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Human-technology integration with industrial conversational agents: A conceptual architecture and a taxonomy for manufacturing

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ABSTRACT

Conversational agents are systems with great potential to enhance human-computer interaction in industrial settings. Although the number of applications of conversational agents in many fields is growing, there is no shared view of the elements to design and implement for chatbots in the industrial field. The paper presents the combination of many research contributions into an integrated conceptual architecture, for developing industrial conversational agents using Nickerson's methodology. The conceptual architecture consists of five core modules; every module consists of specific elements and approaches. Furthermore, the paper defines a taxonomy from the study of empirical applications of manufacturing conversational agents. Indeed, some applications of chatbots in manufacturing are available but those have never been collected in single research. The paper fills this gap by analyzing the empirical cases and presenting a qualitative analysis, with verification of the proposed taxonomy. The contribution of the article is mainly to illustrate the elements needed for the development of a conversational agent in manufacturing: researchers and practitioners can use the proposed conceptual architecture and taxonomy to more easily investigate, define, and develop all the elements for chatbot implementation.

1. Introduction

Conversational agents belong to the systems designed to enable Human-Computer Interaction [1]. These systems represent a new form of interaction between humans and machines, allowing the user to interact using the tool most used by humans: natural language [2]. These interfaces represent a paradigm shift from the current Graphical User Interfaces (GUIs), where interaction is based on a visual representation that includes elements such as icons, sliders, and buttons [3]. The objective of these new interfaces is to offer a new, logical, and intuitive human-computer interaction by representing a cost-effective solution that can facilitate, speed up and increase the efficiency of daily activities [4]. This allows users to intuitively interact with data, resources, and services without the need for GUI training: the user can simply make a request through the use of their own language, and be assisted and supported by the conversational agent [5].

With the term conversational agents are indicated all those software are able to support a conversation with a human being through a textual and/or vocal channel. In literature are used multiple terms to indicate such systems, including: conversational systems, conversational user interfaces, chatbots, voice assistants, virtual assistants, spoken dialog systems, conversational AI [6]. Although there are some differences, the term chatbot is by far the most used to refer to such solutions, terminology that should be intended in its most general definition of conversational agent [5]. Thus, in the paper, the authors use chatbot and conversational agent as synonyms. In the manufacturing sector, the adoption of conversational agents is driving the digital transformation of organizations, to improve both customer and user-experience and make their internal processes more efficient [7]. These technologies are included in the broader scope of eXtended Reality (XR) technologies, which are leading the way toward new forms of interaction with computers. Their goal is to increase the degree of mobility, autonomy, and independence of operators by working on Human-In-The-Loop, user-centered systems, in which operators play the role of decision-makers, entrusting the most repetitive operations to these technologies [8]. With this in mind, the development of conversational agents is focused on both supporting users in interacting with machines [9], databases [10], and information systems [11], and in completing tasks [12], moving towards the notion of smart operators [13]. It is to underline that conversational agents require a proper design even to cope with possible safety and security issues, which are always present in 4.0 technologies [14–16] because the increasing introduction of

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digitalization and automation of work processes lead to the expanded complexity of cyber-socio-technical systems [17].

From the analysis of the few papers devoted to conversational agents in the industrial field, there is no agreement on the elements to be considered and developed for the creation of an industrial conversational agent. In this paper, we evaluate the key elements specific to the industrial conversational agents and we review the literature to build an integrated architecture for developing industrial chatbots.

Therefore, this paper addresses the following research questions:

RQ1: Which logical interconnections and modules are needed for a conversational agent's architecture?

RQ2: What are conceptually grounded and empirically validated design elements for manufacturing conversational agents?

To answer RQ1 architectures available in the literature are first investigated. Then, the research presents and discusses the fundamental concepts for understanding the logical operations of an industrial conversational agent through the definition of its general design and its modules, to propose an architecture, we assume "integrated" since it integrates several literature contributions. Subsequently, attention has been turned towards the development and use of such systems in the manufacturing sector, analyzing their role as an enabling technology for Industry 4.0/5.0. For this purpose, a reference taxonomy was developed to answer RQ2. The research approach for its development follows a revised and adapted version of the taxonomy development model [18]. The taxonomy is then used to classify a sample of 26 manufacturing chatbots, appropriately selected from various scientific databases. The classification confirmed the validity of the taxonomy and underlined the main paths in up-to-date manufacturing conversational agents.

The paper is organized as follows. Section 2 introduces the topic of conversational agents providing literature background information. More specifically chatbot architectures and technical terminology available in literature are underlined. Section 3 describes the conversational agent conceptual architecture for the industry. Section 4 details the research process followed to develop the taxonomy and presents it. Section 5 provides an extensive case study qualitative analysis using the proposed manufacturing chatbot taxonomy. Finally, Section 6 concludes and outlines the follow-up research.

2. Related work and motivation

Although the interest in conversation systems has increased in recent years both in industry and in research [19], the idea of applications capable of interacting with humans was born in 1950, when Alan Turing wondered if machines were able to "think", to link and express ideas [20]. In 1966, Joseph Weizenbaum [21] created ELIZA, which has been historically considered the first conversational system. A first generation of conversational agents whose operation was based on the use of specific rules was developed starting from ELIZA. PARRY (1972) is considered the first chatbot with personality and ALICE (1995) is the first chatbot to be developed with the Artificial Intelligence Mark-Up Language (AIML) [22]. Such systems have seen a significant evolution in recent years due to advances made in the field of Artificial Intelligence (AI). On one side, Natural Language Processing (NLP) techniques have allowed for better syntactic and semantic analysis of text [23] with application in several fields [24]. On the other side, Machine Learning applications have allowed for a move away from rule-based implementation, leading systems to learn directly from a large corpus of data [22]. The explosion of such technologies then occurred with Apple's introduction of Siri in 2010 and followed by Watson Assistant, Alexa, Cortana, and Google Assistant [25].

This widespread use has led to the theorization of multiple reference architectures and functionalities for the development of conversational agents. The logical functioning of a generic conversational agent can be schematized as follows: once it receives the user's input, the system analyses it using Natural Language Processing techniques to identify what the user wants to obtain. Once the chatbot has identified the correct Intent, it must provide the correct or best possible answer by performing one of the corresponding actions [26].

Among the most straightforward architectures is the one proposed by Mc Tear [5]. Despite it is not highly detailed, this architecture applies well to both text-based and voice-based chatbots. The main difference is that the latter type will be equipped with a speech recognition module to process the voice input provided by the user and a text-to-speech module to transform the chatbot output into voice format. Among other research that provides a complete chatbot design architecture is the one by Adamopoulou & Moussiades [25] and more recently the one by Serras et al. [27] that integrates this work also with extended reality (XR) components. Overall, five fundamental modules return across these designs: Automatic Speech Recognition (ASR), Natural Language Understanding (NLU), Dialog Manager (DM), Natural Language Generation (NLG), and Text-To-Speech (TTS).

In terms of functionality, chatbots mainly fall into two different categories: Task-Oriented and Non-task oriented chatbots [5]. In Task-Oriented, the interaction between humans and machines is focused on accomplishing a specific task. They are designed to deal with a specific scenario and perform best with a narrow knowledge domain. On the other hand, non-task oriented are designed to have more extended conversations, to simulate a real conversation between humans. They often have recreational, or entertainment purposes and the conversations are based on a broader knowledge domain. A few authors further subdivide this category into Informative and Conversational. The former is intended to provide the user with specific information (FAQbot, Q&Abot), and the latter is intended to hold generic conversations with users [19]. Further classifications in the literature concern the method of response generation, the knowledge domain, the length of the conversation, the service provided, and the control of the conversation. A distinction is made between the Rule-based Approach and the Neural Network Based Approach, which in turn is divided into the retrieval-based approach and a generative approach [28]. Sometimes in the literature, the terms Rule-based chatbot and Data-driven chatbot (or AI-based chatbot) are also used to indicate the different types of chatbots that can be realized [5]. Classification by knowledge domain is related to the amount of available data, which constitutes the chatbot's knowledge base. One can distinguish between Open-domain and Closed domain chatbots [22]. When talking about Open domain, the conversation with the chatbot can start in one knowledge domain and later move to a different one. In contrast, Closed domains have limited knowledge about a specific domain and are designed to have conversations focused on one or a few specific topics [29]. Based on the length of the conversation, two other types of chatbots can be distinguished: systems based on Short-Term and Long-term relations [1]. A short-term relation is characterized by a one-shot interaction, also called single-turn [30], in which the response is generated solely based on a single message, without collecting the user's information. In contrast, Long-term, also called multi-turns, are chatbots designed to have an extended interaction over time and be able to record relevant information exchanged during the conversation. Furthermore, in user-chatbot interactions, two categories are distinguished based on who drives the dialog: chatbot-driven dialog and user-driven dialog systems [4]. Finally, conversational agents can be classified according to the type of relationship with the user and the type of service they provide [[19], [25]]. Interpersonal chatbots have the sole purpose of giving the requested information and moving on to the next user. Intrapersonal, on the other hand, are those chatbots that have an elevated level of engagement with the users, also performing tasks for them.

As discussed, there are several criteria for classifying chatbots in the literature. These classification criteria should not be understood as mutually exclusive. Two or more criteria may coexist and be used in. combination for the development of a chatbot. Although this is typically the scenario, there are logical relationships between these criteria that must be considered. When designing a chatbot, the options to be implemented depend on its ultimate purpose. Based on the final aim of the chatbot there will be advisable, viable, and avoidable options considering functional suitability, performance efficiency, usability, and security [19]. However, despite diverse chatbot characteristics that have been investigated, empirical research is scarce on how to design chatbots profile. Notably as reported in the survey by Motger et al. [19] there is a lack of structured and synthesized knowledge. They underlined as one of the major challenges in the field of conversational agents is the shift from developing chatbots for simple tasks to moving towards assistants able to perform complex tasks by applying domain and target-specific requirements. This is particularly relevant in the manufacturing sector where the topic of conversational agents is still in its beginning phase, cases presented are unstructured, lacking a common line for their development, evolution, and personalization.

Therefore, from that review, the objective of the current work is to determine which are conceptually all the design elements for a manufacturing chatbot and to address a taxonomy and guideline for its development. The taxonomy will be based on scientific literature and validated through empirical data collected from real manufacturing chatbot case studies.

3. Conversational agent conceptual architecture

An appropriate conversational agent architectural design is the first step to investigate the development of a chatbot. Therefore, several architectural designs have been proposed in the literature. Some of them have been approach specific. For instance, in [31] and [32] the authors propose architecture specific for rule-based chatbots and retrieval-based chatbots. Their review illustrates specific architectures for a corpus-based, intent-based, or recurrent neural network-based chatbot. Other have been function specific such as [33] which has focused on architecture modules for human-computer speech interaction.

Among the first design is the one by Souvignier et al. [34] who present a system architecture focusing on elements fundamental for spoken dialog systems. Their main components are a speech recognizer, a natural language understanding module, a text-to-speech tool, and a dialog manager. The research offers a detailed technical description of the natural language understanding module but lacks other architectural details and there is no technical information on Speech recognition, Speech Synthesis, and Response Generation.

Among the most extensive and complete recent chatbot architecture is the one proposed by Adamopoulou & Moussiades [25]. Their work offers both an architecture and a development approach. Despite its interesting integration of different modules, their design lacks details regarding Natural Language Understanding techniques, Dialog Policies categories, and the Response Generation Component lacks many essential details. An interesting design is proposed by Serras et al. [27] who propose an Interactive XR architecture structured in layers. It integrates a spoken dialog module along with a Device Control Layer, an Interpretation Layer, Domain Knowledge Layer, and Response Generation Layer. However, it is quite abstract as it does not provide essential details for each layer, especially the dialog manger module has not been articulated in its submodules. Besides [30] and [5] present two simplistic designs that on one side lack many essential details but on the other side offer two clear and straightforward approaches for the definition of the main modules a chatbot must have. All the main components are then described in detailed focusing on task-oriented and rule-based dialog systems development.

Finally, this review of chatbot architecture literature has demonstrated an absence of terminological consistency. Terms such as Natural Language Understanding [[5],[30]], Spoken Language Understanding and Semantic Codification [27] or User Message Analysis [22] are used as synonymous. Instead, the term Dialog Manager is widely used, with some differences such as Dialogue State Tracking [30] or Dialogue Policy Optimization [35]. Similarly, Natural Language Generation [[5],[30]], Response Generation Component or Layer [[22],[27]] are used.

Table 1 summarizes what has just been detailed and highlights what has been enhanced and retained in each conversational agent architecture proposed to date in the literature. To do so, the authors have provided a bibliographical reference, a diagram of the architecture analyzed, and a description of its strengths and weaknesses.

Subsequently, the authors compose an architecture that takes into account those developed so far, offering an articulated pathway between the different modules, with details on each step and terminological consistency. The architectural design is at the same time general and detailed including all the modules from the beginning of the conversation to the response generation. The proposed architecture is shown in Fig. 1. It is characterized by 5 core modules, explained below: Automatic Speech Recognition (ASR), Natural Language Understanding (NLU), Dialog Manager (DM), Natural Language Generation (NLG), and Text-To-Speech (TTS), and two Interfaces: Conversational User Interface, and External Devices Interface.

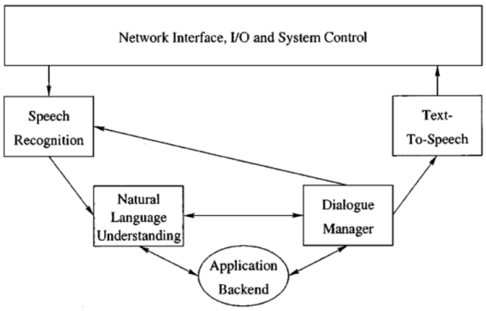
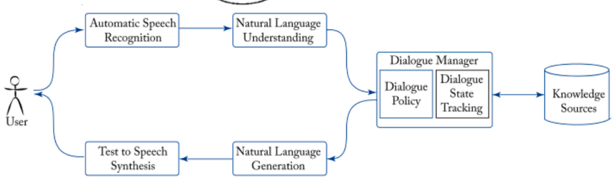
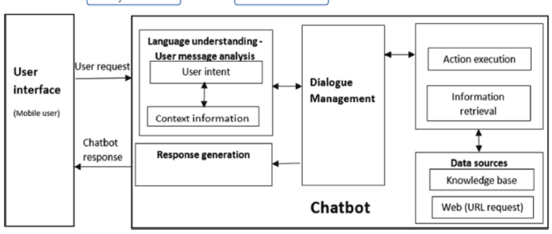
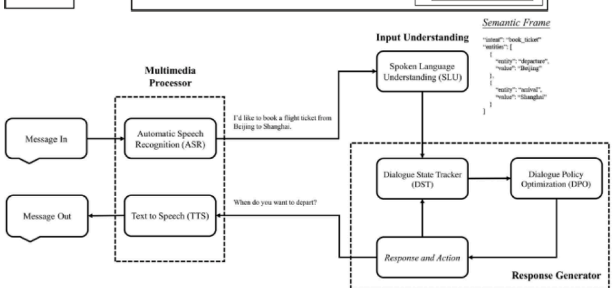
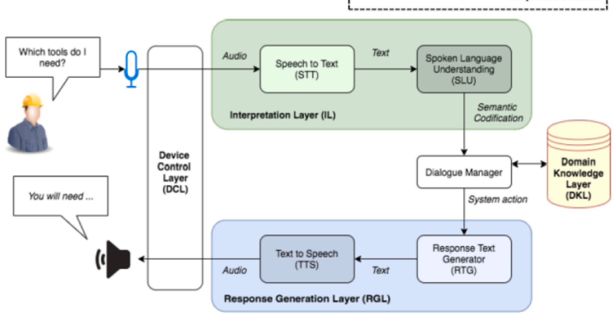
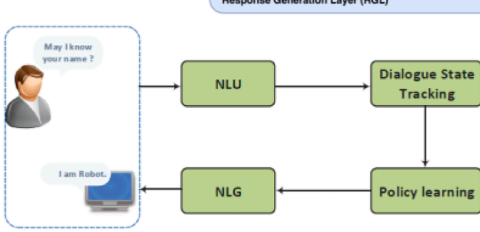
3.1. Conversational user interface

The Conversation User interface detects the user's input. The input may be textual or vocal. The effectiveness of the interface varies depending on specific characteristics encountered in the industrial context in which the conversational agent is installed. One major limitation is the presence of noise, which can impede the accuracy of automatic speech recognition (ASR) modules employed by conversational agents [[36],[37]]. Noise can result from machinery, equipment, or other sources, leading to degraded audio quality and subsequently affecting the system's ability to accurately transcribe and comprehend spoken commands or queries. To address the issue of noise, integrating noise-canceling features into the existing ASR modules can prove beneficial. Such features can effectively suppress ambient noise and enhance speech recognition accuracy. Various approaches can be employed, such as spectral subtraction, adaptive filtering, and statistical modeling, to estimate and subtract noise components from the audio signal. Additionally, the use of advanced machine learning algorithms [38] and deep neural networks specifically trained in noisy manufacturing environments can aid in improving the overall performance of conversational agents. Apart from noise, conversational agents face additional limitations, including the complexity of the domain-specific vocabulary, the ambiguous and context-dependent language used by operators, and variations in accents and dialects. Accents and dialects introduce variations in pronunciation and linguistic patterns, which can lead to errors in speech recognition. One solution to this problem is the use of language chain embeddings [39]. By incorporating language chain embeddings into the ASR models, conversational agents can adapt to specific accents and dialects, improving their ability to accurately understand and respond to user commands [40]. Finally, further problems could be encountered with text typing interfaces. A device with keyboard keys that are too small or a touch screen might be incompatible with operators who are in contexts requiring PPE such as gloves, visors, or protective goggles [41].

3.2. Automatic speech recognition

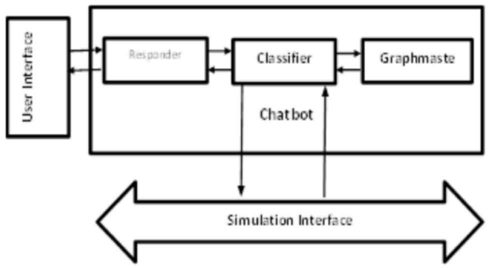
The first module is Speech-to-text. Its task is to capture and transcribe in text format the vocal input given by the user. The purpose is to collect a set of data to be processed by the NLU. Modern ASRs are based on the combination of two probabilistic models: the acoustic model, which calculates the most probable sequence of phonemes corresponding to each part of the speech signal; and the linguistic model, which calculates the most probable sequence of words that match the previously calculated sequence of phonemes [42]. The main goal is to minimize the Word Error Rate. The most used techniques are based on Deep Neural Networks, such as Long-Short-Term-Memory [43] and Hidden Markov Models [44], which allow for achieving a word error rate below 10% [42].

Table 1
- Previous architectures.

Ref.	Architecture	Takeaways for a conceptual architecture
[34]		One of the first architectures proposed in the literature. It presents a system architecture cantered on fundamental elements for spoken dialog systems. It offers a detailed technical description of the natural language understanding module. The architecture lacks technical information on speech recognition, speech synthesis, and response generation.
[5]		A simplistic but clear and straightforward approach for the definition of the main modules of a chatbot. The architecture lacks details on the user interfaces and external interfaces.
[25]		An architecture with an interesting integration of different modules and a development approach. The project lacks details regarding natural language understanding techniques, and dialog policy categories and the response generation component lacks many essential details.
[26]		The proposed architecture focuses on RNN-based chatbots. The modules are well-specified and argued. The solution combines dialog management and response generation modules by reducing the technical details for the generation of responses. It lacks interface modules.
[27]		An Interactive XR architecture structured in layers. It integrates a spoken dialog module along with a Device Control Layer, an Interpretation Layer, Domain Knowledge Layer, and Response Generation Layer. However, it is quite abstract as it does not provide details for each layer. It lacks detailed dialog manager submodules.
[30]		A straightforward approach to design the chatbot's architecture. Interesting poly learning details. The solution lacks the speech component and interface modules.

(*continued on next page*)

Table 1 (*continued*)

Ref.	Architecture	Takeaways for a conceptual architecture
[33]		A function-specific architecture with modules for human-computer speech interaction. The architecture lacks details on natural language generation and dialog management.

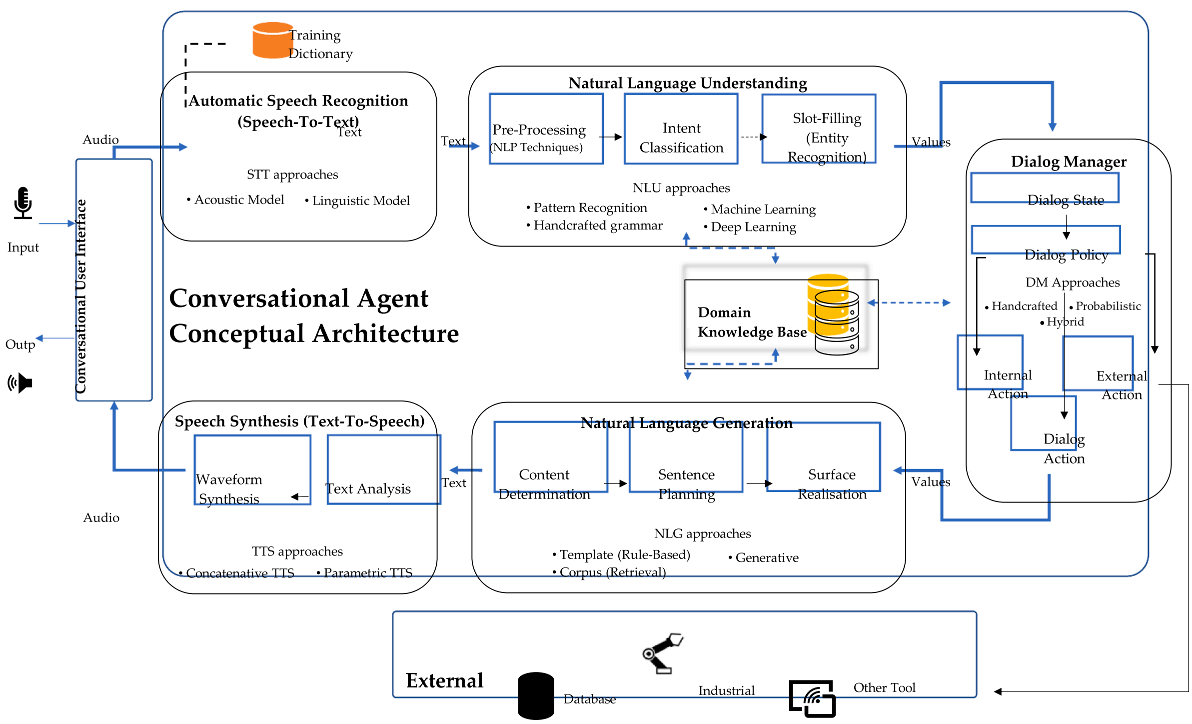


Fig. 1. - Conversational agent conceptual architecture.

3.3. *Natural language understanding*

The Natural Language Understanding module is responsible for analyzing the string provided by the ASR to determine its meaning [5]. It is the process of transforming sentences into structured information. Specifically, two basic functions can be performed in the NLU module: Intent Classification (or Intent detection) and Slot Filling (or entity recognition). The process of text comprehension begins with the use of NLP techniques. The main ones are Token decomposition (Tokenization); morphological and lexical analysis through Part-Of-Speech (POS); syntactic analysis through the generation of a Parse Tree. Other techniques that can be used are Lemmatization, Stemming, and Sentiment Analysis. Once the text has passed the NLP phase, it proceeds with intent classification and eventually slot-filling. These functions can be performed following rule-based approaches or machine learning. Early chatbots were based on pattern-matching algorithms [22]. These involve the creation of several categories, each with corresponding patterns and templates. The user's phrases are then matched with a pattern and the content of the template is given in response. The major issue with this approach is the required perfect match between input and pattern. Another type are rule-based chatbots. These are used to extract context, intent, and slots from the user's sentence to match certain keywords, using Handcrafted Grammars [5]. HGs contain all the rules required to cover the expected user inputs, adding a degree of flexibility to possible inputs over pattern matching. They also involve specific rules for each input by requiring different rules for sentences having the same meaning but a different structure. To date, the most widely used technique for NLU is the use of Machine Learning methods to extract intents and slots from user inputs. With this approach, the NLU module requires a corpus, i.e., a set of sentences, used to train the chatbot. For each intent, a list of training utterances is provided, on which the chatbot is trained. In this approach, the identification of a phrase with a specific intent is treated as a classification problem, and supervised Machine Learning algorithms are used. This approach is more robust than Handcrafted Grammars; in fact, inputs can be linked to an intent even when the sentence wording is not the same as the examples in the corpus. Moreover, conversational agents using machine learning techniques are also characterized by slot-filling capabilities. With slot filling the system continuously parses the user's responses for information that it uses to guide the conversation. This means the agent can recognize information that the user has already provided or that is missing, ask clarifying questions if needed, and continue with the dialog. Finally, recently the use of Deep Learning and neural networks (Recurrent Neural Networks) has become more widespread, mainly employed for the development of generative chatbots [[35],[28]].

3.4. Dialog manager

The DM is the core module of a conversational agent, it manages the conversation and decides, at each iteration, which actions must be performed based on the input (Intent) provided by the user. It manages the conversation with the user to achieve the goal expressed. The module consists of two main components : Dialog State and Dialog Policy.

The Dialog State tracks Intent and slots and is updated at each user iteration. The Dialog Policy is the strategy aimed at acquiring the missing slots to correctly complete the query [42]. Here the system decides the action to be taken based on what is reported in the dialog state. Depending on the moment of the conversation, 3 different types of actions can be performed in the dialog policy: dialog, external and internal action. Dialog actions correspond to a message sent to the user in response to his request and allow dialog with the user. They can be a confirmation action, a request for further information, or an answer to the user's query. External actions are actions that allow the conversational agent to interact with services provided by other software or databases to satisfy the user's request (e.g., activate robots or extract information). Finally, Internal Actions are actions that the agent uses to modify its behavior and improve its performance. Ultimately, the approaches used for the development of DM, and in particular Dialog Policy, fall mainly into 3 categories: handcrafted, probabilistic, and hybrid [45] depending on the possible states and transitions between states of the conversation. The Handcrafted Approach defines both the state of the system and its policy through a set of rules that establish the state of the conversation and which actions are possible for each state. In the Probabilistic Approach, the system learns the rules from real conversations (from a corpus). The corpus contains examples of responses and conversations. Specifically, corpus-based chatbots select the most correct answer by matching the user's request with an example contained in the corpus that is used as the answer. Finally, the Hybrid Approach combines the advantages of purely rule-based and data-driven approaches.

3.5. Natural language generation

The NLG module is responsible for generating the response text, based on the decision made by the DM. The DM communicates the relevant information contained in the dialog state to the NLG, which is responsible for structuring that information into words and sentences. The NLG module involves three processes: content determination, sentence planning, and surface realization. Content determination is the process of deciding what information should be realized. This step has to deal with the selection, abstraction, and filtering of the input data removing irrelevant information. Sentence planning is the process of ordering and grouping semantic information into chunks that are coherent and desirable. Finally, surface realization is the process of placing the structure, relevant words, and producing a well-formed sentence that fits the rules of grammar. The most appropriate response is generated based on three different possible approaches: Rule-based, Retrieval, and Generative approach. In Rule-based, the response has a predefined structure and is contained in a specific template. Conversely, in Retrieval, the best possible answer is selected from a predefined corpus containing answer examples by Machine Learning algorithms. Finally, in Generative, the answer is completely generated by the chatbot through Deep Learning algorithms, not making use of any kind of predefined answers.

3.6. Text-to-speech

The Text-to-speech or Speech Synthesis module is the last module that makes up the architecture of a conversational agent and is tasked with converting text generated by the NLG and synthesizing it to generate output in speech format [46]. To accomplish its task, the TTS module relies on two steps: Text Analysis, in which the text to be read is transformed into a representation consisting of phonemes and prosodic information, and Waveform Synthesis, in which the internal representation is converted into a waveform that can then be output as a voice message [5]. There are two specific methods for conversion: concatenative TTS and parametric TTS. In concatenative TTS appropriate "speech units" contained in a speech corpus are selected and concatenated to obtain the final waveform. Parametric TTS instead uses digital signal processing technologies to synthesize speech from text. There are mainly two models used for concatenative TTS: one based on Linear Prediction Coefficients (LPCs) and the other based on Pitch Synchronous OverLap Add (PSOLA). As for parametric TTS, the most used methods are Hidden Markov Models (HMMs) and Deep Neural Networks (DNNs) [46].

3.7. External devices interface

The external device interface allows the chatbot to handle actions with external devices. Specifically, it is possible to activate actions to retrieve information from databases, activate other software or tools

Based on the above, as can be seen from Fig. 1, the architecture is grounded on a principle of close collaboration between modules which, while being independent, affects the performance of subsequent modules and operate in synergy. For example, training the Automatic Speech Recognition (ASR) module through an appropriate training dictionary, allows the NLU to simplify the process of identifying the intent and slots. On the other hand, a highly effective NLU module can make the DM perform better by shortening the duration of the conversation with the agents [45].

4. Taxonomy of design elements for manufacturing chatbots

Conversational agents represent one of the solutions to drive organizations' digitization process. This technology offers potential support for various processes and activities within industrial plants to enable a new degree of interaction, control, and efficiency. To date, there is a small number of applications, in literature a few application cases can be found ranging from operator assistance in production, maintenance, training, and information collection. However, as far as the authors know, there are no specific taxonomies to support the selection of manufacturing chatbot elements.

Taxonomies are widely recognized and utilized in the fields of information systems and human-computer interaction research [18]. They serve a crucial role in enabling the formulation of design principles that can guide the development of future artifacts, such as chatbots. This is accomplished through the empirical examination of structural patterns present in existing artifacts [47]. A taxonomy comprises multiple dimensions, each of which encompasses a subset of characteristics.

In the literature two relevant taxonomies are referenced: the one by Janssen et al. [48] and the one by Nißen et al. [49]. However, their proposals focus on a taxonomy for closed-domain conversational agents with no reference to a particular domain and/or context. The manufacturing field, on the other hand, has specific characteristics, based on a task-oriented logic. These types of chatbots are designed to achieve a specific purpose and assist the user in one or a few specific tasks [19]. Such systems are short-conversation agents [50] and work through the execution of preconfigured actions oriented towards the achievement of a specific goal [51] in a closed domain with limited knowledge. Starting from the most generic reference taxonomies and detailing them by exploiting application cases of chatbots in manufacturing we present below a taxonomy of design elements for manufacturing chatbots.

4.1. Methodology

The research develops a taxonomy by readapting the steps suggested by Nickerson's model [18]. The methodology is structured in seven steps.

The first step is based on the identification of the purpose and meta-characteristics. The purpose is the intended objective of the taxonomy and should correspond to its anticipated utilization. Meta-characteristics are defined as general design dimensions that will be the basis for the choice of the final characteristics.

The second step is devoted to defining the ending conditions. The methodology follows an iterative approach, which means it requires specific conditions to determine when it should stop. These conditions encompass both objective and subjective aspects. One crucial objective ending condition is that the taxonomy must adhere to our defined criteria of a taxonomy. In particular, this means that it should include dimensions with characteristics that are mutually exclusive and collectively exhaustive.

Following these steps, the methodology presents the option to proceed with either an empirical approach or a conceptual approach. The selection of the appropriate approach is contingent upon the availability of data regarding the objects being studied and the researcher's familiarity with the domain of interest.

In the empirical-to-conceptual steps, a specific subset of objects to classify is identified. These objects typically come from the scientific literature and existing case studies. Subsequently, the researcher identifies shared traits among these objects, ensuring that these characteristics are a logical consequence of the meta-characteristic. The objects are refined and grouped.

The conceptual-to-empirical steps rely on the researcher's understanding of similarities and dissimilarities among objects. Since it is a deductive process, there are limited guidelines, apart from relying on the researcher's knowledge, experience, and judgment to deduce relevant dimensions. Each dimension comprises characteristics that logically derive from the meta-characteristic. Therefore, a dimension's suitability is assessed by whether its characteristics logically stem from the meta-characteristic. Throughout this process, dimensions that are not appropriate can be eliminated.

At the end of either of these steps, the researcher checks if the ending conditions have been met with the current version of the taxonomy. If not, another iteration is started.

4.2. Taxonomy development procedure

The following section details the application of the methodology used to answer RQ2. In the definition section the authors detail steps 1 and 2. In the following, the iterations conducted, both empirical to conceptual and conceptual to empirical, are presented.

4.2.1. Definition

First, the purpose of our taxonomy is to provide a design taxonomy to guide researchers and practitioners in the development and comprehension of manufacturing conversational agents. Second, meta-characteristics are defined. [18] defines them as the basis for the choice of taxonomy characteristics and underlines the importance of considering expected end users of the taxonomy. [49] focuses on the importance of human-like interactions proposing three related perspectives: intelligence, interaction, and context. [48] instead stress visible or experiential human-chatbot interaction. Our scenario takes up the rationale of defining meta-features based on the concepts of machine interaction, however, believing that it is important in a production context to also provide the developer with a more technical perspective and not just interaction related. For this reason, we identified two perspectives: the Chatbot perspective and the Chatbot-User interaction perspective. The first one identifies all those design elements that directly concern the development of the chatbot and its functionalities. The second one refers to dimensions and features that qualify the interaction between chatbot and user. Regarding the selection of ending conditions, this study adopted all objective and subjective conditions suggested by Nickerson et al. [18].

4.2.2. Iterations

Iteration 1 – Conceptual to empirical: Merging chatbot taxonomies

The difference with [18] proposed approach can be traced to this iteration. Our research restarts from the latest iterations of [[49],[48]] works and from these restarts by customizing and extending their taxonomies. The study of the literature has shown how well these taxonomies describe the characteristics of conversational agents however when focusing on a specific domain these are not sufficient to guide the development of chatbots. In particular, the manufacturing context is characterized not only by strong human-chatbot interaction but also by a need for human-chatbot-machine coordination to be taken into account when developing chatbot conversations [13]. In addition, the objectives of chatbots in manufacturing are varied: training, operator assistance, data collection, etc., and each of them needs a detailed definition of dimensions and characteristics.

Specifically, in this first iteration we reviewed [49] and [48] taxonomies and merged them to derive an initial set of design dimensions. Duplicates have been removed.

Iteration 2 – Conceptual to empirical: Refinement of the taxonomy for a task-oriented perspective

As mentioned in the previous paragraphs, the analysis of the literature has underlined that in the manufacturing environment, task-oriented conversational agents find major applications. This class of systems is designed to achieve a well-defined purpose and to assist the user in one or a few specific tasks [19]. In this second conceptual to empirical iteration, we aimed at analyzing each dimension and to evaluate to which extent they might be design-relevant for task-oriented chatbots.

Therefore, dimensions such as Application Domain, Collaboration Goal, Motivation for chatbot use, and Primary Communication Style, which are suitable in the reference taxonomies to identify the application domain and functionality of chatbots, are removed because they are representative of generic characteristics of Closed-Domain chatbots and do not meet the ultimate purpose of our taxonomy.

Iteration 3 – Empirical to conceptual: classification of manufacturing conversational agents' dimensions

For the third iteration, we chose an empirical-to-conceptual approach to customize the taxonomy from a manufacturing perspective. We have selected twenty-six published manufacturing chatbot case studies retrieved from three main scientific databases: Scopus, ResearchGate, and Google Scholar. The keywords to query these databases were a combination of the synonyms for chatbot, specifically 'conversational agent'; 'digital intelligent assistant'; 'voice bot'; 'virtual assistant'; 'digital intelligent agent'; 'dialog system', with the term 'manufacturing'. To determine the case studies, the search was done by keywords and then by analyzing articles cited in the text and contributions that cited the selected cases. Each case study has been analyzed to identify which design dimensions and characteristics researchers focused on when developing a manufacturing chatbot. For this reason, only case studies that presented the real application and not simply a theoretical description of the approach used were included in the selection. The collection is not intended to be exhaustive, however, the presence of a few application cases in the manufacturing sector is also evidenced by recent articles [52–54]. To determine the case studies, the search was done by keywords and then by analyzing articles cited in the text and contributions that cited the selected cases. Each case study has been analyzed to identify which design dimensions and characteristics researchers focused on when developing a manufacturing chatbot. Each dimension and related characteristics identified were compared with existing ones to assess their similarity. Similar dimensions have been merged. Some characteristics have been revised or added. When no similar dimension was identified it was added as a new taxonomy dimension.

Fig. 2 shows in detail all the dimensions added and the following paragraph will explain their meanings.

Iteration 4: Empirical to conceptual: Refinement of the taxonomy

In this iteration, we chose the empirical-to-conceptual path again. Dimension names have been revised for a more complete understanding and to be consistent with manufacturing terminology. It was finally decided to leave some dimensions even though these were not found in the manufacturing articles. The choice was made by observing how in similar contexts in terms of human-machine interaction and process complexity (e.g., healthcare, cybersecurity) these dimensions have been used. Therefore, as explained in detail it was deemed important to leave these dimensions in the taxonomy. In this iteration, no new dimensions have been added and all the ending conditions were fulfilled, and the taxonomy process was completed.

4.3. Taxonomy description

All the iterations which encompass the integration of reference taxonomies, conversational agents' literature, and the cross-reading of manufacturing chatbot application cases allowed to define the 18 design dimensions that make up the final taxonomy. Moreover, 42 characteristics have been determined, which can be divided into chatbot and chatbot-user interaction perspectives. Table 2 shows the proposed taxonomy for task-oriented conversational agents in manufacturing. The following paragraph details each taxonomy dimension.

4.3.1. Chatbot perspective

The first dimension defined is D1 Primary Goal which defines the purpose of the chatbot. For task-oriented manufacturing chatbots, 4 primary goal characteristics can be distinguished in relation to the primary purpose for which the chatbot is implemented [19]: user support, action execution, data processor, and coaching. User Support supports the user in the operational execution of their activities guiding them step by step to improve the user experience. Data processors (or Information request) support the decision-making process of operators by offering quick and easy access to corporate databases and collecting data for and from users [55]. Action execution enables control through voice commands of other integrated systems and software [56]. Finally, Coaching (or User training) are chatbots focused on training, evaluation, and dissemination of corporate know-how [57].

D2 Knowledge Domain dimension refers to the extent of the chatbot's knowledge domain. Through this dimension, the degree of specialization of conversational agents in manufacturing is analyzed by assessing how many different tasks or contexts it can handle within its closed domain. Depending on the extent of the knowledge domain, two categories are defined: Specific domain and Restricted domain. The first refers to chatbots with only one context or task defining its domain, such as LARRI [55] and Max [56]. The second instead refers to systems that can handle several different activities from each other, such as Bot-X [58] and chatbot coaching [57].

D3 Intelligence Framework dimension indicates the type of chatbot. A chatbot may be classified as Classic Rule-based, AI Rule-Based, and Retrieval. To date, these are the most widely used approaches for implementing chatbots in manufacturing. Specifically, this subdivision gives insight into the technical principles of chatbot development to understand and analyze user input (NLU), process information (DM), and select response (NLG). Fig. 1 shows the differences between NLU, DM, and NLG according to the selected feature.

D4 Service Integration refers to the Inter-agent classification criterion [[19],[25]] and is intended to indicate whether the chatbot can offer additional third-party services (e.g., activate robots, place orders, manipulate GUIs, etc.). The identified features are divided into None, when a chatbot has no additional services beyond the one for which it is implemented (LARRI [55]), Single, when it is capable of performing only one additional service (Agroexpert [59]), and Multiple, when it provides two or more services (Xiadong [60]).

Dimension D5 Additional Human support analyzes whether the chatbot offers the possibility of contacting an external operator (human agent) for direct assistance or in circumstances where the chatbot is unable to provide an answer to the user's query. With the D6 Gamification design dimension proposed in [49], we want to analyze whether or not game elements (such as quizzes) are present in a generic chatbot to support users' learning or entertainment activities. Although these latter features can be considered on a par with a service offered by the chatbot and therefore included within the more generic D4 dimension, it was decided to distinguish these dimensions as potentially representing an interesting design element. Although available case studies in

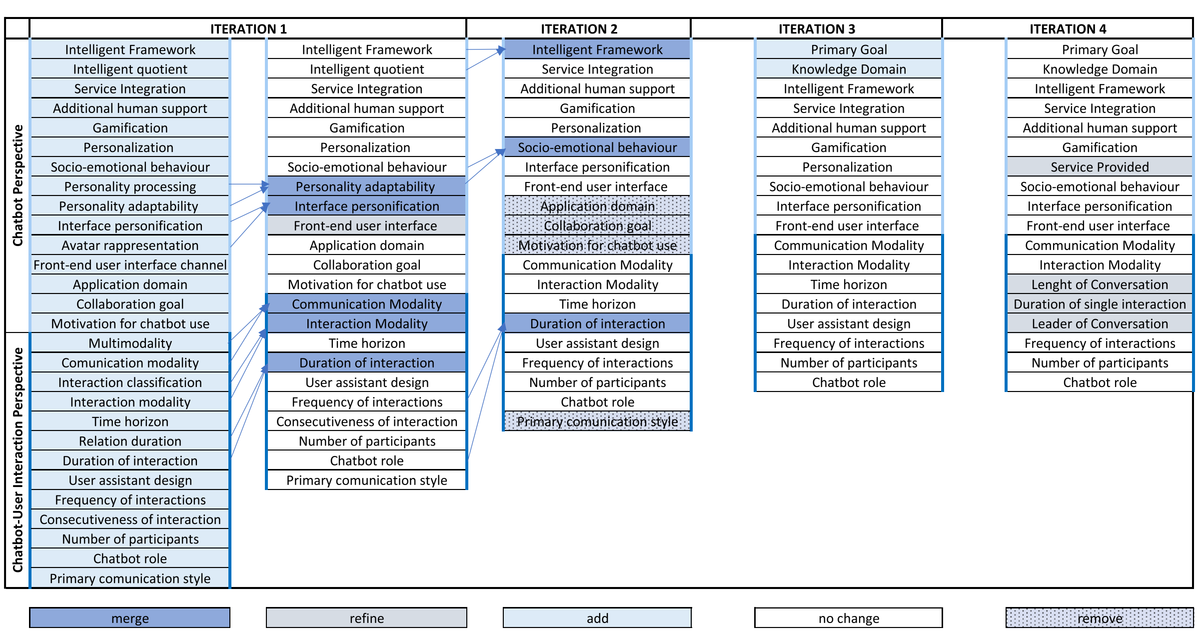


Fig. 2. - Taxonomy development process.

Table 2
- Taxonomy of design elements for manufacturing chatbots.

Perspective	Design Dimension		Characteristics
Chatbot	*D1*	**Primary Goal**	User support Action execution Coaching Data processor
	D2	**Knowledge Domain**	Specific Domain Restricted Domain
	D3	**Intelligence Framework**	Classic Rule-based AI Rule-based Retrieval Hybrid
	D4	**Integrated Service**	None Single Multiple
	D5	**Additional Human Support**	Present Not present
	D6	**Gamification**	Present Not present
	D7	**Service Provided**	Interpersonal Intrapersonal
	D8	**Socio-emotional Behaviour**	Present Not present
	D9	**Interface Personification**	Present Not present
	D10	**Front-end User Interface**	App Tool or Device
Chatbot-User Interaction	*D11*	**Communication Modality**	Only voice Multimodality
	D12	**Interaction Modality**	Graphical Interactive
	D13	**Lenght of Conversation**	Singol-turn Multi-turn
	D14	**Duration Single Interaction**	Short Interaction Medium-Long Interaction
	D15	**Leader of Conversation**	Chatbot-driven User-driven Mixed
	D16	**Frequency of Interactions**	Always When Required
	D17	**Number of Participants**	Individual Two or More
	D18	**Chatbot Role**	Facilitator Expert

manufacturing seem to suggest little use of such elements in the manufacturing domain, it is pointed out that in other domains such elements have some relevance, for example considering the healthcare domain for Additional Human Support [[61],[62]] and the e-learning domain for Gamification [[63],[64]]. Furthermore, although chatbot applications with a gaming component are few, the manufacturing sector has begun to integrate this dimension into training processes with other innovative technologies. Specifically, a recent study [65] recounts the inclusion of gamification components in a Virtual Reality with a voice integration application. In their paper, the authors point out how gamification can serve as an effective tool for learning and training complex procedures, machinery operations, and safety protocols, significantly improving user engagement [52].

D7 Service provided dimension indicates whether the chatbot falls within the user's personal domain and if it has user memory or not [[19],[22]]. The first category of D7 is Static chatbots that deal with users by simply delivering the service and have no memory of the operators, such as Max [56] and Bot-X [58]. In contrast, Adaptive are those chatbots that have a memory of the users and tasks they have previously performed, such as LARRI [55] and Chip [66].

Finally, through the design dimensions D8 Socio-emotional behavior, D9 Interface Personification lies in the desire to analyze chatbots from the point of view of human similarity, i.e., the degree to which a user perceives his or her digital interlocutor to be similar to a human being [19]. Specifically, the D8 represents a synthesis of the dimensions of Socio-emotional behavior and Personality processing/adaptability [[49],[48]]. Its purpose is to indicate whether the chatbot can show empathy. D9, on the other hand, is inspired by the Interface personification and avatar representation dimensions and aims to indicate whether the chatbot possesses virtual personification through a name and an avatar. Finally, D10 Front-end User Interface indicates whether it is developed as an App, and thus downloadable to various devices, or whether it is integrated directly into enterprise tools and devices.

4.3.2. *Chatbot-user interaction perspective*

The first dimension identified to characterize the interaction between the chatbot, and the user is D11 Communication modality. This element refers to the architecture presented in section X and indicates whether the chatbot can receive input and/or respond through a single interaction channel (Text or Voice) or multiple modalities (text, voice, video, etc.).

Dimension D12 Interaction Modality aims to classify a chatbot according to the type of interaction allowed by the software. Specifically, it subdivides chatbots with graphical interaction from chatbots with interactive interaction. In the former, the interaction between the user and the chatbot occurs through text buttons containing predefined choices. In the latter case, interaction can occur through free text, without restrictions on input.

D13 Length of Conversation dimension evaluates the total number of turns the chatbot considers to respond [[4],[50],[29]] Specifically, in Single-turn chatbots, the response is One-shot (e.g., Xiadong [60]), and for instance, provided by considering only the user's current message. In Multi-turn chatbots instead, multiple iterations are considered to respond (e.g.,[55])

D14 Duration Single interaction indicates the average duration of a single interaction with the chatbot. This dimension takes as reference the dimensions relation duration and duration of interaction proposed by the reference taxonomies.

In addition, for the development of a chatbot, it is necessary to set who is the conversation leader [4]. Specifically, D15 Leader of Conversation distinguishes conversational agents into User-driven, in which the user is the leader of the conversation, and Chatbot-driven in which the chatbot leads the conversation, and finally mixed solutions in which the leaders alternate.

Dimension D16 Frequency of Interactions distinguishes manufacturing chatbots into two categories and highlights the frequency of the use of the chatbot by users. The first indicates those chatbots used every time the operator needs to perform the task. The second refers to those chatbots used only when necessary.

D17 Number of Participants classifies the chatbot in relation to the number of possible participants during a single interaction with the conversational agent. Although cases analyzed reported 1:1 interaction, this dimension was still included in the taxonomy to emphasize the possibility of multiple interactions with the chatbot, for instance in a station with multiple operations and workers.

Finally, dimension D18 Chatbot Role indicates what kind of role the chatbot takes during the conversation. A chatbot may be classified as a facilitator if it facilitates the performance of the activity, or it may be classified as an expert if it transfers information that the operator does not know.

Following a software engineering methodology [67], we can divide the use of the conceptual architecture and the taxonomy proposed into the methodology's steps: analysis, design, deployment, and testing. In the analysis phase, is studied what develops and what functional specifications, requirements, and application boundaries provide for the agent. In this phase, the taxonomy of design features will be used. Next, in the design step, the agent is programmed. In this phase, we study how to develop the agent. One realizes the operating logic of the software using the functionalities chosen in the analysis phase as input. In this design phase, the architecture and its modules are used. The technical specifications of each module are evaluated. However, since both constructs belong to the same domain, they have a few elements in common. For instance, the decision to develop a conversational agent with Intelligence Framework Retrieval (D3) will necessarily impact and be tied to the NLU and NLG modules where I will be forced to choose Machine Learning and Corpus-based approaches.

5. Extensive case studies analysis

To confirm and demonstrate how manufacturing chatbot case studies identified are distributed among characteristics an extensive analysis has been conducted. Each chatbot has been deeply investigated and mapped across the eighteen dimensions and forty-two characteristics. The authors have opted for two analyses: a first qualitative analysis of the diffusion of each characteristic among the manufacturing case studies and a second analysis by the parallel chart to show trends in the relationship between characteristics. For those cases where it was not possible to confidently identify a characteristic, a named characteristic "not available N/A" was added.

5.1. Qualitative analysis

Table 3 shows the results achieved because of mapping each case with its characteristics. It is important to emphasize that since this is a small sample of observations, only a few qualitative hypotheses can be made, which should be properly validated through the classification of a larger sample.

However, the analysis carried out showed that there is a slight preference for developing conversational agents to assist operators when performing their tasks (46% User support). Furthermore, in line with the papers found on various scientific databases (Scopus, ResearchGate, Google Scholar), it is highlighted that the use of chatbots for the activation of robots or mechanical components is still at an early stage of research. Another interesting result concerns the Intelligent Framework (D3) dimension. Findings showed that the Rule-based approach is the most widely used when it comes to conversational agents in manufacturing. Although an apparent balance of the characteristics of this dimension can be observed in Table 3Table 3, it is worth mentioning that AI Rule-based uses Machine Learning techniques exclusively for the

Table 3
- Qualitative analysis.

Number of Chatbot used for classification = 26

	Design Dimension	Charateristics	Results	%
Chatbot Perspective	**D1 Primary Goal**	User support	12	46%
		Action execution	2	8%
		Coaching	7	27%
		Data processor	5	19%
	D2 Knowledge Domain	Restricted Domain	18	69%
		Specific Domain	8	31%
	D3 Intelligent Framework	Classic Rule-based	7	27%
		AI Rule-based	7	27%
		Retrieval	7	27%
		N/A	5	19%
	D4 Service Integration	None	9	35%
		Single	4	15%
		Multiple	13	50%
	D5 Additional Human Support	Present	5	19%
		Not present	21	81%
	D6 Gamification	Present	0	0%
		Not Present	26	100%
	D7 Service Provided	Interpersonal	15	58%
		Intrapersonal	8	31%
		N/A	3	12%
	D8 Socio-emotional Behaviour	Present	7	27%
		Not present	19	73%
	D9 Interface Personification	Present	10	38%
		Not present	16	62%
	D10 Front-end User Interface	App	10	38%
		Tool or Device	11	42%
		N/A	5	19%
Chatbot-User Interaction Perspective	**D11 Communication Modality**	Only voice	17	65%
		Multimodality	9	35%
	D12 Interaction Modality	Graphical		0%
		Interactive	25	96%
		N/A	1	4%
	D13 Lenght of Conversation	Multi-turn	12	46%
		Single	6	23%
		N/A	8	31%
	D14 Duration Single Interaction	Short Interaction	14	54%
		Medium-Long Interaction	12	46%
	D15 Leader of Conversation	Chatbot-driven	4	15%
		User-driven	15	58%
		Mixed	7	27%
	D16 Frequency of Interactions	Always	6	23%
		When Required	20	77%
	D17 Number of Participants	N/A	26	100%
	D18 Chatbot Role	Facilitator	14	54%
		Expert	12	46%

NLU module. Thus, it attests to a slight trend to turn toward a classical, rule-based approach, although the use of ML techniques is not discouraged when useful for a better understanding of the operator's voice. Concerning the knowledge domain (D2), the analysis also highlighted that the trend in manufacturing is to develop chatbots with an unreduced degree of specialization. Most studies identify themselves as chatbots with Restricted knowledge domain (69%). This means it is preferred to develop chatbots specialized in a certain area (or a set of activities or processes) rather than on a single, specific activity. Taking maintenance activities as an example, there has been a shift from chatbots such as LARRI [55] focused on assisting the activity of repairing a specific code (mechanical parts of an airplane), to more complex chatbots both capable of guiding operators in repair activities and assisting them in other processes. Examples include support in maintenance planning activities, process monitoring, predictive maintenance [68] and report writing [69].

58% of the conversational agents analyzed identify themselves as Interpersonal chatbots, service providers without the ability to store operator information. In addition, about 58% of the conversational agents are designed to activate at least one third-party service. As previously mentioned, regarding Gamification and Additional Human Support, the cases analyzed did not feature information concerning the presence or absence of these characteristics. The analysis also shows that most chatbots are developed with a low degree of "humanization," resulting in a low degree of interest in Human Similarity. Specifically, 73% of the observed conversational agents exhibit neither the ability to show empathy nor possess virtual personification. Regarding the mode of interaction with the user, there is a tendency to develop chatbots with a single channel of voice communication (65%), although multimodality solutions are not disdained. The analysis also allows for characterizing the interaction between operators and conversational agents developed in manufacturing. There is a tendency to develop chatbots based on an interaction of short duration (54% Short), guided totally or partially by the operator rather than by the conversational agent (58% User-driven), which occurs in most cases when operators express the need to use the chatbot (77% When Required). These results would suggest that this technology is being used in industrial facilities as a valuable support tool that can be relied upon to retrieve relevant information rapidly.

5.2. Parallel coordinates chart analysis

From an in-depth reading of the cases and because of the qualitative analysis, it was noted that two classes of chatbots can be distinguished in manufacturing. The first includes those agents designed to be a source of information for users and to build data storage. These are not necessarily tied to an operational activity. The second class includes conversational agents designed as tools to support operational activities. These may also include data storage.

The first class, called Operative Support, includes conversational agents with Primary Goal "User Support" and "Action Execution." In contrast, the second class, called Knowledge Source includes "Data Processor" and "Coaching."

The analysis conducted in this section aims to evaluate feature deviations between the two chatbot classes and assess whether there are distinctive feature patterns within each class. For a qualitative assessment, Parallel Coordinates Plots were used. Each chatbot is represented by a single curve passing through each dimension and indicating for each the chatbot's design feature. This graphical representation provides an opportunity to easily identify any recurring patterns, as the curves of the conversational agents will tend to overlap and create areas of higher density at common features [70]. To diversify the two classes, the color blue was assigned to represent the curves of Operative Support, and the color red for those belonging to the Knowledge Source class. The graph is shown in Fig. 3. This second-level analysis confirmed that there is no clear distinction in the design characteristics of conversational agents based on the purpose for which they are implemented. This result indicates how, when deciding to implement a chatbot in manufacturing, there are no defined rules or standards. The choice is left to a functional analysis of the development team, turning out to be strictly dependent on the needs of the scenario to be implemented. A confirmation of this result is the comparison of the classes in terms of the Intelligent Framework dimension (D3). It is possible to observe a balance of

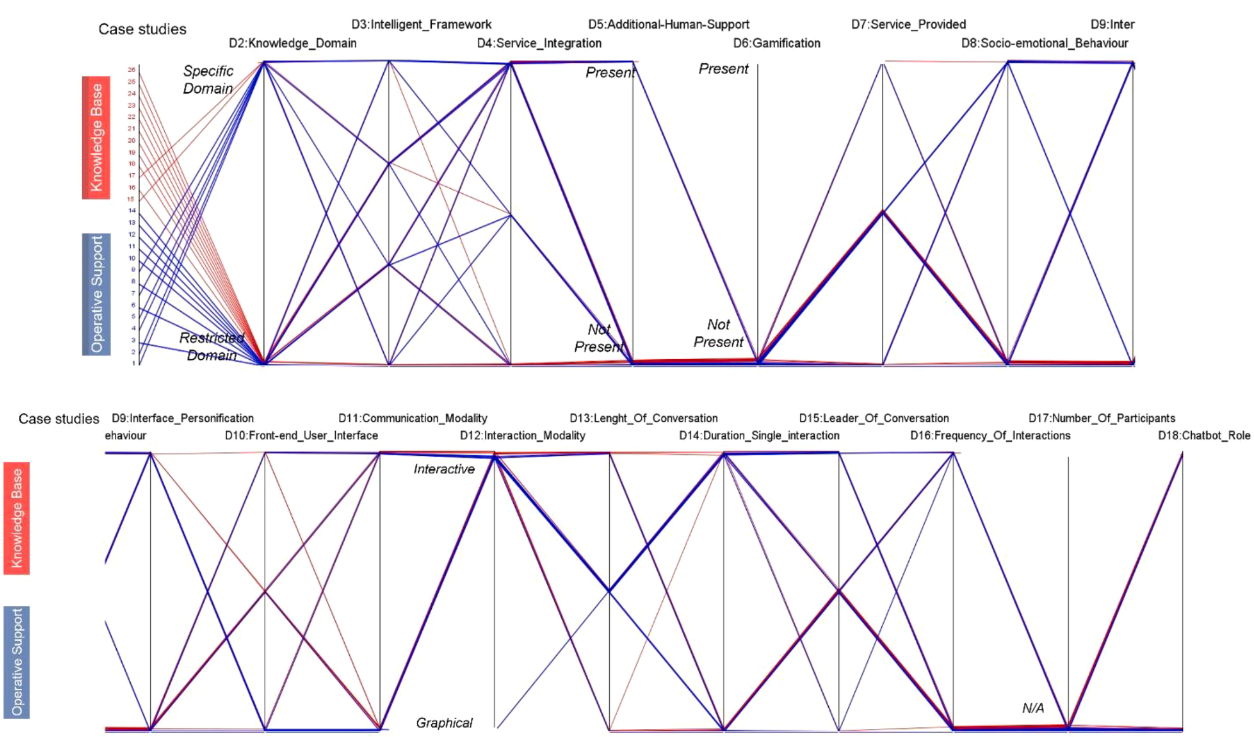


Fig. 3. - Coordinates parallel chart.

approaches used for implementation for each class. Results observed here are to be considered interesting, as one would have expected more characterization of the conversational agent classes and more differentiation in terms of individual design features. When analyzing the differences between the two classes, it can be seen that Knowledge Source chatbots tend to be developed with a more extensive knowledge domain (80% Restricted), while there would seem to be a balance for the characteristics of the D2 dimension with regard to Operational Support. These results can be considered a rationale for the nature of Knowledge Sources. Indeed, it is natural to think that conversational agents, whose ultimate goal is to represent a source of information for operators, should be developed with a broader knowledge domain to provide support in various business contexts. Knowledge Source chatbots also show a tendency not to be programmed to provide third-party services (50% None), while for Operative Support ones there is a pattern of having at least one service (79%). On the other hand, it is interesting to note that Operative Support chatbots tend to play the role of facilitators (72%), while Knowledge Source seems to lean more toward the role of experts (67%). These results suggest an important hypothesis in relation to the nature and purpose for which the chatbot is implemented. It is safe to assume that chatbots designed to support operational activities primarily play the role of facilitators by offering in most cases functionality to activate third-party services useful in the execution and completion of respective tasks. Conversely, it is equally safe to assume that Knowledge Source chatbots, generally play the role of experts on a task, for whom access to third-party services is most often not necessary since they are designed to be large sources of information themselves. Another distinction between the two classes relates to the Leader of Conversation and Front-end User Interface dimensions. In fact, Knowledge Source conversational agents have a strong tendency to be developed through a User-driven approach (75%), while in the Operational Support cases there is an increase in the number of applications where the conversation is totally or partially guided by the chatbot.

As far as the technical solution for implementing the chatbot, Operative Support seems to show a tendency to be developed as standalone tools or devices (70%), while Knowledge Source tends to be developed more as applications that can be downloaded directly to various devices (67%). Again, these results could be justified by the nature of the two chatbot classes. In fact, it is reasonable to assume that Operational Support conversational agents guide the operator step-by-step in the execution and completion of their tasks and that, such software, are developed with an independent device placed near the workstation. On the other hand, as far as Knowledge Source class is involved, chatbots are often developed through an application that can be downloaded to one's devices to maximize accessibility, and that the user guides the conversation to directly obtain the information he or she needs. Finally, it is interesting to note that, in Knowledge Source systems, there is a tendency to show a recurring pattern of features. In Fig. 3, it is possible to observe areas of curve overlap at dimensions D8 -D9 and especially between dimensions D10-D18. In contrast, Operational Support, although relationships between dimensions can be identified here as well, suggests an apparent absence of any recurring pattern.

6. Conclusion

With this research, the authors contribute to the recent human-machine interaction literature by proposing a conceptual architecture and a taxonomy to integrate conversational agents in industrial contexts. The research suggests several takeaways which can be described by dividing them into theoretical and practical implications.

6.1. Theoretical implications

Conversational agents technology represents a simple, intuitive, and innovative solution that aims to revolutionize the field of Human-Machine Interaction in the manufacturing context. Although to date this technology has shown great potential and the various conversational agents have been developed in a variety of application areas, this technology is still in the early adopter stage.

The research underlined the absence of a reference standard and a general lack of mastery about their logical operation and characteristics. This is also reflected in the literature, in which conflicting statements about the classification criteria, general architecture, and internal logic of operation of such systems are often found. Thus, from a theoretical point of view, a conceptual general architecture was developed to identify key development modules.

The paper confirms that only a handful of conversation systems have been studied in a real-world manufacturing context using industrial robots, even though they have received much attention from the dialog research community [[54],[71]]. The literature analysis emphasized that in the specific manufacturing sector, the conversational agents are configured as smart solutions applicable to various processes [52]. The case studies analysis showed that conversational agents intervene both in alienating and repetitive operations and in hazardous operations where the operator needs to have hands and eyes free [[41],[72]]. The literature and analysis of application cases in manufacturing have shown the lack of common classification criteria and design features. In such a scenario, a reference taxonomy for conversational agents developed in manufacturing was developed following Nickerson's model. The taxonomy revealed important relationships among manufacturing chatbot design dimensions, bringing interesting insights to domain experts interested in manufacturing chatbot design. Cases in manufacturing revealed the Rule-based approach is the most widely used, and this is credibly the next frontier that will be overcome, thanks to the increasingly widespread adoption of LLMs (ChatGPT, BARD, etc.), representing a significant advancement in scientific literature. On the other hand, it will be necessary to harness generative AI systems towards a restricted knowledge domain, as research has demonstrated its prevalent characteristic in industrial applications. The gathered evidence reveals a limited inclination towards humanizing conversational agents, the absence of empathy, the interaction of short duration, highlighting some additional characteristics that current Language Models (LLMs) can overcome. The introduction of these characteristics presents an intriguing research opportunity.

6.2. Practical implications

The research suggests several insights for industry professionals wishing to introduce conversational agents, pursuing a positive integration between humans and machines.

The research presented the technical characteristics and functional aspects to be considered in the development of a conversational agent, highlighting the importance of guiding the organization through the process. By adopting a systematic and guided approach, organizations can harness the potential of conversational agents and navigate the evolving landscape of human-machine collaboration in manufacturing. Specifically, to effectively integrate conversational agents into production systems, and improve productivity and operational performance, practitioners can use the taxonomy and architecture presented here. The taxonomy guides the choice of which functionalities to give to the chatbot. Specifically, questions should be asked both on dimensions related to the chatbot's perspective and on dimensions related to human-chatbot interaction. In the first perspective, the study guides practitioners to ask themselves what objective they want to pursue (e.g. whether to develop a solution for training or to support the operator in complex operations) and how to achieve it (e.g. to include integrations with other tools, to give the chatbot a personification that takes into account the context in which the chatbot fits). In the second perspective, the study guides the choices regarding the type of interaction (e.g. by defining the duration of the conversation or the leader). The case studies analyzed demonstrated on the one hand the lack of a structured approach in the definition of functionalities and on the other hand the great variety of customizations. Each organization must therefore be supported in prioritizing functionalities that can address their challenges, such as real-time data retrieval, process monitoring, and troubleshooting assistance, which can have a significant impact on productivity and overall efficiency. Furthermore, the developed architecture also helps in the practical development of the chatbot. It provides practitioners with an outline of the technical aspects to choose from according to the functionalities they wish to achieve by clarifying the possible interfaces and approaches available (e.g. rule-based, retrieval…). Another insight is that in the realm of operational activities, it can be postulated that chatbots primarily serve as facilitators, offering a range of functionalities to activate third-party services, thereby aiding in the execution and completion of respective tasks. On the other hand, in the domain of Knowledge Source chatbots, it is reasonable to assume that they assume the role of task experts, possessing vast reserves of information themselves, thereby rendering the need for third-party services largely unnecessary.

Finally, as with all research, this work has some limitations, which offer opportunities for future research directions. While the authors thoroughly followed an established taxonomy development procedure [18], the limitations of this study mainly arise from the subjective choices inherent in any qualitative research approach. Notwithstanding, we applied a systematic empirical evaluation process and maintained a consistent unit of analysis throughout each case study investigated. In addition, such innovative topics often have few case studies to use to validate the research. This has made the application of our taxonomy to case studies limited. However, the authors consider the insights obtained an important step for more extensive analysis of new future manufacturing application cases. It is indeed expected that this technology will see an increase in application cases in the manufacturing context. In this regard, this work would serve as a tool for all partitioners to guide organizations toward greater understanding and adoption of such technology representative of beneficial Human-machine Interaction. Furthermore, from a functional point of view, also considering the deployment of LLM such as GPT-3 or GPT-4, future research will have to take into account ethical considerations such as privacy and data fairness within the modules of the architecture, which must be addressed through robust guarantees and transparency. Furthermore, algorithms must be able to guarantee privacy protection and accountability against potential risks.

CRediT authorship contribution statement

Silvia Colabianchi: Conceptualization, Methodology, Software, Validation, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Andrea Tedeschi:** Conceptualization, Investigation, Resources, Data curation, Formal analysis. **Francesco Costantino:** Conceptualization, Validation, Investigation, Resources, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

Classes	Case study	Conversational agent	Reference
Operative Support	1	Larri	[55]
	2	Max	[56]
	3	Bot-X	[58]
	4	Multi-modal	[9]
	5	Robot by voice	[36]
	6	Probot	[73]
	7	Ramp-Up	[74]
	8	CNC	[75]
	9	JAST	[76]
	10	Maintenance	[69]
	11	ToD4IR	[71]
	12	IRWOZ	[53]
	13	Little Helper	[77]
	14	Predictive Maintenance DIA	[68]
Knowledge Base	15	Xiaodong	[60]
	16	Training new employees	[57]
	17	FRASI	[78]
	18	MES	[79]
	19	Agriculture-Bot	[80]
	20	Agroexpert	[59]
	21	Transformer Mass-customization	[54]
	22	(Chip) Onboarding	[81]
	23	BPMN	[82]
	24	AECO industry	[83]
	25	COALA	[84]
	26	POPEYE	[12]

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