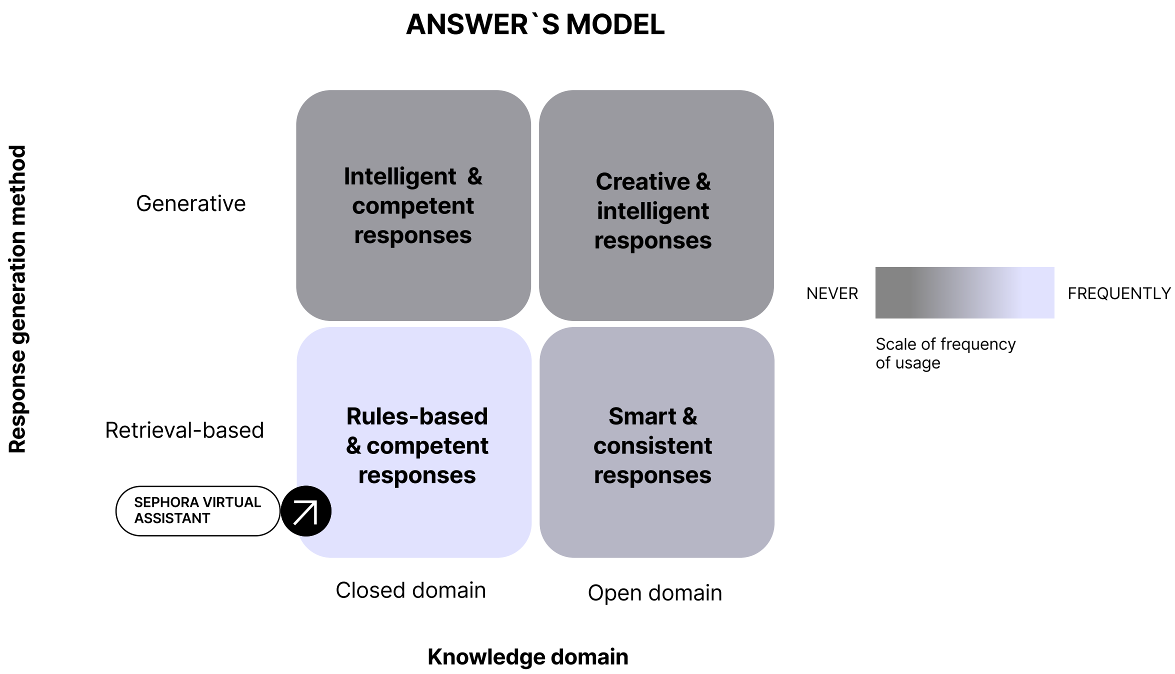


Fig.10 AI powered conversational system configurations based on response generation model and type of domain with appropriate answer`s model as configuration-generating attributes

Response generation method

a configuration quite commonly used in context of e-commerce as it forms conversational system that provide rules-based and competent responses
[68] with **reliable and consistent** information(Surendran et al., 2020). It is safe from unpredictable outcomes, but has limited conversational flexibility and less suitable to develop a personality, which could be an important trait for brand differentiation in some cases. Retrieval-based models in open domain allow to reach a consistency in responses being quite smart thanks to large datasets they were trained on. However they are quite predictable. While generative models in closed domain could potentially **engage** customers with novel and creative responses which can help build a stronger relationship with the
[67] customer and enhance their overall experience(Kapočiūtė-Dzikienė, 2020). However, for now they are quite complex to be widespread in context of e-commerce.

Generative models in open domain in context of e-commerce are also still relatively new, however the experts in technologies and marketing assure that it has strong potential to transform the way that customers interact with online stores. ChatGPT just that example of generative model in open domain that according to Open.ai, has the primary intention of interacting in a friendly way with human users, and making them benefit from it, receiving human-like support on different phases of their journey. The experts in industry like N. Parsad, practice lead for emerging tech at Tinuiti predict ChatGPT to be used as an onsite personal shopper for those who have an expansive e-commerce experience. "And now your personalization experience gets a little bit more thought out. ChatGPT can remember conversations and context. So as it gets to know a person that experience both onsite and in ongoing messaging is really interesting" said Parsad.

Personality. Retrieval-based systems can provide a consistent tone of voice and conversational style for a brand, as they rely on pre-defined responses that are designed to reflect the brand's values and personality. While generative systems have the potential to be more creative, warm and playful in their responses, which can be appealing to customers. In this context the personality of the conversational system could be supported with its **appearance**. Even though the recent research by Raunio(2021) did not reveal
[36] significant effects of the chatbots' **visual appearance** or the **conversational style** on perceived ease of use, usefulness, helpfulness, competence, trust, or attitude towards using conversational systems. Their impact on how the

Response generation method

[70] customer perceive brand was proved to affect the loyalty(Farhat&Khan, 2011).
[36] Raunio`s interview results revealed that the users slightly preferred a chatbot with a human or a robot avatar and a human-like, informal conversational style.

Engagement. In terms of engagement, generative systems have the potential to provide a higher level of engagement than retrieval-based systems. This is because generative systems can create more personalized and human-like responses, which can help to build a stronger connection with the user. Additionally, generative systems can handle a wider range of questions and inputs, allowing for a more natural and free-flowing conversation. However, another factors such as the quality of the responses, the user interface, and the overall design of the conversational experience can also have a significant impact on engagement.

Due to the repository of handcrafted responses, retrieval-based methods don't make **grammatical mistakes**. However, they may be unable to handle unseen cases for which no appropriate predefined response exists. For the same reasons, these models can't refer back to contextual entity information like names mentioned earlier in the conversation. Generative models are "smarter". They can refer back to entities in the input and give the impression that you're talking to a human. However, these models are hard to train, are quite likely to make grammatical mistakes (especially on longer sentences), and typically require huge amounts of training data.

Flexibility and adaptability: Generative systems are more flexible and adaptable than retrieval-based systems, as they can generate responses for a wider range of customer queries, including those that may not have been pre-defined. This can be particularly beneficial for e-commerce businesses that have a diverse product range or customers with unique needs.

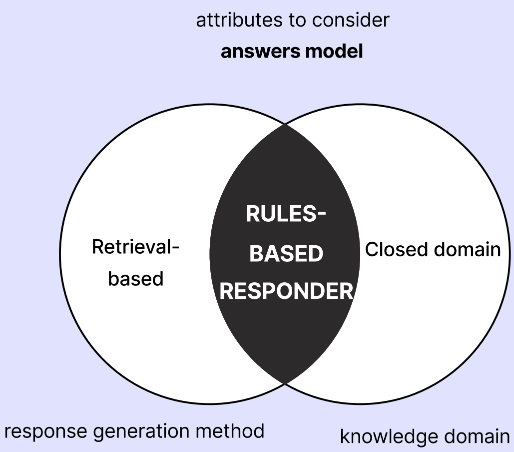
While selecting between two models **time-to-market** should be also considered. Retrieval-based systems are generally **easier and faster to implement** than generative systems. They rely on pre-existing knowledge, such as a database of pre-defined responses or rules, which can be quickly developed and updated as needed. On the other hand, generative conversational systems require more time and resources to develop and train. This is because they use machine learning algorithms, such as neural networks
[71] or Markov chains (Harshvardhan GM, et al., 2020), to generate responses on the fly. This requires a large amount of training data and computing resources,

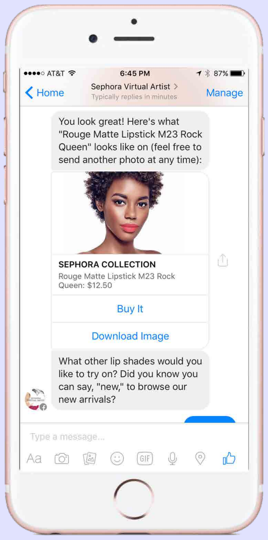
.

as well as expertise in machine learning and natural language processing. As a result, the development and deployment of a generative system can take **longer and may require more investment** in terms of resources and expertise. However both approaches are commonly used in industry and time-to-market may depend on a variety of factors, such as the specific goals and requirements of the system, the size and complexity of the dataset, the availability of resources and expertise, and other technical and logistical considerations.

SEPHORA VIRTUAL ARTIST

configuration and models involved





task-oriented | text-based with image processing | autonomous | intrapersonal | integrated | proactive | brand logo

configuration-generating attribute

answers model - **RULES-BASED RESPONDER**

description of the configuration`s relevance for CX

Deciding between beauty products can be a daunting experience as traditionally the process consists of applying and removing different shades, repeating the process until the desired results are achieved(Saettle, 2020).This configuration with addition of image processing technologies allows Sephora provide **accurate, competent and relevant** for the customer responses. Thanks to ML technologies, the conversational system is able to learn during every dialogue and **improve accuracy of responses** and recommendations provided. This form of configuration applied by Sephora could be perceived by customers as **competent consultant** aiming a specific goal and following the particular rules during conversation. Sephora`s rules-based responder is familiar with brand products and experienced in personalized colours matching that allow the system to provide **personalized responses**, solving the customers' issues in engaging way.

limitations

However as the responses are predefined, the **lack of human empathy** if to compare with instore experience, could be sensed. Also the system is not able to overcome **limited scope of knowledge domain** and ready to solve only **specific tasks** it was designed for.

Exploration of the taxonomy

Response generation method

Summary

	STRENGTHS	LIMITATIONS	ATTRIBUTES TO CONSIDER WHILE IMPLEMENTING
RETRIEVAL-BASED	accuracy in responding consistent responses support brand personality with consistent tone of voice safe from grammatical mistakes faster to develop and deploy can be trained on a small set of data	limited to pre-defined Reponses out-of-scope questions feel less personal or human-like	knowledge domain costs complexity of the problem training data availability time-to-market brand identity customers needs and preferences
GENERATIVE	perceived more human-like more flexible and adaptable sounds more engaging and social	require huge amounts of training data development process is longer may require more investments can be less consistent in tone of voice	

customer experience

deveopment

business

5.4. Natural language VS Others. User input.

[13] According Motger et al.(2021) As available for modern AI conversational systems mechanisms of processing user inputs could be considered **natural language** processing mechanisms involving text or voice recognition or both of
[6] them. However, Adamopoulou and Moussiades report **image** processing as another valuable mechanism for user interaction able to support and extend the limitations of natural language communication. Moreover, this mechanism could have additional value for the customer experience in the context of e-commerce as it can propose more personalized experiences based on
[33] customer`s photo as a start input for instance (Yi Kei, 2021).

While voice-based systems may also have advantages in certain scenarios, such as **“hands free” and on-the-go scenarios**, text-based systems are generally considered more suitable for the e-commerce context, as they
[72] provide a **convenient and reliable** shopping experience. Grudin & Jacques, (2019) in their research mentioned phenomenon of “chatbot tsunami” which lies on spread of text-based chatbots in a variety of application domains. Even though text-based model cannot exploit ‘enhanced’ communication attributes like facial expressions, gestures and tone of voice, many studies on person-to-person through text messages (e.g., instant messaging) have consolidated the
[73] idea that this form of interaction has unique advantages (Werry, 1996) and, despite the **lack of cues from body language and vocal tones**, is still able to
[74] communicate emotions as in person communication (Derks et al, 2008) and what is more important, to respond to customers issues efficiently.
The popularity and prevalence of text-based models is cased by following common for customer experience in e-commerce factors:

Accessibility and convenience. Customers can interact with text-based systems at their own pace and on their own time, in an appropriate for them environment without having to worry about time constraints or interruptions. However, the same approach could be a limitation in some cases as it requires hands free and attention span while interacting. Text-based systems are more accessible to customers with hearing or speech impairments, improving the **inclusivity** of e-commerce platforms.

Efficiency. Text-based systems can provide quick and accurate responses, reducing the time and effort required for customers to find what they are
[75] looking for. However studies by Gnewuch et al.(2018) have revealed that **word**

frequency, **response latency**, and conversational **styles** influence the extent to which the conversational system is **anthropomorphized** and consequently affect customers` expectations and level of trust.

Minimises the risks of misunderstanding arising from human factors like different accents or contextual factors like noisy unfavourable environment.

Multitasking. Text-based systems allow customers to multitask while they communicate with businesses, such as browsing the website or completing other tasks. It allows to control the conversational flow without having to worry about time constraints or interruptions.

Long-term value. Text-based conversation systems provide a record of the conversation that can be referred to later by business as well as customers, making it easier to resolve issues and keep track of customer interactions.
At the same time, voice-based models that are gaining popularity with raising voice shopping trend reveal new opportunities for the customers but also new challenges like **gaining trust** and development of such a trusted relationship
[32] that affect customers decisions in e-commerce(Mari, Algesheimer, 2021). The feeling of trust in this context is based on several factors such as **confidence in relevant recommendations** (Mari, Algesheimer, 2021), **concerns about appropriate use of personal data collected and financial transactions safety.**

[76] However, a study by Chai et al., (2001)found that most users liked the idea that they can express their needs in their language without being restricted to menu choices and that the conversational system does all the work for them. While voice is not a mandatory element in conversational agents, the relative **novelty** of voice-based interactions may mean that people are **more engaged** and more willing to accept their recommendations than those received via
[77] screen-based interfaces(Voorveld&Araujo, 2020). Voice-based models makes the conversation more **natural**. As voice is strongly **anthropomorphic** feature it could positively impact **trust.** For instance, if a conversational system is more human-like and approaches customers personally, it can reduce the privacy
[78], [79] issues and raise the trust and reliability. (Przegalinska et al., 2019; Følstad et al., 2018).

Voice-based systems allow the users to **multitask** while performing a primary task (driving or cooking). Voice-based systems can provide quick and accurate responses, reducing the time and effort required for customers to find what they are looking for.

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Exploration of the taxonomy

User input

[80] The **efficiency and easiness** of speech input is a value proposition is what plays a role. According to Luger and Sellen (2016), customers feel it is often easier and more convenient to use speech input than to type, one reason being that speech was felt to be **faster.** This can lead to **improved customer satisfaction and loyalty**. A research conducted in 2021 showed that speech exhibits **higher perceived efficiency, lower cognitive effort, higher enjoyment, and higher service satisfaction** than text-based interaction, but these effects depend on the task's goal-directedness.

But there are also some other limitations of voice-based model be necessary to mention in context of e-commerce:

Possible lack of visual component. Voice-based systems have limited capabilities when it comes to displaying visual information, such as product images and videos, which are essential in e-commerce, while affecting decision making process. this is even more pronounced in devices without a screen, called "headless devices", which generate a growing portion of the voice traffic. Several studies were exploring **psychological impulsivity**,
[81] defined as the urge to buy (Parboteeah et al. 2009) affected by visual aspects, in particular by selling platform`s designs.

Linguistic recognition problems. Voice-based systems may not support all languages, which can limit their use in certain regions. It could be probably limited by other linguistic recognition problems caused by e.g. **unclear pronunciation, environmental noise, grammatical errors, accents or**
[82] **dialects**(Knackstedt, 2022).

While selecting between models based on type of user input, the type of **service provided** could be also considered as a factor determining the choice and affecting **customers expectations.**
However, customers expectations in this case are strongly interrelated with **variables such as age, gender, technological experience**, that don't allow to form unequivocal configuration.

But in the field of e-commerce there are also cases of exploitation of a **combination of both models** that allow compensation to one or another deficiency of the system. And as was
mentioned previously, besides models based on natural language processing mechanisms, there are also some cases of implementation recognition

mechanisms of alternative variants of user`s input types in the context of e-commerce. In particular, **the image processing mechanism** could possibly be joint with one of the natural language processing mechanisms mentioned above to extend customers expectations or compensate the limitations of natural language communication.
The configurations formed by different combinations of processing mechanisms form properly the **type of information** that needs to be conveyed during the conversation(Fig. 11). Text-based systems are better for conveying detailed information such as product specifications, and combined with visual component such as image processing mechanisms could enhance customer experience dramatically. There are some successful cases of providing text-based personalised services and recommendations based on image input. While voice-based systems are better for simple commands and fast orders and reorders.

The first factor to consider is the **preferences of the target customers**. Conducting customer research and analyzing their behavior and preferences can help determine which type of conversational system would be more effective for engaging and serving your customers.

The **cost** of implementing the conversational system should also be considered, as voice-based systems are generally more expensive than text-based systems.

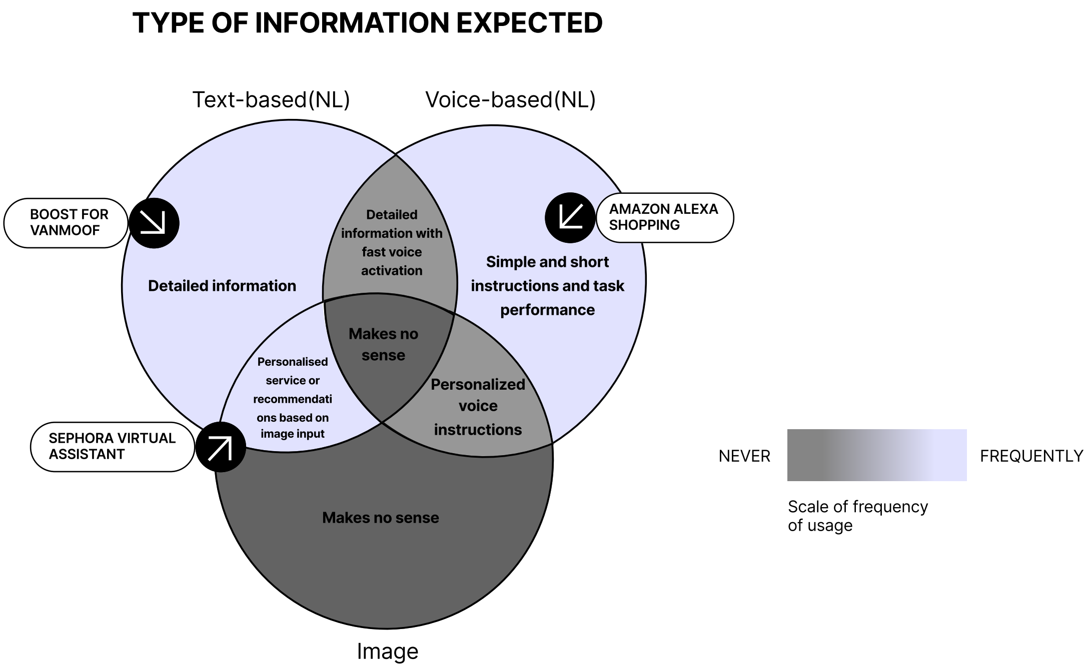


Fig.11 AI powered conversational system configurations based on user input control models with type of information expected by customer as configuration-generating attributes

AMAZON ALEXA SHOPPING

attributes to consider

type of information

configuration and models involved

SIMPLE AND SHORT INSTRUCTIONS AND TASK PERFORMANCE

voice-based

user input

open-domain | retrieval-based | autonomous | no-task-oriented | standalone application

configuration-generating attribute

type of information - **SIMPLE AND SHORT INSTRUCTIONS AND TASK PERFORMANCE**

description of the configuration`s opportunities for CX improvement:

[83]

Voice-based model allows Alexa to accompany the user's daily routine providing assistance in more **natural** for human way with **lower cognitive effort (Pagani et al. 2019)**. However, the amount of valuable for customer information should be reduced in this case due to the **limitation of human cognitive capabilities that should be always considered**. For instance, the comparison between numerous products without visual component could be quite challenging as it places a greater **burden on memory**.(Munz & Morwitz, 2019) It follows therefore, that another approach should be used in order to allow the system to provide **short targeted and relevant responses**. Alexa could make a **quick reorder**, searching the customers` order history. The system remembers **customers` preference**s and gives priority to particular brands or could find similar product. It could also find **deals and discounts** or answer **s**hopping related questions like: "Alexa, what's the most popular dog food?"

[84], [85]

In this case, Voice-based system of Alexa provide the opportunity of **multitasking** or allows to perform **tasks on-the-go, while driving in the car for instance** when text-based models would have failed. Voice as strong anthropomorphic feature can foster **trust, affinity, and pleasure** (Lee & Nass, 2004), (Qiu & Benbasat, 2009).

limitations

Lack of visual component

Inability to compare numerous products

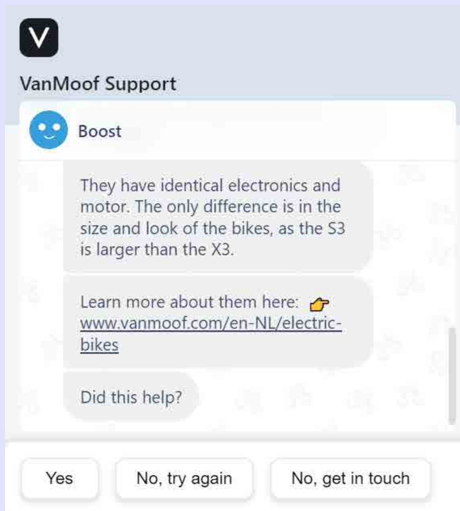
burden on memory

"BOOST" FOR VANMOOF

attributes to consider

type of information

user input



configuration and models involved

closed domain | task-oriented | retrieval-based | human-mediated | avatar | interpersonal | web-based service

configuration-generating attribute

type of information - **DETAILED INFORMATION**

description of the configuration`s opportunities for CX improvement:

[86], [87]

Since customers are often forced to search and browse a website for a long time, text-based conversational systems represent a **fast, uncomplicated and efficient** alternative to retrieve such information in the fastest possible way(Zumstein&Hundertmark, 2017). Moreover, according to Xu et al.,(2020), problem-solving appears to be a key element in evaluating service performance and thus to play a mediating role in customer preference for either chatbots or human customer service. Boost build with text-based model can handle more than 70% of customer queries in **different languages** (chatlayer.ai). It is able to navigate the customers through the catalogue of products, providing written **detailed information** about different models and **comparing characteristics** to let the customer make the right choice. When necessary, the chatbot also makes sure that the riders get a **smooth transfer to an agent** in order to close all the customers questions and add **human touch**.

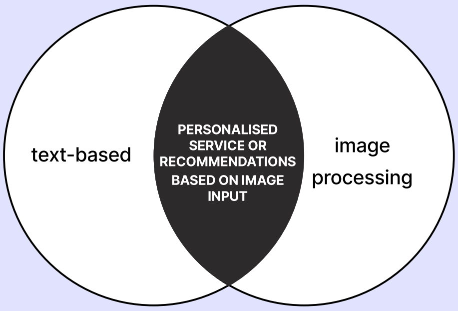
limitations

"hands free" and attention span scenarios

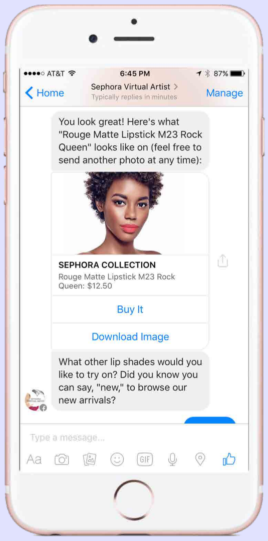
SEPHORA VIRTUAL ARTIST

attributes to consider

type of information



user input



configuration and models involved

retrieval-based | task-oriented | autonomous | closed domain | intrapersonal | integrated | proactive | brand logo

configuration-generating attribute

type of information - **PERSONALISED SERVICE OR RECOMMENDATIONS BASED ON IMAGE INPUT**

description of the configuration`s relevance for CX

This configuration allows Sephora provide **extended personal assistance** getting closer to the level of assistance in brick-and-mortal stores and **enhance relationships** with the clients. The applied ML technologies could **understand the content of the images** provided by the customer, whether it be an object like dress, another cosmetic product, or a celebrity's face. To develop the app Sephora partnered with ModiFace, a leading creator of augmented reality technology for the beauty industry. This way the system could identify the most prominent colors in a photo and let the customer select one of the colors. Then the customer will be returned to a list of the most suitable lipsticks available from Sephora that could be virtually tried on, and then purchased using the link provided by the system. The system is able to understand what customers are looking for, and also to learn more about customers preferences and behavior over time. This way, image processing mechanisms bring **personalisation** to a new level, **improving the engagement** and **strengthening loyalty** from the customers side.

limitations

Even though the system is able to strengthen relationships between customers and brand thanks to personal approach to service, **lack of human touch** and **human empathy** still could be noted.

Exploration of the taxonomy

User input

Summary

	STRENGTHS	LIMITATIONS
TEXT-BASED	accessibility and convenience efficiency with quick and accurate responses minimises the risks of misunderstandi ng control of the conversational flow Record keeping	“hands free” and attention span scenarios lack of human touch
VOICE-BASED	on-the-go and multitasking scenarios more natural conversation anthropomorphic impact on trust novelty affect impact on engagement perceived efficiency, lower cognitive effort	Linguistic recognition problems(languages, accents, dialects) noisy unfavourable environment require development of trusted relationships Lack of visual component

ATTRIBUTES TO CONSIDER WHILE IMPLEMENTING

- scenario of conversation
- context and environment of conversation
- type of information required by customer
- possible language barriers(accents, dialects)
- short-term or long-term value of the responses for customers
- customers expectations
- variables such as age, gender, technological experience
- appearance of conversational system
- type of service provided(interperson al, intrapersonal, inter-agent)
- inclusivity
- cost

customer experience

deveopment

business

5.5. Autonomous VS Human-mediated. Level of human aid.

[13] As Motger et al. describe human aid depicts the degree of autonomy in which the conversational system can be handled, whether it is designed as a **human-**
[6] **mediated** or an **autonomous**. According Adamopoulou and Moussiades, human-mediated refers to models which require from human computation at
[88] some point in the conversational process to be operated(Kucherbaev et al., 2018). On the other hand, autonomous models are fully operated autonomously by users without human assistance in the loop. In both cases the models have some evident benefits considering customer experience in context of e-commerce.

The appropriate type of model is primarily determinant from the **goal** or task that the system is required to perform for the customer. In this context, the configurations could be based on fully autonomous or several forms of human-mediated models. These forms, also known as hybrid, are differentiated by level of human aid and join the strengths of human-mediated and autonomous
[27] AI conversational models in varying proportions(Dellermann et al., 2019). Any particular model provide different **rooms for customer service improvement** in configurations formed by task-oriented and non-task-oriented models(Fig.9). Autonomous models are equally efficiently used with task-oriented as well as non-task oriented models, bringing availability 24/7 as indisputable advantage. Conversational system with human handover(CS>human) is one of the form of human-mediated models. In this type of hybrid approach, an autonomous chatbot handles routine inquiries, and if the inquiry becomes too complex or requires a human touch, the chatbot can transfer the conversation to a human agent seamlessly. This approach allows businesses to offer **quick and efficient support** while still providing a **human touch** when needed. There is also an approach when both human agents and AI conversational system work together to provide support in collaborative chat. In this type of hybrid system for instance, a chatbot may handle initial inquiries in social domain, while a human agent can jump in when the inquiry requires more **personalized or nuanced support**.
Live agent support with AI-powered conversational model assistance (human>CS) is another form of human-mediated models. In this type of hybrid system, an AI powered task-oriented model assists to human`s live conversation with customer by performing conversation understanding tasks like noting conclusions, listing important information, like topics and open

issues, personalized recommendations and support. This approach can **reduce response times and improve efficiency of service** provided also by **collecting relevant for business data**.

Overall, each type of model has its own unique advantages and limitations, and the choice of which type to implement will depend on the **specific needs of the business and its customers**.

On the one hand, autonomous AI conversational systems offer the advantage of **24/7 availability**, which can **improve response times** and reduce customer wait times. They can also provide **consistent and accurate responses to frequently asked questions, freeing up human agents** to handle more complex inquiries. However, autonomous AI systems may **lack the empathy and emotional intelligence** of human agents, which can be important in certain customer interactions. They may also **struggle with understanding complex or ambiguous customer inquiries**, which can lead to frustrating experiences for customers.

Human-mediated conversational models could help to **build rapport** by offer the advantage of **human empathy and emotional intelligence,** also by **reducing frustration** when autonomous conversational systems are unable to provide appropriate response or **increase customers satisfaction** when they prefer to
[64] interact with human operators(Oshrat et al. 2022). In this case **customers preferences** and **variables like age, gender and technological experience** should be considered primarily while selecting suitable model.

Human-mediated conversational models are able to provide **personalized and nuanced responses** to customer inquiries, which can enhance the overall customer experience. However, human-mediated systems can be **costly to maintain and scale**, and their **availability may be limited by time zones, staffing constraints, or language barriers**.

Overall, it is important to consider some factors when selecting between autonomous and human-mediated conversational systems considering their implementation in e-commerce to improve customer experienced:

Scalability. Autonomous systems are generally more scalable than human-mediated systems, as they can handle a high volume of inquiries without the need for additional human agents. Businesses should consider their growth plans and whether they will need to scale their support system in the future.

Level of human aid

Response urgency. Human-mediated systems could be more time-consuming than autonomous systems regarding the response time, as they sometimes require a human agent to be available to respond to inquiries. It is important to consider whether business has the time and resources to provide timely support to their customers.

Complexity of inquiries. Human-mediated agents are better equipped to handle complex inquiries that require emotional intelligence and personalized support. Autonomous systems, on the other hand, are better suited for handling routine inquiries that can be resolved quickly and efficiently.

Integration. The implementation of conversational systems requires integration with existing systems and processes. Businesses should consider the level of effort required to integrate each system and whether they have the necessary technical expertise to do so.

Exploration of the taxonomy

Level of human aid

Summary

<table>
<tr><th></th><th>STRENGTHS</th><th>LIMITATIONS</th><th>ATTRIBUTES TO CONSIDER WHILE IMPLEMENTING</th></tr>
<tr><td>AUTONOMOUS</td><td>24/7 availability
accuracy in frequently asked questions
scalability
reduce customer`s wait time
consistency
relieve the work load of human agents</td><td>lack of empathy and emotional intelligence
understanding complex and ambiguous customer inquiries</td><td rowspan="2">goal or task to perform
room for customers service improvement
complexity of inquiries level of empathy required
Scalability
Integration capabilities
Response urgency
specific needs of the business and its customers
variables: age, gender, technological experience</td></tr>
<tr><td>HUMAN-MEDIATED</td><td>human empathy and emotional intelligence
building rapport
reduce frustration
service quality improvement
personalized and nuanced responses
complex and ambiguous customer inquiries</td><td>costly to maintain and scale
limited by human availability
complexity of scaling</td></tr>
</table>

customer experience

deveopment

business

5.6. Avatar(cartoon-like image) VS Human photo VS Brand logo. Appearance

[34] Research that was conducted by Rifki et al.(2021) pointed on the conversational system`s visual **appearance** as one of the relevant attributes of conversational system that could affect customers attitude toward the system and toward brand at the end. Under the term appearance in this research meant visual component of the model that could use avatar/cartoon-like image, human photo or brand/company logo. However, researchers emphasise the strong impact of **preference`s differences** between user segments that were called **descriptive variables** in the particular research. Descriptive variables include **demographics, personality and experience in using chatbots**. For the purpose of this research these variables would be just mentioned as factors to consider, but will not be investigated closely.

[89] Ciechanowski et al.,(2019) studied chatbots' **perceived competence** in the context of **anthropomorphism**, attempting to investigate the extent to which participants are willing to collaborate with bots on different anthropomorphic levels. To manipulate anthropomorphism, the authors tested two chatbots without and with an avatar. The results showed that the less a chatbot was perceived as human, the less competent it seemed to the participants. Thus, it can be hypothesized that a chatbot that **appears more human would be**
[36] **perceived as more competent** by the users (Raunio, 2021).

In this context it is also important to consider the **uncanny valley effect**(More, 1970) that describes how human-like entity might paradoxically induce a negative affective state when it fails to sufficiently resembles real human
[90] features (MacDorman & Chattopadhyay, 2016). In this hypothesis, a negative affect is defined as the **feeling of eeriness** experienced towards **human-like, yet imperfect entities** (e.g., robots, chatbot). In line with this notion, the study
[91] of Shin et al. (2019) found that enhancing the human-likeness of an artificial entity (i.e., avatar) **can affect the perceived trustworthiness of the entity.** Subsequently, this leads perceivers to reject the entity as the uncanny valley effect activates a negative affective state. This finding suggests that enhancing the human-likeness of chatbots in the context of chatbot customer support may likewise bias user perceptions in a negative way. Nonetheless, this speculation has not been tested in the context of human-chatbot
[92] interaction(Lierop, 2021).

Trust attribute, which is affected by **visual representation and identity cues**,
[93] such as portrait pictures (Oh et al, 2018) was studied by numerous researchers. Especially when the perception of traits, such as warmth and competence, is involved, the topic of trust arises because there is a link

Exploration of the taxonomy

Appearance

[94] between competence and trust especially in context of conversational systems and customer support(Seiler&Schär, 2021)

[36] Some other investigations (Raunio, 2021) revealed a strong dependence of impact on customer experience **correlation between appearance and conversational style** in text-based systems. Hence, **type of user input** should be also considered as determining factor. The research by Raunio revealed some preferences from the user`s side, but these preferences did not show direct affect on customers experience and in particular on perceived ease of use, usefulness, helpfulness, competence, trust, or attitude towards using conversational systems.

[95] However, this dependence allow to form several configurations that in different variations create different **first impression**, that could be used by brands to build appropriate relationships with customers(Fig. 12) A salesperson is judged within seconds and clients decide, whether the salesperson is helpful or too pushy (Ambady et al., 2006) and this is also relevant for e-commerce context. The inferences were made on the basis of Raunio`s interviews.

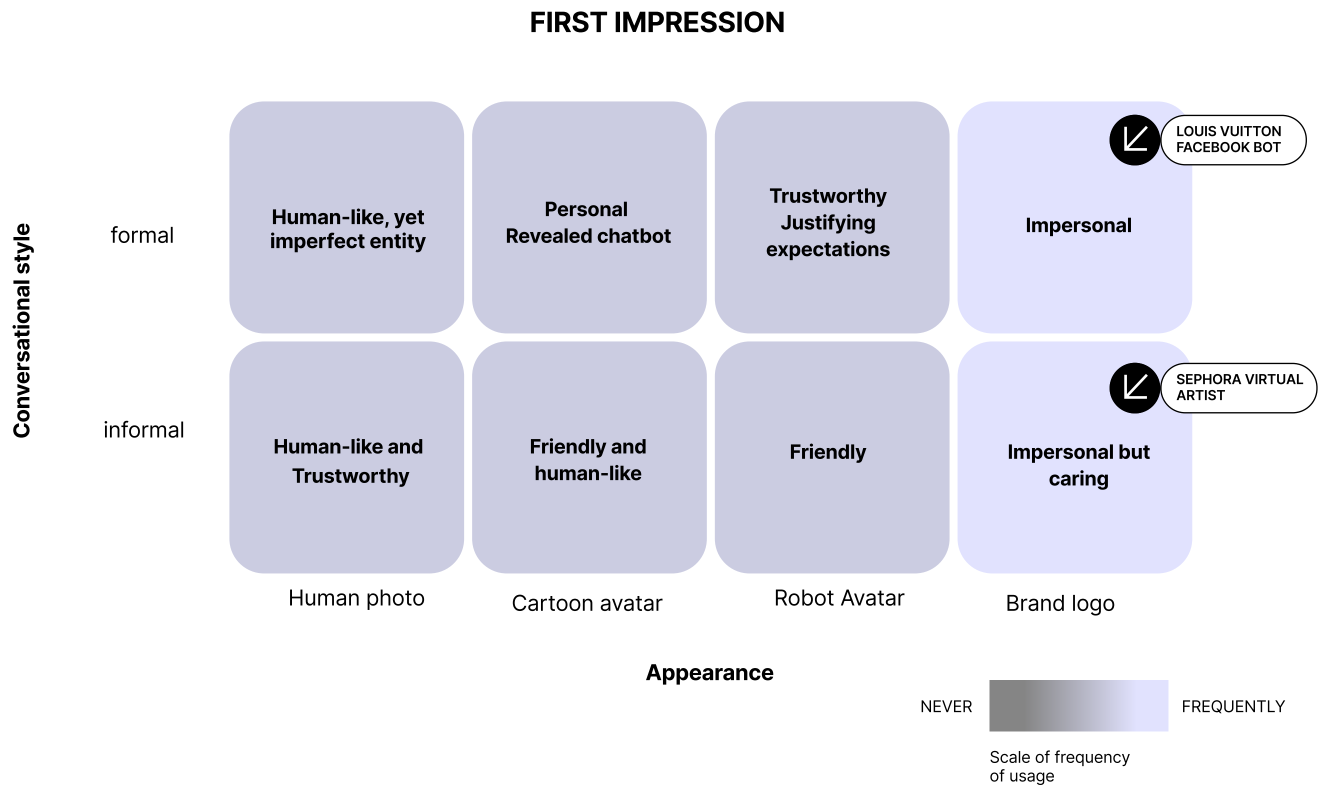


Fig.12 AI powered conversational system configurations based on system`s appearance and conversational style with first impression as configuration-generating attribute

Exploration of the taxonomy

Appearance

Human photo allows the clients to **expect more** from the conversational system and **gain more trust** in cases of accurate and relevant responses, but at the same time provokes strong rejection and disappointment if the system is not able to act like a human as it is pretend to be (Mimoun & Poncin & Garnier 2012). **Cartoon-like human avatar** feels more **personal and prepossessing** and allow to decrease high level of expectation disclosing chatbot`s option. **Robot avatar** with formal conversational style showed **inability to build relationship**, as they perform too robotic, however some participants pointed on **tendency to trust** more machines than people as they are less likely to make mistakes. **Brand logo strengthens** relation with brand, however provokes disappointment as some interview participants pointed on lack of awareness
[36] regarding who they are talking with(Raunio, 2021).

Even though the study of 29 cases in retail industry on chatbotguide.org revealed only one case of human image usage as an avatar(Covergirl Bot) and one case of cartoon-like avatar usage(TJMaxx Bot) while all the rest companies gave the preference to brand logo, all configurations created may be seen in e-commerce as each of the model could serve its particular purpose depending on the **task and objectives of the business.** At the same time, the impact of each of the particular models on customer experience is not well studied for now as there are not too many studies and tests conducted. Moreover, Raunio (2021) declared a need to consider a wider range of factors that jointly with first impression have the ability to affect customer experience.

What is important to mention is that the same interviews revealed **transparency** about the service agent's nature as an important aspect in an online customer service setting. In other words, the conversatinal system should disclose itself as a computer at the beginning of the conversation.
[96] Some authors advise against disclosing chatbots' identity (De Cicco et al, 2020) due to users' tendency to trust computers less than humans.

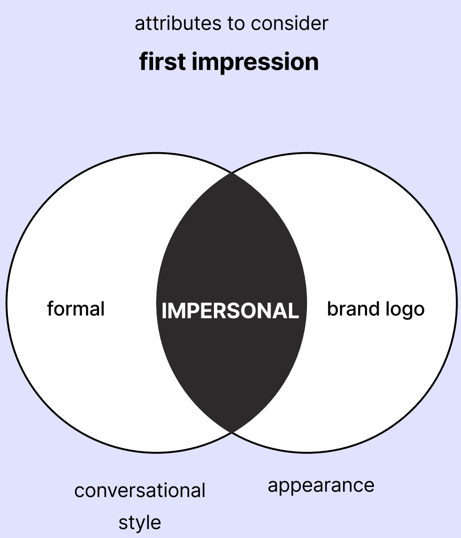
While each type of model has its strengths and weaknesses, the choice of suitable approach should depend on particular **task and customers expectations.** As customers tend to expect more from a highly
[35] anthropomorphised human avatar (e.g., a photo of an actual human)(Mimoun &
[97] Poncin & Garnier 2012). Moreover, research by Kristine L. Nowak(2006) revealed that a less anthropomorphic avatar was received better than a more

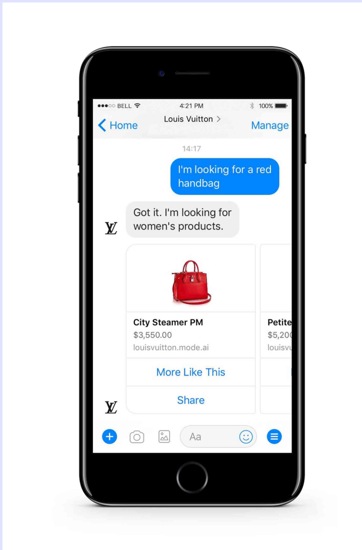
[97] [99]

anthropomorphic one or one without an avatar (Nowak 2004). Furthermore Baylor(2009) found that the presence of a visual avatar could alleviate feelings of frustration and increase enjoyment of the interaction.

Form of communication and social role could be also considered as relevant factor affecting the appropriate model selection.

LOUIS VUITTON FACEBOOK BOT





configuration and models involved

closed-domain | retrieval-based | task-oriented | text-based | autonomous | interpersonal | reactive | integrated

configuration-generating attribute

first impression - **IMPERSONAL**

description of the configuration`s opportunities for CX improvement:
[100]

In context of luxury segment this kind of configuration could convey to customers an expected sense of **respect and suitable for this niche level of distancing,** as casual tone with customers could detract from the luxury experience that they expect. Research in sociology and, more recently, consumer research has shown that the service encounter plays a significant role in the status game (Dion et al, 2017)

limitations

Lack social presence

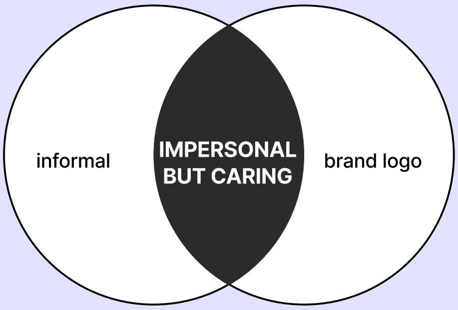
Exploration of the taxonomy

Appearance

Case studies

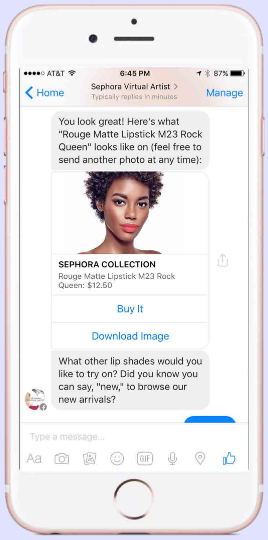
SEPHORA VIRTUAL ARTIST

attributes to consider
first impression



conversational style

appearance



retrieval-based | task-oriented | text-based+image | autonomous | closed domain | intrapersonal | integrated | proactive

configuration and models involved

configuration-generating attribute

first impression - **IMPERSONAL BUT CARING**

description of the configuration`s opportunities for CX improvement:
[101], [102]

This configuration aims to reach a higher level of social presence with **friendliness, expertise and personalization** that could be considered as key drivers of **satisfaction** with a conversational system (Verhagen et al., 2014).
Similarly, Kim et al. (2019) stated that a casual informal conversation style produced **higher enjoyment** and brand logo builds **positive association with brand**.

limitations

could be perceived impersonal

Exploration of the taxonomy

Appearance

Summary

	STRENGTHS	LIMITATIONS
BRAND LOGO	strengthens relation with brand	lack of personality
ROBOT AVATAR	Trustworthy	inability to build relationship
CARTOON AVATAR	feels more personal and prepossessing allow to decrease high level of expectation	discloses chatbot
HUMAN PHOTO	Trustworthy	clients tend to expect more risks of disillusion

ATTRIBUTES TO CONSIDER WHILE IMPLEMENTING

- descriptive variables: demographics, personality and experience in using chatbots
- perceived anthropomorphism and competence
- perceived trustworthiness
- uncanny valley effect
- correlation between appearance and conversational style
- type of user input
- first impression

- customer experience
- deveopment
- business

5.7. Informal VS Formal. Conversational style

[34] As was discovered previously, also in the research by Wijaya and Sari, conversational style can affect conversational systems` **anthropomorphism**, such as empathy, personalization, informal attitude that finally has impact on customer experience. Past research revealed that anthropomorphism affects human perception and behavior in human-computer interactions by, for example, increasing **trust and connectedness** or **stimulating social response**
[103], [36] **behaviors**(Seeger et al.,2021). According to Raunio, in general, two types of conversational styles could be distinguished as formal and informal or competent and warm according to Wijaya & Sari.

If to compare, formal conversational style tend to use more complex words and phrases, and avoid slang. It could be also differentiated by more complex sentence structures with more serious and neutral tone. While informal conversational style could use more common words and slang with more relaxed and informal tone suitable for target audience. Informal conversations tend to have simpler sentence structures and use more colloquial grammar.

The interrelation of conversational style and **appearance** was already
[36] mentioned and studied peviously by Raunio (2021). The configurations formed on the basis of these two parameters describe the customer`s **first impression** from the interaction with conversational system(Fig. 12).

In the literature, some researchers pointed on interrelation between
[104] conversational style and **goal** (Van Dolen et al., 2007). This way a social-oriented conversational style was characterized by informal language, greetings and small talk whereas a task-oriented conversational style involves formal language and on-task dialogues to achieve functional goals
[21] (Chattaraman et al., 2019). However in context of e-commerce nowadays the particular conversational style don`t need to have this direct dependence. And task-oriented models for instance could exploit informal conversational style in order to fit business goals.

[105] Verhagen et al. (2014) found that a social-oriented informal conversational style elicits a higher level of **social presence** compared to a task-oriented formal conversational style. The authors revealed that social presence with **friendliness, expertise, and personalization** are key drivers of **satisfaction** with a conversational system (Verhagen et al., 2014).

Exploration of the taxonomy

Conversational style

[101] Similarly, Kim et al. (2019) stated that a casual informal conversation style produced **higher enjoyment** compared to a formal conversational style.

[106] Liebrecht&Sander (2021) research revealed a conversational system`s informal communication style induced a higher perceived social presence which in turn positively influenced **quality of the interaction and brand attitude**. Besides the positive effects, an informal communication style can also backfire, for example when **perceived as inappropriate**. This has been
[107] shown in Gretry et al.'s (2017) research. They illustrated that not only the conversational style can be essential for the perceived appropriateness of the customer service message, but also the sender of the message, i.e., the brand (Gretry et al., 2017). According to Gretry, success of interactions depends on the appropriateness of the behavior of the interaction partner in regard to their **social roles**. If interaction partners are strangers, a formal conversational style is considered appropriate compared to interacting with an acquaintance or friend. This theory explains the results found by Gretry et al. (2017): participants perceived an informal conversational style as appropriate when they were familiar with the brand, but as inappropriate when they were unfamiliar with the brand.

[96] A study by De Cicco et al. (2020) revealed another important factors to consider such as **demographic factors**. The researchers addressed the implications that conversational systems' conversational styles have on **younger consumers** using them in context of online food delivery services. The findings revealed that the interaction with the social-oriented chatbot with informal conversational style **increased users' perception of social presence and perceived enjoyment**. However, the researchers did not find a significant effect of the interaction style on trust and intention to use (De Cicco et al., 2020).

[108] Elsholz et al. (2019) tested two different language styles and found that a more modern chatbot version was more often referred to as being **'easy to use'**, whereas the "Shakespearean" chatbot version was more often referred to as
[109] being '**fun to use**'. Likewise, Liebrecht and van Hooijdonk (2020) found several linguistic elements, which should be incorporated in conversaional system in order to **increase anthropomorphism: empathy, support, humour, informal attitude.**

Conversational style

An informal style can make the conversation feel more **personal and relatable, potentially increasing brand loyalty and trust**. However, it's essential to ensure that the informal style is consistent with the brand image and voice. For example, a luxury fashion brand may not want to use a casual tone with its customers as it could detract from the luxury experience that they expect.

On the other hand, a formal style can convey a sense of **professionalism and expertise**, which can be especially important when dealing with more complex and technical products or services. It may also be more appropriate for certain customer interactions, such as addressing complaints or resolving issues.

Overall, both formal and informal conversational AI styles can be effective in e-commerce, but businesses need to choose the style that best fits their brand and **customer expectations** while being adaptable to each customer's communication styles.

Conversational style

Summary

	STRENGTHS	LIMITATIONS	ATTRIBUTES TO CONSIDER WHILE IMPLEMENTING
FORMAL	● sense of professionalism and expertise ● reliable and convincing	● could sound robotic	perceived anthropomorphism perceived trustworthiness correlation between appearance and conversational style first impression goal brand attitude and social role customers expectations demographics
INFORMAL	● social presence ● higher enjoyment ● personal and relatable	● irrelevance in some cases	

● customer experience

5.8. Interpersonal VS Intrapersonal VS Inter-agent. Type of service provided.

According "An Overview of Chatbot Technology" published online in 2020 as part of IFIP International Conference on Artificial Intelligence Applications and Innovations the criteria that could be valuable for determining modern conversational systems should be considered a type of **service provided.**
[6] According Adamopoulou&Moussiades (2020) under this term should be understood a sentimental proximity of the chatbot to the user or the amount of intimate interaction that takes place. The typology defined in this paper implies three possible models: interpersonal, intrapersonal and inter-agent.

The application of one or another type of the model is primarily determined by **certain task** the conversational system is aim to
[6] perform(Adamopoulou&Moussiades, 2020). However, there are some critical factors that have to be considered while implementing any particular model mentioned above in the context of e-commerce to improve customer experience:

Customers expectations regarding the process they are going to pass through in order to receive the result desired. Which are affected in their turn by a number of considerations that were studied more than once and could involve personal needs, individual characteristics, past experience, third party inputs, the social and cultural environment, and communications from
[110] vendors(Archer et al, 2001).

Brand`s position and the **type of relationships** they are going to build with clients which could be based on credibility or intimacy for instance.

Conversational models in interpersonal domain are not required to build strong relationships with the customer. They are not companions of the user, but they are available to assist the customer in his problems solving by collecting specific information and answering with relevant data or action. They can have a personality, can be friendly, and will probably remember information about the user, but they are not required or expected by the customers to do so. What is more relevant for the customer in the borders of interpersonal model is the ability to **solve the problem and resolve miscommunication**. Recent researches in the field of conversational systems adoption by the final
[111] user(Sheehan et al.,2020) revealed that consumers are unlikely to reject a customer service chatbot for simply seeking **clarification** – providing that the clarification could compensate any miscommunication. This occurs even if the

additional effort by the user required in order to respond to the clarification request. As miscommunication happens between two human interlocutors quite frequently, this makes sense conceptually. This way, the researchers pointed out that ability to resolve miscommunication appears to be as effective as avoiding it. It means that when developing conversational models in interpersonal domain a great emphasis should be placed on providing **relevant, reliable, personalized, precise, and up-to-date information in a**
[104] **useful format (Ashfaq et al, 2020).**

However if clarification require too much time the factor as **lengths of**
[112] **conversation** may affect customers **satisfaction** (Telner, 2021). The time parameter could also involve the **system response time** that has been identified as a critical factor for user satisfaction and productivity (Hoxmeier
[113] and DiCesare, 2000). In cases of exploitation of autonomous models, the system could obtain higher rates. However, this index may vary with use of human-mediated models. Thus the criteria of **level of human aid** should be also considered.

Intrapersonal conversational models exist within the personal domain of the
[6] user (Adamopoulou&Moussiades, 2020). In context of e-commerce this means that it much more **aware of customers personal data** as in comparison with interpersonal domain, it is permitted to operate closest to the customer`s private life. Conversational system with intrapersonal model implemented could **be integrated** with instant massagers application or social media
[43] (Sanchez, 2019), storing the user's opinion, preferences etc in order to propose personalised experiences with special relevance. They are companions to the user and understand the user like a human and partner does.

In this context, its **role and form of communication are expected to be more social**. Studies that have explored the CASA paradigm (computers are social
[114], [115] actors)(Nass et al., 1994, Nass and Moon, 2000) state that people tend to
[116] respond socially to computers (Voorveld&Araujo, 2020). And even minimal social cues can influence this reaction and particular behavior. Conversational systems with intrapersonal model are often designed to be **more human like**
[117] and interact socially. For instance, Araujo(2018) stated that a human-like conversation felt better for customers and is enlarging customer trust. This way, **social cues** are a potentially key component of intrapersonal conversational system's persuasive capabilities, that have been studied on

Exploration of the taxonomy

Type of service provided

[118] many occasions(Feine et al., 2019) and also in context of e-commerce(Liew et
[119] al., 2017). High level of personalisation expected from intrapersonal models
require to pay attention on attributes of **trust.** The aspects like competence,
integrity and benevolence were studied frequently in context of e-commerce
[120], [121] (Chen & Dhillon, 2003; Guo et al, 2022).
To **privacy issues** much attention was also payed by researchers who suggest
[122] to enhance security and be more transparent about the policy(Shi et al, 2020).

Inter-agent model could be implemented to handle communication between
[6] two conversational systems. (Adamopoulou&Moussiades, 2020). In particular, intrapersonal model could be joint with interpersonal model or another intrapersonal model in order to provide extended opportunities.(e.g Ask Perry Ellis).

Potentially in combination with **appearance and conversational style** configuration each model bases on type of service provided could form a particular type of **relationship.** However, there are not enough studies at the moment able to reveal and prove this interrelation. Hence, within this research a hypothetical configuration will be formed.

Exploration of the taxonomy

Type of service provided

Summary

	STRENGTHS		LIMITATIONS	ATTRIBUTES TO CONSIDER WHILE IMPLEMENTING
INTERPERSONAL	solving the problem and resolving misscommunic ations relevant, reliable, personalized, precise, and up-to-date information in a useful format	building strong relationships with customers	lengths of conversation level of human aid	certain task
INTRAPERSONAL	understanding customer`s preferences social role for strengthening relationships more human-like	privacy issues	social cues level of human-likeness trust attributes	customers expectations brand`s position and type of relationships system response time
INTER-AGENT	extended opportunities	complexity of systems	possibility of integration	

customer experience

deveopment

business

5.9. Reactive VS Proactive. Behavior.

Another types of models based on type of behavior were mentioned by Wijaya and Sari. According the paper, chatbots could behave as **proactive** or **reactive** while interacting with user. In this context a proactive chatbot is programmed to take some initiatives in providing messages without being asked directly by the user. Meanwhile, reactive chatbots tend to deliver messages only based on what the user is asking or ordering.

[123]

According to Følstad & Halvorsrud, (2020) research, proactive chatbots demonstrated their ability to provide relevant information to users, improving **conversational efficiency**, that led to a **good impression of service**. In context of e-commerce this type of model could provide suggestions or recommendations based on customer`s browsing or purchase history or can help guide customers to product pages, offer promotions or discounts, and provide personalized recommendations based on their interests and preferences. Proactive chatbots can enhance the customer experience by providing a more **personalized and convenient** shopping experience.

But on the other hand, a chatbot's proactive attitude could also give a bad impression in the cases when it was **considered as disturbing** for some people and intruding on one's **privacy**, thus proactive behavior should be designed with care.

[123]

[124]

A key motivation for users to engage with conversational system is to get easy and accessible help and information. Følstad & Halvorsrud findings revealed that also when communicating service offers it is critical to design for **efficiency** in conversation. This way, the key determinant of the benefit of proactive approaches noted by Følstad & Halvorsrud is the **perceived relevance** of the service offer. Unless the service offer is perceived as relevant to the conversation at hand, it likely will be regarded as unwanted and invasive(Liao et al., 2016). This study revealed that varying levels of proactiveness in chatbot communication may be in line with **user preferences**. That is, users see **benefits** with both reactive and proactive approaches. But, if the perceived relevance of a service offer cannot be determined, implementation of proactive model could be a riskier approach.

This way, while implementing any type of model based on behavior model it is important to consider **individual differences in user tolerance** for proactivity in conversational design. Because of this, as suggested by the participants of

Behavior

[123] Følstad & Halvorsrud`s research, it could be important to communicate service offers in a **cautious manner and allow users easily discard them** to be potentially helpful but not to place any undue demand on the user.

Reactive approaches leave the user in control and are more in line with **user expectations**. That is, users will likely be satisfied by the customer service conversational system provided they get the needed service offers upon request. Reactive behavior in conversational system involves responding to customer inquiries or messages. In e-commerce, this typically means answering questions about products, order status, shipping, and returns as they are raised by customers. This type of model can be highly effective in providing immediate support and resolving customer issues with **speed and efficiency**. However, if the conversational system is not able to answer the customer's question or solve their issue, it still could result in frustration for the customer and a negative experience.

[123] The participants of Følstad & Halvorsrud`s investigation also noted that reactivity may lead to users remaining **unaware of relevant service offers**, that is, a lack of proactivity may lead to users potentially missing out on relevant information or opportunities. This also will negatively affect **business` opportunities** to attract users and get clients. In consequence, well-crafted proactive approaches may be considered valuable, reflecting good customer
[125] service. This complies with previous findings by Chaves& Gerosa(2018), suggesting that proactivity in chatbots may lead to beneficial exploration by users, and is also in line with findings from service research where proactivity in relevant service offerings often is appreciated by users.

In summary, the most effective chatbots in e-commerce will likely strike a balance between the two, providing reactive support when needed and proactively engaging with customers in a way that feels helpful and relevant.

Exploration of the taxonomy

Behavior

Summary

	STRENGTHS	LIMITATIONS	ATTRIBUTES TO CONSIDER WHILE IMPLEMENTING
REACTIVE	speed and efficiency align with customer's expectations	unawareness of relevant service offers	user preferences and expectations individual differences in user tolerance
PROACTIVE	conversational efficiency personalization convenient shopping experience	could be considered as disturbing privacy issues unguaranteed relevance of suggestions	

customer experience

business

5.10. Standalone application VS Web-based VS Integrated. Messaging channels.

Exploring the wide typology of available on the market AI conversational applications, it is important to mention one more parameter described by
[42] Smutny, Schreiberova(2020) in their classification. This parameter was defined as **messaging channels type** in this research and implies the division of all conversational applications into: **standalone applications(desktop or mobile), web-based service(integrated on the web or individual), integrated(to instant messaging apps or communication and collaboration platform).** This way, channels represent the connectors between the users and the chatbot application. It is important to mention that to standalone type could be added also smart devices that are gaining popularity with the raise of voice shopping
[126] (Hu et al., 2022)

All types mentioned above are commonly used in the field of e-commerce and the use of one or another type depends firstly on **demographic factors and** brand`s **target audience** that these channels aim to reach. In his research
[43] Sanchez(2019) made an example of WeChat that is the most used app in China, that provide an opportunity for Chinese brands to provide value for potential customers with integrated model. Facebook Messenger, Slack, Kik and Telegram are the most commonly used platforms for integration that join different audience according their age, nationality and entire lifestyle. While Web-based models for instance could meet the needs of old-age groups that could be less familiar with mobile applications or instant messaging apps.

The expected from the client **social role** of the conversational system could be also mentioned
as determining factor for selection of the appropriate messaging channel. As integrated to instant messaging apps model could potentially build more **intimate and trustworthy relationship** between the customer and brand. Similar level of **loyalty and trust** could be reached with standalone applications that was proved by numerous researches who explored customers behavior
[32] towards smart speakers such as Amazon Alexa or Google assistant(Mari &
[60] Algesheimer, 2021), (Moriuchi, 2019) and who studied CASA phenomenon in
[117] this context (Araujo, 2018) .

One or another type could be also more suitable for a **certain task and context of interaction.** The study conducted by Drift, Survey Monkey, Salesforce and Myclever was dedicated to the issues of how people are buying and communicating with businesses and the related emerging opportunities. One of the most common answers included websites being hard to navigate (34%). It implies that the online experiences businesses are not providing an experience matching the **customers expectations**. In this perspective, web-based conversational models can enhance the customer experience predicting and providing the information they are looking for **quickly and easily**.

Accessibility. Standalone application and integrated models potentially could be easier and faster to reach both by the user and by the business in comparison to web-based models as they don't require using browser to access. However in this context the issue of the appropriate conversational system`s **behavior model** should be considered as proactive models are **risking to seem annoying and disturbing.**

One of the important factors to consider is **building opportunities**. Messenger-based AI conversational agents have the advantage of being **easily build** on the basis of existing messaging applications even without professional development support. Usually, messenger platforms offer APIs and SDKs that can be used for development, making the development process faster and cheaper. On the other hand a wide range of available now Software libraries, ready-to-use services with already trained algorithms, that developers can integrate easily with particular system(i.e., IBM Watson, Cortana, etc.) allow to facilitate the process of development of standalone and web-based models that, however could be more expensive.

Standalone agents generally have the most extended **functionality** as they are not limited by the technical constraints of a web browser or messaging application. This could possibly lead to more engagement from the customers side, however this aspect of customer experience is not well studied for now.

Security. Standalone and web-based conversational models may have higher levels of security as they are not integrated into third-party platforms. While messenger-based conversational models may have additional security risks associated with being integrated into messaging applications.

Overall, the choice between standalone, web-based, and messenger-based AI conversational agents will depend on the specific needs and constraints of the context of AI conversational system implementation..

Exploration of the taxonomy

Behavior

Summary

	STRENGTHS	LIMITATIONS	ATTRIBUTES TO CONSIDER WHILE IMPLEMENTING
STANDALONE	accessibility higher level of security extended functionality	could be expansive and time-consuming	demographic factors target audience certain task and context of interaction customers preferences and expectations social role behavior model costs time-to-market level of security
WEB-BASED	could be more accessible by old-age groups	accessibility	
INREGRATED	easy fast and cheap to develop accessibility could potentially gain more trust and build more personal relationships	security risks	

customer experience

deveopment

business

6. Make meaning with data linking. From Taxonomy to Ontology of AI conversational models in context of customer experience in e-commerce.

The exploration of each model through the research questions stated allowed to discover some objective strengths and weaknesses of every model and distinguish a range of attributes that jointly have to be considered by designers and businesses while implementing any particular AI conversational system in any e-commerce strategy. Here it is important to mention that these attributes, being selected from specific studies and specific contexts, could not be considered as incontrovertible factors that ensure the success of a system implementation, but primarily highlight potential pain points that need to be addressed in design and development of any possible AI conversational system in context of customer experience and e-commerce.

During the investigation, there were also discovered some significant interrelations between models revealing its potential to be joined under a specific concept that could affect a particular dimension of customer experience and could bring valuable insights for designers working on enhancing customer experience. That allowed the formation of an **ontology** of AI conversational systems in order to **make more meaning with the data linking and achieve a higher level of awareness by providing richer information about the relationships among models**(Fig.13). This ontology created provides a basic **understanding of any AI conversational application as system** consisted of different components - models that in different combinations could form certain aspect of customer experience such as **perceived by customer form of communication and social role, suitable answer`s model, first impression, type of information expected by customer and room for entire service improvement**.

Within this work five concepts of interrelations, that in context of this work were called “configurations” were formed, described and supported with relevant researches and case studies to illustrate the dependence of the models on each other and their shared ability to form customer experience. However, some configurations were mentioned as hypothetical due to lack of reliable information in the form of relevant studies that could substantiate the estimated impact on customer experience in context of e-commerce.

Conclusions

The need for this research in particular, the need of a systematic approach to analysing a wide market of AI conversational technologies and systems, arose with a rapid grow of these technologies that continuously change the way people behave during their daily routine and their expectations regarding the service provided by companies to meet their needs in context of customer experience. Businesses are in search of new opportunities to strengthen the relationship with customers and new technological capabilities look tempting, however the amounts of unstructured information available online don`t provide a clear overview of the AI conversational applications and their opportunities regarding the impact on customer experience in e-commerce. The role of the designer here is to keep abreast and understand all modern AI conversational applications as system in order to be able to manage its elements to fit any business problem properly.

Several findings mentioned in this work allow contribute to general knowledge about AI conversational systems in the context of customer experience in e-commerce. First of all, the research part that aimed to review the most significant to-date classifications, allowed to define those parameters of AI conversational systems that make sense for customer experience in the context of e-commerce. This allowed to create a faceted taxonomy of AI conversational systems and provide an approach to understanding any possible AI conversational application as a system that consists of different components - models which in different combinations could form appropriate to particular context customer experience. Within this work, each of the models was explored from the point of view of its objective strengths and weaknesses regarding its impact on customer experience. Moreover, other important attributes of each model that have to be considered by designers and stakeholders during AI conversational system development in order to address the most probable pain points of the designed experience were defined. Finally, the remarkable interrelations between models and their shared impact on different spheres of customer experience were defined. This allowed to create the ontology of AI conversational models that help to make more meaning with the data linking and achieve a higher level of awareness regarding AI conversational system implementation to enhance the customer experience in the context of e-commerce.

Conclusions

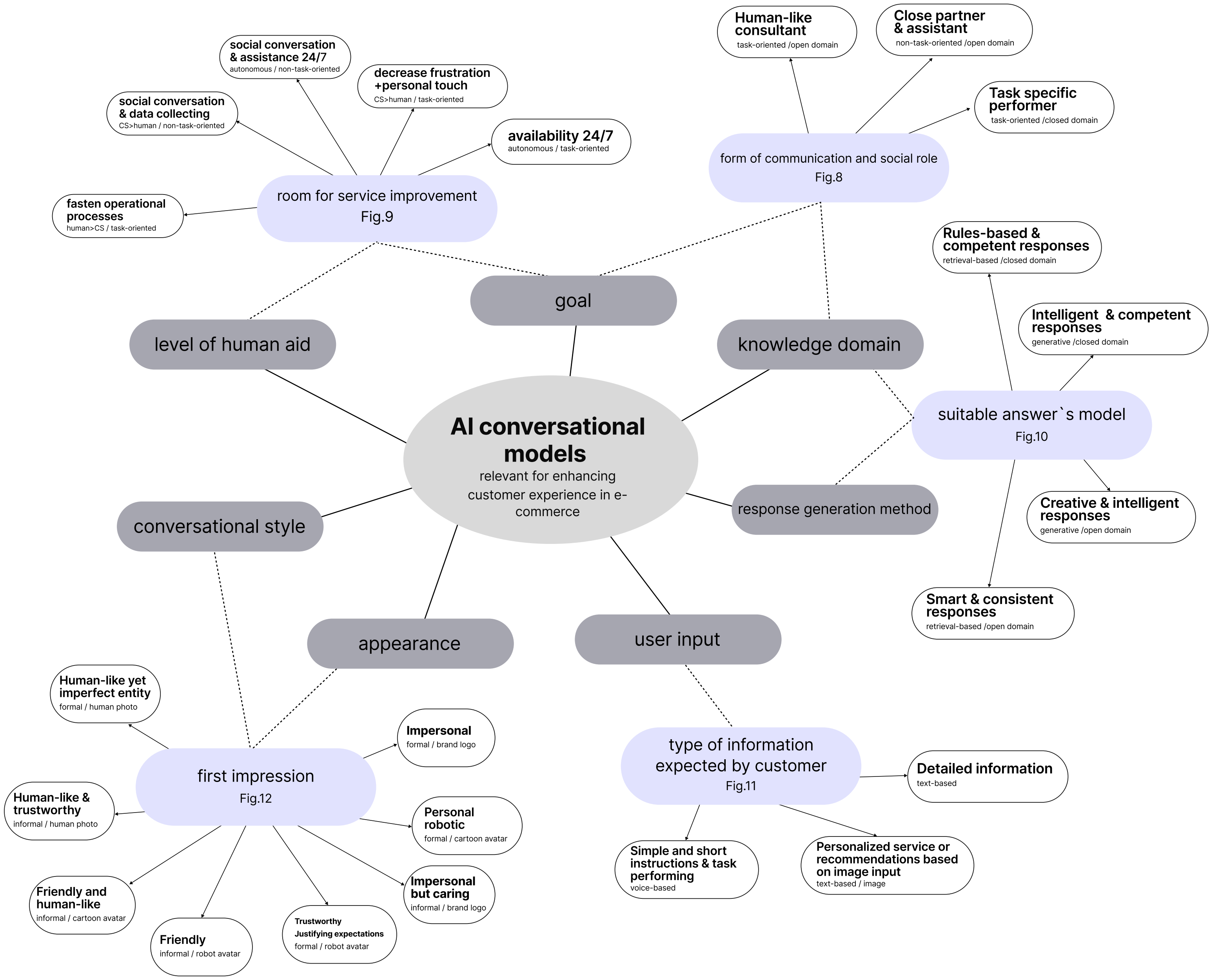


Fig.13 Ontology of AI conversational models relevant for enhancing customer experience in e-commerce.

Limitations and future research directions.

Within this work the approach to analyzing a wide market of AI conversational systems was provided. The configurations which were framed do not constitute the only possible option and represent the concepts within the ontology. The knowledge about every particular model although reflects its significant aspects, is limited by a number of researches and academic papers that were reviewed and mentioned in this work.
in addition, the paper involves case studies based on configurations that, according to the results of the investigation, turned out to be the most frequently used in the context of e-commerce, though some other promising configurations mentioned require more testing and detailed study in the future.

Bibliography

[1] Bughin, Seong, Manyika, Chui, & Joshi, 2018 ‘Notes from the AI frontier: Modeling the impact of AI on the world economy’. Available at: https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy.

[2] Dale, 2019 ‘Voice assistance in 2019’. Available at: https://www.cambridge.org/core/journals/natural-language-engineering/article/voice-assistance-in-2019/46F9A70F32292B5E382FD4F7628C69B3.

[3] Sheetal Kusal; Shruti Patil; Jyoti Choudrie; Ketan Kotecha; Sashikala Mishra; Ajith Abraham, 2022 ‘AI-Based Conversational Agents: A Scoping Review From Technologies to Future Directions’. Available at: https://ieeexplore.ieee.org/document/9864589.

[4] Nicolescu, Tudorache 2022, ‘Human-Computer Interaction in Customer Service: The Experience with AI Chatbots—A Systematic Literature Review’. Available at: https://www.mdpi.com/2079-9292/11/10/1579.

[5] Elayne Ruane, Abeba Birhane, Anthony Ventresque, 2019, ‘Conversational AI: Social and Ethical Considerations’. Available at: https://www.researchgate.net/publication/337925917_Conversational_AI_Social_and_Ethical_Considerations.

[6] Adamopoulou, Moussiades, 2020, ‘An Overview of Chatbot Technology’. Available at: https://link.springer.com/chapter/10.1007/978-3-030-49186-4_31.

[7] Huma Shah, Kevin Warwick, 2017, ‘Trust and Decision-Making in Turing’s Imitation Game’. Available at: https://www.researchgate.net/publication/314087973_Trust_and_Decision-Making_in_Turing's_Imitation_Game.

[8] Joseph Weizenbaum, 1966, ‘ELIZA—a computer program for the study of natural language communication between man and machine’. Available at: https://dl.acm.org/doi/10.1145/365153.365168.

[9] Lorenz Cuno Klopfenstein,Saverio Delpriori, Silvia Malatini, Alessandro Bogliolo, 2017, ‘The Rise of Bots: A Survey of Conversational Interfaces, Patterns, and Paradigms’. Available at: https://www.researchgate.net/publication/317418656_The_Rise_of_Bots_A_Survey_of_Conversational_Interfaces_Patterns_and_Paradigms.

[10] Soffar, H., 2019 ‘Artificial Intelligence in Education, AI Tutors Features, Advantages & Disadvantages.’. Available at: cirp.org/(S(351jmbntv-nsjt1aadkposzje))/reference/referencespapers.aspx?referenceid=2771168.

[11] Daniel Adiwardana, Minh-Thang Luong, David R. So, Jamie Hall, Noah Fiedel, Romal Thoppilan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, Quoc V. Le, 2020 ‘Towards a Human-like Open-Domain Chatbot’. Available at: https://arxiv.org/abs/2001.09977.

[12] Shanahan, 2022 ‘Talking About Large Language Models’. Available at: https://arxiv.org/pdf/2212.03551.pdf.

[13] Quim Motger, Xavier Franch, Jordi Marco, 2021, ‘Conversational Agents in Software Engineering: Survey, Taxonomy and Challenges’. Available at: https://arxiv.org/abs/2106.10901.

[14] Alnefaie, Ahlam; Singh, Sonika; Kocaballi, A. Baki; and Prasad, Mukesh, 2021, ‘Factors Influencing Artificial Intelligence Conversational Agents Usage in the E-commerce Field: A Systematic Literature Review’. Available at: https://aisel.aisnet.org/acis2021/47/.

[15] Julija Skrebeca, Paula Kalniete, Janis Goldbergs, Andrejs Romanovs et al., 2021, ‘Modern Development Trends of Chatbots Using Artificial Intelligence (AI)’. Available at: https://www.researchgate.net/publication/356487897_Modern_Development_Trends_of_Chatbots_Using_Artificial_Intelligence_AI.

[16] Weng Marc Lim, Satish Kumar, Sanjeev Verma, Rijul Chaturvedi, 2022, ‘Alexa, what do we know about conversational commerce? Insights from a systematic literature review’. Available at: https://onlinelibrary.wiley.com/doi/full/10.1002/mar.21654.

[17] Panitan Muangkammuen, Narong Intiruk, Kanda Runapongsa Saikaew, 2018, ‘Automated Thai-FAQ Chatbot using RNN-LSTM’. Available at: https://gear.kku.ac.th/~krunapon/research/pub/2018/thaifaq.pdf.

[18] María D. Illescas-Manzano, Noé Vicente López, Nuno Afonso González, Carmen Cristofol Rodríguez, 2021, ‘Implementation of Chatbot in Online Commerce, and Open Innovation. Available at: https://www.mdpi.com/2199-8531/7/2/125.

[19] Mari, Alex, 2019 'Voice Commerce: Understanding Shopping-Related Voice Assistants and their Effect on Brands'. Available at: https://www.zora.uzh.ch/id/eprint/197725/1/VoiceCommerce_VoiceAssistants_AlexMari_UZH_2019.pdf.

[20] Shafquat Hussain, Omid Ameri Sianaki, Nedal Ababneh, 2019 'A Survey on Conversational Agents/Chatbots Classification and Design Techniques'. Available at: https://www.researchgate.net/publication/331746678_A_Survey_on_Conversational_AgentsChatbots_Classification_and_Design_Techniques.

[21] Veena Chattaraman, Wi-Suk Kwon, Juan E. Gilbert, Kassandra Ross, 2019 'Should AI-Based, conversational digital assistants employ social- or task-oriented interaction style? A task-competency and reciprocity perspective for older adults'. Available at:https://www.sciencedirect.com/science/article/abs/pii/S0747563218304230?fr=RR-2&ref=pdf_download&rr=7b4e0c703a8b076d.

[22] Anirban Majumder, Abhay Pande, Kondalarao Vonteru, Abhishek Gangwar, Subhadeep Maji, Pankaj Bhatia & Pawan Goyal, 2018, 'Automated Assistance in E-commerce: An Approach Based on Category-Sensitive Retrieval'. Available at: https://link.springer.com/chapter/10.1007/978-3-319-76941-7_51.

[23] Amir Vakili Tahami, Kamyar Ghajar, Azadeh Shakery, 2020, 'Distilling Knowledge for Fast Retrieval-based Chat-bots'. Available at: https://dl.acm.org/doi/abs/10.1145/3397271.3401296.

[24] Ajie Kusuma Wardhana; Ridi Ferdiana; Indriana Hidayah et al., 2021, 'Empathetic Chatbot Enhancement and Development: A Literature Review'. Available at:https://ieeexplore.ieee.org/abstract/document/9466027.

[25] Meng Chen, Ruixue Liu, Lei Shen, Shaozu Yuan, Jingyan Zhou, Youzheng Wu, Xiaodong He, Bowen Zhou, 2020, 'The JDDC Corpus: A Large-Scale Multi-Turn Chinese Dialogue Dataset for E-commerce Customer Service'. Available at: https://arxiv.org/pdf/1911.09969.pdf.

[26] Kucherbaev, Pavel; Bozzon, Alessandro; Houben, Geert-Jan, 2018, 'Human Aided Bots'. Available at: https://pure.tudelft.nl/ws/portalfiles/portal/55206288/08371205.pdf.

[27] Dellermann, D.; Ebel, P.; Söllner, M. & Leimeister, J. M., 2019, 'Hybrid Intelligence' Available at: http://pubs.wi-kassel.de/wp-content/uploads/2019/09/JML_744.pdf.

[28] Ali Trawnih, Sultan Al-Masaeed , Malek Alsoud and Amer Muflih Alkufahy, 2022 'Understanding artificial intelligence experience: A customer perspective.' Available at: https://www.growingscience.com/ijds/Vol6/ijdns_2022_65.pdf.

[29] Xusen Cheng, Ying Bao, Alex Zarifis, Wankun Gong, Jian Mou, 2021 'Exploring consumers' response to text-based chatbots in e-commerce: the moderating role of task complexity and chatbot disclosure.' Available at: https://www.emerald.com/insight/content/doi/10.1108/INTR-08-2020-0460/full/pdf?title=exploring-consumers-response-to-text-based-chatbots-in-e-commerce-the-moderating-role-of-task-complexity-and-chatbot-disclosure.

[30] M.Mamatha, C.Sudha, 2021, 'Chatbotfor E-Commerce Assistance:based on RASA.' Available at: https://turcomat.org/index.php/turkbilmat/article/view/6943/5695.

[31] Peng Hu, Yaobin Lu, Bin Wang, 2022, 'Experiencing power over AI: The fit effect of perceived power and desire for power on consumers' choice for voice shopping'. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0747563221004143#bib36.

[32] Mari & Algesheimer, 2021, 'The Role of Trusting Beliefs in Voice Assistants during Voice Shopping'. Available at: https://aisel.aisnet.org/hicss-54/in/ai_based_assistants/7/.

[33] Liew Yi Kei, 2021, 'Chatbot ± Beauty Skin Care Products Recommendations'. Available at: http://eprints.utar.edu.my/4739/1/fyp_IB_2021_LYK.pdf.

[34] Rifki Ryandra Wijaya and Hasrini Sari, 2021, 'Understanding Heterogeneity in CRM Chatbot User Preference'. Available at: http://ieomsociety.org/proceedings/2021indonesia/658.pdf.

[35] Mohamed Slim Ben Mimoun, Ingrid Poncin, Garnier Marion, 2012, 'WITHDRAWN: Case study: Embodied virtual agents: An analysis on reasons for failure'. Available at: https://www.researchgate.net/publication/271560720_WITHDRAWN_Case_study_Embodied_virtual_agents_An_analysis_on_reasons_for_failure.

[36] Katja Raunio, 2021, ‘Chatbot anthropomorphism: Adoption and acceptance in customer service’ Available at: http://essay.utwente.nl/86151/1/Raunio_MA_BMS.pdf.

[37] Ben Sheehan, Hyun Seung Jin, Udo Gottlieb, 2020 ‘Customer service chatbots: Anthropomorphism and adoption.’ Available at: https://www.sciencedirect.com/science/article/abs/pii/S0148296320302484.

[38] Martin Adam, Michael Wessel & Alexander Benlian, 2020 ‘AI-based chatbots in customer service and their effects on user compliance.’ Available at: https://link.springer.com/article/10.1007/s12525-020-00414-7.

[39] Følstad & Halvorsrud, 2020, ‘Communicating Service Offers in a Conversational User Interface: An Exploratory Study of User Preferences in Chatbot Interaction.’ Available at: https://dl.acm.org/doi/pdf/10.1145/3441000.3441046.

[40] Francisco A. M. Valério,Tatiane G. Guimarães,Raquel O. Prates,Heloisa Candello, 2020, ‘Comparing users' perception of different chatbot interaction paradigms: a case study’. Available at: https://dl.acm.org/doi/pdf/10.1145/3424953.3426501.

[41] Hermès Meerschman, Juan Verkeyn, 2019, ‘TOWARDS A BETTER UNDERSTANDING OF SERVICE QUALITY ATTRIBUTES OF A CHATBOT’. Available at: https://libstore.ugent.be/fulltxt/RUG01/002/784/388/RUG01-002784388_2019_0001_AC.pdf.

[42] Smutny, Schreiberova, 2020, ‘Chatbots for learning: A review of educational chatbots for the Facebook Messenger’. Available at: https://www.sciencedirect.com/science/article/pii/S0360131520300622.

[43] J u a n M a r c o s Sa n c h e z, 2019, ‘Facebook Messenger Chatbots - How businesses can benefit from this opportunity’. Available at: https://www.politesi.polimi.it/bitstream/10589/148735/1/Facebook%20Messenger%20Chatbots%20-%20How%20businesses%20can%20benefit%20from%20this%20opportunity.pdf.

[44] Tom Young, Frank Xing, Vlad Pandelea, Jinjie Ni, Erik Cambria, 2022, ‘Fusing Task-Oriented and Open-Domain Dialogues in Conversational Agents’. Available at: https://ojs.aaai.org/index.php/AAAI/article/view/21416.

[45] Jing Xu, Da Ju, Margaret Li, Y-Lan Boureau, Jason Weston, Emily Dinan, 2021, 'Recipes for Safety in Open-domain Chatbots' Available at: https://arxiv.org/pdf/2010.07079.pdf.

[46] Zekang Li, Jinchao Zhang, Zhengcong Fei, Yang Feng, Jie Zhou, 2021 'Addressing Inquiries about History: An Efficient and Practical Framework for Evaluating Open-domain Chatbot Consistency.' Available at: https://arxiv.org/pdf/2106.02228.pdf.

[47] Yixin Nie, Mary Williamson, Mohit Bansal, Douwe Kiela, Jason Weston, 2020 'I like fish, especially dolphins: Addressing Contradictions in Dialogue Modeling, 2020 'AI-based chatbots in customer service and their effects on user compliance.' Available at: https://arxiv.org/abs/2012.13391.

[48] Janarthanan Balakrishnan & Yogesh K. Dwivedi, 2020, 'Conversational commerce: entering the next stage of AI-powered digital assistants.' Available at:https://link.springer.com/article/10.1007/s10479-021-04049-5.

[49] William Seymour, Xiao Zhan, Mark Cot´e, and Jose Such, 2022, 'A Systematic Review of Ethical Concerns with Voice Assistants'. Available at: https://arxiv.org/pdf/2211.04193.pdf.

[50] Shrikant Malviya; Rohit Mishra; Santosh Kumar Barnwal; Uma Shanker Tiwary, 2021, 'HDRS: Hindi Dialogue Restaurant Search Corpus for Dialogue State Tracking in Task-Oriented Environment'. Available at: https://ieeexplore.ieee.org/abstract/document/9376978.

[51] David Gefen, Elena Karahanna, Detmar Strauba, 2003, 'Trust and TAM in Online Shopping: An Integrated Model'. Available at: https://www.researchgate.net/publication/220260204_Trust_and_TAM_in_Online_Shopping_An_Integrated_Model.

[52] Graeme McLean, Kofi Osei-Frimpong, Jennifer Barhorst, 2021, 'Alexa, do voice assistants influence consumer brand engagement? – Examining the role of AI powered voice assistants in influencing consumer brand engagement'. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0148296320307980.

[53] Keng-Boon Ooi, Jun-Jie Hew & Binshan Lin, 2018, 'Unfolding the privacy paradox among mobile social commerce users: a multi-mediation approach'. Available at: https://www.tandfonline.com/doi/abs/10.1080/0144929X.2018.1465997.

[54] Ryan Fellows, Hisham Ihshaish, Steve Battle, Ciaran Haines, Peter Mayhew, J. Ignacio Deza, 2021 'Task-oriented Dialogue Systems: performance vs. quality-optima, a review.' Available at: https://arxiv.org/pdf/2112.11176.pdff.

[55] Lukas E.P. Hageman, 2021 'Training Data for Task-Oriented Conversational Agents: The Representation of User Requests from Spoken Two-Person Dialogues by User Requests from Written Self-Dialogues.' Available at: http://arno.uvt.nl/show.cgi?fid=156944.

[56] Asbjørn Følstad & Petter Bae Brandtzaeg, 2020, 'Users' experiences with chatbots: findings from a questionnaire study.' Available at: https://link.springer.com/article/10.1007/s41233-020-00033-2.

[57] Jan H. Blümel, Gautam Jha, 2023, 'Designing a conversational AI agent: Framework combining customer experience management, personalization, and AI in service techniques'. Available at: https://scholarspace.manoa.hawaii.edu/server/api/core/bitstreams/b85ce478-aac4-48b3-b285-ebf7ec441b6a/content.

[58] Alan Ritter, Colin Cherry, William B. Dolan, 2011, 'Data-Driven Response Generation in Social Media'. Available at: https://aclanthology.org/D11-1054/.

[59] Graeme McLean, Kofi Osei-Frimpong, 2019, 'Hey Alexa … examine the variables influencing the use of artificial intelligent in-home voice assistants'. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0747563219301840.

[60] Emi Moriuchi, 2019, 'Okay, Google!: An empirical study on voice assistants on consumer engagement and loyalty'. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/mar.21192.

[61] Ying Xu, Jianyu Zhang, Rui Chi, Guangkuan Deng, 2022, 'Enhancing customer satisfaction with chatbots: the influence of anthropomorphic communication styles and anthropomorphised roles'. Available at: https://www.emerald.com/insight/content/doi/10.1108/NBRI-06-2021-0041/full/html?skipTracking=true.

[62] Yuping Liu-Thompkins, Shintaro Okazaki & Hairong Li, 2022, 'Artificial empathy in marketing interactions: Bridging the human-AI gap in affective and social customer experience'. Available at: https://link.springer.com/article/10.1007/s11747-022-00892-5.

[63] Theo Araujo, Ward van Zoonen, and Claartje ter Hoeven, 2022 'A Large Playground": Examining the Current State and Implications of Conversational Agent Adoption in Organizations.' Available at: https://www.worldscientific.com/doi/full/10.1142/S0219877022500249.

[64] Yaniv Oshrat, Yonatan Aumann, Tal Hollander, Oleg Maksimov, Anita Ostroumov, Natali Shechtman, Sarit Kraus, 2022 'Efficient Customer Service Combining Human Operators and Virtual Agents.' Available at: https://arxiv.org/pdf/2209.05226.pdf.

[65] Matthew L. Meuter, Amy L. Ostrom, Mary Jo Bitner et al., 2000, 'Self-Service Technologies: Understanding Customer Satisfaction with Technology-Based Service Encounters.' Available at: https://journals.sagepub.com/doi/abs/10.1509/jmkg.64.3.50.18024?journalCode=jmxa.

[66] Guendalina Caldarini, Sardar Jaf and Kenneth McGarry, 2022, 'A Literature Survey of Recent Advances in Chatbots'. Available at: https://www.mdpi.com/2078-2489/13/1/41#B16-information-13-00041.

[67] J. Kapočiūtė-Dzikienė, 2020, 'A Domain-Specific Generative Chatbot Trained from Little Data'. Available at: https://www.semanticscholar.org/paper/A-Domain-Specific-Generative-Chatbot-Trained-from-Kapo%C4%8Di%C5%ABt%C4%97-Dzikien%C4%97/1478e2c7d8c06f63a63bcc9e9d5e089fa710317d.

[68] Aiswarya Surendran, Reena Murali and Remesh K. R. Babug, 2020, 'Conversational AI - A Retrieval Based Chatbot'. Available at: https://yahootechpulse.easychair.org/publications/preprint_download/LnTd.

[69] Reshma Farhat, Dr. Bilal Mustafa Khan, 2011, 'Importance of Brand Personality To Customer Loyalty: A Conceptual Study'. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/mar.21192.

[70] Ying Xu, Jianyu Zhang, Rui Chi, Guangkuan Deng, 2022, 'Enhancing customer satisfaction with chatbots: the influence of anthropomorphic communication styles and anthropomorphised roles'. Available at: https://www.academia.edu/download/7940574/Importance%20of%20Brand%20Personality%20to%20Customer%20Loyalty.pdf

[71] Harshvardhan GM, Mahendra Kumar Gourisaria, Manjusha Pandey, Siddharth Swarup Rautaray, 2020 'A comprehensive survey and analysis of generative models in machine learning.' Available at: https://www.sciencedirect.com/science/article/abs/pii/S1574013720303853.

[72] Jonathan Grudin, Richard Jacques, 2019 'Chatbots, Humbots, and the Quest for Artificial General Intelligence' Available at: http://library.usc.edu.ph/ACM/CHI2019/1proc/paper209.pdf.

[73] C. Werry, 2000, 'Linguistic and interactional features of Internet relay chat.' Available at: https://www.semanticscholar.org/paper/Linguistic-and-interactional-features-of-Internet-Werry/f773573e933141db0fd32811c27a4a2dc7165bd3.

[74] Daantje Derks, Arjan E R Bos, Jasper von Grumbkowy, 2008, 'Emoticons in Computer-Mediated Communication: Social Motives and Social Context'. Available at: https://www.researchgate.net/publication/5577399_Emoticons_in_Computer-Mediated_Communication_Social_Motives_and_Social_Context.

[75] Ulrich Gnewuch, Stefan Morana, Marc T. P. Adam, Alexander Maedche, 2018, 'Faster Is Not Always Better: Understanding the Effect of Dynamic Response Delays in Human-Chatbot Interaction'. Available at: https://www.researchgate.net/publication/324949980_Faster_Is_Not_Always_Better_Understanding_the_Effect_of_Dynamic_Response_Delays_in_Human-Chatbot_Interaction.

[76] Joyce Chai, Jimmy Lin, Wlodek Zadrozny, Yiming Ye, Margo Stys-Budzikowska, Veronika Horvath, Nanda Kambhatla & Catherine Wolf, 2001, 'The Role of a Natural Language Conversational Interface in Online Sales: A Case Study'. Available at: https://link.springer.com/article/10.1023/A:1011316909641.

[77] Hilde A.M. Voorveld andTheo Araujo, 2020, ‘How Social Cues in Virtual Assistants Influence Concerns and Persuasion: The Role of Voice and a Human Name’. Available at: https://www.liebertpub.com/doi/full/10.1089/cyber.2019.0205

[78] Aleksandra Przegalinska, Leon Ciechanowski, Anna Stroz, Peter Gloor, Grzegorz Mazurek, 2019 ‘In bot we trust: A new methodology of chatbot performance measures.’ Available at: https://www.sciencedirect.com/science/article/abs/pii/S000768131930117X.

[79] Asbjørn Følstad, Cecilie Bertinussen Nordheim & Cato Alexander Bjørkli, 2018 ‘What Makes Users Trust a Chatbot for Customer Service? An Exploratory Interview Study’. Available at: https://link.springer.com/chapter/10.1007/978-3-030-01437-7_16.

[80] Ewa Luger, Abigail Sellen, 2016, ‘Like Having a Really Bad PA": The Gulf between User Expectation and Experience of Conversational Agents.’ Available at: https://www.researchgate.net/publication/301931234_Like_Having_a_Really_Bad_PA_The_Gulf_between_User_Expectation_and_Experience_of_Conversational_Agents.

[81] D. Veena Parboteeah, Joseph S. Valacich, John D. Wells, 2009, ‘The Influence of Website Characteristics on a Consumer's Urge to Buy Impulsively’. Available at: https://www.researchgate.net/publication/220079844_The_Influence_of_Website_Characteristics_on_a_Consumer's_Urge_to_Buy_Impulsively.

[82] Mira Knackstedt, 2022, ‘LIMITATIONS AND ADVANTAGES OF VOICE BOTS IN CUSTOMER SERVICE – USING THE EXAMPLE OF A CONTACT CENTER’. Available at: https://run.unl.pt/bitstream/10362/143222/1/2021-22_spring_46421_mira-knackstedt.pdf.

[83] Kurt Munz, Vicki Morwitz, 2019, ‘Sound Judgment: Evaluability and Memory in Speech-based Product Evaluation and Choice’. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3462714.

[84] Kwan Min Lee, Clifford Nass, 2006, ‘The Multiple Source Effect and Synthesized Speech: Doubly-Disembodied Language as a Conceptual Framework’. Available at: https://academic.oup.com/hcr/article-abstract/30/2/182/4336799?login=false.

[85] Lingyun Qiu & Izak Benbasat, 2014, 'Evaluating Anthropomorphic Product Recommendation Agents: A Social Relationship Perspective to Designing Information Systems'. Available at: https://www.tandfonline.com/doi/abs/10.2753/MIS0742-1222250405.

[86] Darius Zumstein and Sophie Hundertmark, 2017 'CHATBOTS – AN INTERACTIVE TECHNOLOGY FOR PERSONALIZED COMMUNICATION, TRANSACTIONS AND SERVICES.' Available at: https://www.iadisportal.org/ijwi/papers/2017151107.pdf.

[87] Yingzi Xu, Chih-Hui Shieh, Patrick van Esch, I-Ling Ling, 2020 'AI customer service: Task complexity, problem-solving ability, and usage intention'. Available at: https://www.sciencedirect.com/science/article/pii/S1441358220300240б.

[88] Kucherbaev, Pavel; Bozzon, Alessandro; Houben, Geert-Jan, 2018, 'Human Aided Bots.' Available at: https://pure.tudelft.nl/ws/portalfiles/portal/55206288/08371205.pdf.

[89] Leon Ciechanowski, Aleksandra Przegalinska, Mikolaj Magnuski, Peter Gloor, 2019, 'In the shades of the uncanny valley: An experimental study of human–chatbot interaction'. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0167739X17312268.

[90] MacDorman & Chattopadhyayt, 2016, 'Reducing consistency in human realism increases the uncanny valley effect; increasing category uncertainty does not'. Available at: https://www.sciencedirect.com/science/article/pii/S0010027715300755.

[91] Mincheol Shin, Se Jung Kim, Frank Biocca, 2019, 'The uncanny valley: No need for any further judgments when an avatar looks eerie'. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0747563219300251.

[92] C.M.H. (Marjolijn) van Lierop, 2021, 'The Uncanny Valley: The paradoxical effects of enhancing the human-likeness of customer support chatbots on perceived trust and satisfaction'. Available at: http://arno.uvt.nl/show.cgi?fid=155101.

[93] Catherine S. Oh, Jeremy N. Bailenson and Gregory F. Welch, 2018, 'A Systematic Review of Social Presence: Definition, Antecedents, and Implications'. Available at: https://www.frontiersin.org/articles/10.3389/frobt.2018.00114/full.

[94] Roger Seiler and Annemarie Schär, 2021 'CHATBOTS, CONVERSATIONAL INTERFACES, AND THE STEREOTYPE CONTENT MODEL.' Available at: https://digitalcollection.zhaw.ch/bitstream/11475/21508/3/2021_Seiler-Schaer_Chatbots-Conversational-Interfaces-and-the-Stereotype-Content-Model.pdf.

[95] Nalini Ambady, Mary Anne Krabbenhoft, Daniel Hogan, 2008 'The 30-Sec Sale: Using Thin-Slice Judgments to Evaluate Sales Effectiveness'. Available at: https://myscp.onlinelibrary.wiley.com/doi/abs/10.1207/s15327663jcp1601_2.

[96] Roberta De Cicco, Susana Cristina Lima da Costa e Silva, Riccardo Palumbo, 2020, 'Should a Chatbot Disclose Itself? Implications for an Online Conversational Retailer.' Available at: https://dl.acm.org/doi/10.1007/978-3-030-68288-0_1.

[97] Kristine L. Nowak, Christian Rauh, 2006, 'The Influence of the Avatar on Online Perceptions of Anthropomorphism, Androgyny, Credibility, Homophily, and Attraction'. Available at: https://onlinelibrary.wiley.com/doi/full/10.1111/j.1083-6101.2006.tb00308.x.

[98] Kristine L. Nowak, Christian Rauh, 2016, 'Reducing consistency in human realism increases the uncanny valley effect; increasing category uncertainty does not'. Available at: https://www.sciencedirect.com/science/article/pii/S0010027715300755.

[99] Amy L. Baylor, 2009, 'Promoting Motivation with Virtual Agents and Avatars: Role of Visual Presence and Appearance'. Available at: https://www.jstor.org/stable/40538149.

[100] Delphine Dion et al, 2017, 'Managing Status: How Luxury Brands Shape Class Subjectivities in the Service Encounter'. Available at:https://journals.sagepub.com/doi/full/10.1509/jm.15.0291?journalCode=jmxa#bibr3-jm-15-0291.

[101] Tibert Verhagen, Jaap van Nes, Frans Feldberg, Willemijn van Dolen, 2014, ‘Virtual Customer Service Agents: Using Social Presence and Personalization to Shape Online Service Encounters’. Available at: https://academic.oup.com/jcmc/article/19/3/529/4067591.

[102] Youn-Kyung Kim & Pauline Sullivan, 2019 ‘Emotional branding speaks to consumers’ heart: the case of fashion brands.’ Available at: https://fashionandtextiles.springeropen.com/articles/10.1186/s40691-018-0164-y.

[103] Anna-Maria Seeger et al., 2008 ‘Texting with Humanlike Conversational Agents: Designing for Anthropomorphism’. Available at:https://aisel.aisnet.org/jais/vol22/iss4/8/.

[104] Willemijn M. van Dolen, Pratibha A. Dabholkar, Ko de Ruyter, 2007, ‘Satisfaction with Online Commercial Group Chat: The Influence of Perceived Technology Attributes, Chat Group Characteristics, and Advisor Communication Style.’ Available at: https://www.sciencedirect.com/science/article/abs/pii/S0022435907000280.

[105] Tibert Verhagen, Jaap van Nes, Frans Feldberg, Willemijn van Dolen, 2014, ‘Virtual Customer Service Agents: Using Social Presence and Personalization to Shape Online Service Encounters’. Available at: https://academic.oup.com/jcmc/article/19/3/529/4067591?login=false

[106] Christine Liebrecht, Lena Sander, Charlotte van Hooijdonk, 2021, ‘Too Informal? How a Chatbot’s Communication Style Affects Brand Attitude and Quality of Interaction’. Available at: https://www.researchgate.net/publication/348967621_Too_Informal_How_a_Chatbot's_Communication_Style_Affects_Brand_Attitude_and_Quality_of_Interaction.

[107] Anaïs Gretry, Csilla Horváth, Nina Belei, Allard C.R. van Riel, 2017, ‘“Don't pretend to be my friend!” When an informal brand communication style backfires on social media’. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0148296317300255.

[108] Ela Elsholz, Jon Chamberlain, Udo Kruschwitz, 2019, ‘Exploring Language Style in Chatbots to Increase Perceived Product Value and User Engagement’. Available at: https://dl.acm.org/doi/abs/10.1145/3295750.3298956.

[109] Christine Liebrecht & Charlotte van Hooijdonk, 2020, ‘Creating Humanlike Chatbots: What Chatbot Developers Could Learn from Webcare Employees in Adopting a Conversational Human Voice’. Available at: https://link.springer.com/chapter/10.1007/978-3-030-39540-7_4.

[110] Norm Archer, Milena Head, and Yufei Yuan, 2001 ‘MATCHING CUSTOMER EXPECTATIONS AND PERCEPTIONS IN E-COMMERCE.’ Available at: https://macsphere.mcmaster.ca/bitstream/11375/5436/1/fulltext.pdf.

[111] Ben Sheehan, Hyun Seung Jin, Udo Gottlieb, 2020 ‘Customer service chatbots: Anthropomorphism and adoption’. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0148296320302484.

[112] Jason Telner, 2021, ‘Chatbot user experience: Speed and content are King’ Available at: https://books.google.it/books?hl=en&lr=&id=BW03EAAAQBAJ&oi=fnd&pg=PA47&dq=chatbot+customer+service+spees+of+problem+resolving+effect+on+satisfaction&ots=In9RU-zMh6&sig=weFzvgKmdhmJC_F6P3Bu98SgLRc&redir_esc=y#v=onepage&q=chatbot%20customer%20service%20spees%20of%20problem%20resolving%20effect%20on%20satisfaction&f=false.

[113] John A. Hoxmeier, Chris DiCesare, 2000, ‘System Response Time and User Satisfaction: An Experimental Study of Browser-based Applications’. Available at: https://aisel.aisnet.org/amcis2000/347/

[114] Clifford Nass, Jonathan Steuer, Ellen Siminoff, 1994, ‘Computer are social actors’. Available at: https://www.researchgate.net/publication/221517042_Computer_are_social_actors.

[115] Clifford Nass, Youngme Moon, 2000, ‘Machines and Mindlessness: Social Responses to Computers’. Available at: https://www.researchgate.net/publication/229068013_Machines_and_Mindlessness_Social_Responses_to_Computers.

[116] Hilde A.M. Voorveld, and Theo Araujo, 2020, ‘How Social Cues in Virtual Assistants Influence Concerns and Persuasion: The Role of Voice and a Human Name’. Available at: https://www.liebertpub.com/doi/full/10.1089/cyber.2019.0205.

[117] Theo Araujo, 2018, ‘Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions’. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0747563218301560.

[118] Jasper Feine, Ulrich Gnewuch, Stefan Morana, Alexander Maedche, 2019 ‘A Taxonomy of Social Cues for Conversational Agents.’ Available at:https://www.sciencedirect.com/science/article/abs/pii/S1071581918305238.

[119] Tze Wei Liew, Su-Mae Tan & Hishamuddin Ismail, 2017 ‘Exploring the effects of a non-interactive talking avatar on social presence, credibility, trust, and patronage intention in an e-commerce website. Available at: https://link.springer.com/article/10.1186/s13673-017-0123-4.

[120] Sandy C. Chen & Gurpreet S. Dhillon, 2003, ‘Interpreting Dimensions of Consumer Trust in E-Commerce’ Available at: https://link.springer.com/article/10.1023/A:1022962631249#auth-Sandy_C_-Chen.

[121] Yunsan Guo, Jian Wang, Runfan Wu, Zeyu Li & Lingyun Sun, 2022, ‘Designing for trust: a set of design principles to increase trust in chatbot’. Available at: https://link.springer.com/article/10.1007/s42486-022-00106-5

[122] Xiao Shi et al., 2020, ‘AI VS. HUMANS: THE IMPACT OF DIFFERENT CONVERSATION AGENTS ON PRIVACY PERCEPTION AND PRIVACY DISCLOSURE’. Available at: https://aisel.aisnet.org/ecis2020_rip/69/.

[123] Asbjørn Følstad, Ragnhild Halvorsrud, 2020, ‘Communicating Service Offers in a Conversational User Interface: An Exploratory Study of User Preferences in Chatbot Interaction’. Available at:https://dl.acm.org/doi/pdf/10.1145/3441000.3441046.

[124] Vera Liao, Matthew Davis, Werner Geyer, Michael Muller, N. Sadat Shami, 2016, ‘What Can You Do?: Studying Social-Agent Orientation and Agent Proactive Interactions with an Agent for Employees’. Available at: https://dl.acm.org/doi/pdf/10.1145/2901790.2901842.

[125] Ana Paula, Chaves Steinmacher, Marco Aurelio Gerosa, 2018, ‘Single or Multiple Conversational Agents? An Interactional Coherence Comparison’. Available at: https://www.researchgate.net/publication/323255891_Single_or_Multiple_Conversational_Agents_An_Interactional_Coherence_Comparison.

[126] Peng Hu, Yaobin Lu, Bin Wang, 2022, ‘Experiencing power over AI: The fit effect of perceived power and desire for power on consumers' choice for voice shopping’. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0747563221004143#bib36.

[118] Jasper Feine, Ulrich Gnewuch, Stefan Morana, Alexander Maedche, 2019 ‘A Taxonomy of Social Cues for Conversational Agents.’ Available at:https://www.sciencedirect.com/science/article/abs/pii/S1071581918305238.

[119] Tze Wei Liew, Su-Mae Tan & Hishamuddin Ismail, 2017 ‘Exploring the effects of a non-interactive talking avatar on social presence, credibility, trust, and patronage intention in an e-commerce website. Available at: https://link.springer.com/article/10.1186/s13673-017-0123-4.

[120] Sandy C. Chen & Gurpreet S. Dhillon, 2003, ‘Interpreting Dimensions of Consumer Trust in E-Commerce’ Available at: https://link.springer.com/article/10.1023/A:1022962631249#auth-Sandy_C_-Chen.

[121] Yunsan Guo, Jian Wang, Runfan Wu, Zeyu Li & Lingyun Sun, 2022, ‘Designing for trust: a set of design principles to increase trust in chatbot’. Available at: https://link.springer.com/article/10.1007/s42486-022-00106-5

[122] Xiao Shi et al., 2020, ‘AI VS. HUMANS: THE IMPACT OF DIFFERENT CONVERSATION AGENTS ON PRIVACY PERCEPTION AND PRIVACY DISCLOSURE’. Available at: https://aisel.aisnet.org/ecis2020_rip/69/.

[123] Asbjørn Følstad, Ragnhild Halvorsrud, 2020, ‘Communicating Service Offers in a Conversational User Interface: An Exploratory Study of User Preferences in Chatbot Interaction’. Available at:https://dl.acm.org/doi/pdf/10.1145/3441000.3441046.

[124] Vera Liao, Matthew Davis, Werner Geyer, Michael Muller, N. Sadat Shami, 2016, ‘What Can You Do?: Studying Social-Agent Orientation and Agent Proactive Interactions with an Agent for Employees’. Available at: https://dl.acm.org/doi/pdf/10.1145/2901790.2901842.

[125] Ana Paula, Chaves Steinmacher, Marco Aurelio Gerosa, 2018, ‘Single or Multiple Conversational Agents? An Interactional Coherence Comparison’. Available at: https://www.researchgate.net/publication/323255891_Single_or_Multiple_Conversational_Agents_An_Interactional_Coherence_Comparison.

Websites

https://www.ibm.com/

https://www.uniphore.com/

https://scienceline.org/

https://www.artificial-solutions.com/

https://www.ocf.berkeley.edu/

https://www.cleverbot.com/

https://www.eviebot.com/en/

https://www.boibot.com/en/

https://en.wikipedia.org/

https://www.techtarget.com/

https://chatbotsmagazine.com/

https://web.zepeto.me/en

https://www.cognigy.com/blog/author/akshay-warikoo

https://oxylabs.io/

https://www.britannica.com/dictionary

https://symbl.ai/blog/

https://crafter.ai/en/conversational-ai-for-e-commerce-en/

https://chatlayer.ai/live-chats-and-chatbots/

https://gettalkative.com/info/what-is-agent-assist

https://openai.com/

https://tinuiti.com/

https://www.retaildive.com/ex/mobilecommercedaily/sephora-reflects-on-cosmetic-sampling-trend-with-augmented-reality-mirror

https://www.chatbotguide.org/

https://www.amazon.com/Perry-Ellis-Ask/dp/B075LLDPTB