Designing Conversational Agents for Empowering Human Work

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Abstract

Conversational agents have become increasingly prevalent in various domains, from customer service to healthcare and education. Their role in empowering human work and experiences is gaining significant attention due to advancements in helping workers in their practices. This paper explores the design principles, challenges, and potential applications of conversational agents in enhancing human productivity and improving user experiences. It examines the impact of conversational agents on different aspects of human work and interactions, highlighting the opportunities they present for empowerment and augmentation. By synthesising existing research and specific case studies, this paper provides insights into the effective design, deployment and evaluation of conversational agents to empower human endeavours.

Keywords 1

User-Chatbot interaction, Conversational recommender systems, End-User Development, Human empowerment, Design principles

1. Introduction

Conversational agents have emerged as versatile tools for facilitating human-computer interactions. These agents simulate human-like conversations, enabling users to interact with computers more naturally and intuitively. The potential of conversational agents to empower human work and experiences lies in their ability to automate tasks, provide personalised assistance, and augment human capabilities. This paper investigates conversational agents' design considerations and applications in various domains, focusing on their role in enhancing human work productivity and experiences.

Conversational agents, also named chatbots, offer several ways to empower human work across different industries and domains. For example, in the healthcare domain, virtual health agents can assist caregivers such as doctors and nurses in providing patients with personalised medical advice, scheduling appointments, and delivering medication reminders, improving access to healthcare services [1,2]. In education, conversational agents support personalised teaching experiences, helping teachers when they have to assist students with homework, tutoring, and access to educational resources [3-5]. Finally, chatbots integrated into working platforms streamline communication and task management in productivity sectors, facilitating workers' productivity [6,7]. Despite their potential benefits, designing and deploying conversational agents present several challenges. Primarily, they have to be able to gain user acceptance and trust. Building trust and acceptance among users requires transparent communication about the capabilities and limitations of conversational agents [8]. To do so, conversational agents must accurately interpret user inputs and understand the context of

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conversations to provide relevant responses. Moreover, they should be able to maintain context across interactions, remembering previous conversations and user preferences to deliver personalised experiences. A second important issue concerns how to integrate humans into a recommender system based on conversational agents. The challenge aims to consider workers' feedback, leveraging their expertise, intuition, and understanding of preferences to enhance the recommendation process. The primary step is to give users transparency in how recommendations are generated and allow them to control the recommendation process. This solution could involve explaining the reasoning behind specific recommendations or offering options to adjust recommendation criteria or preferences. The second step is to provide workers with a strategy to present their feedback through ratings, comments, or explicit actions (e.g., purchasing or ignoring a recommendation). The idea is to use this data to refine the recommendations and improve future suggestions provided by the agents.

To achieve these objectives, we investigated End-User Development (EUD) strategies [9-14] to design conversational agents that empower non-expert users to facilitate their working practices, make their decision-making processes more efficient, and suit their specific needs and preferences without requiring extensive programming or technical expertise. These strategies incorporate user-friendly interfaces and intuitive communication principles, enabling workers to act effectively in their context or domain.

Based on these considerations, this paper investigates the challenges, opportunities, and weaknesses of designing conversation agents to support workers' activities. This study stems from the development of different CAs in two contexts of use: health care and education. For each one of these case studies, we designed an agent to provide workers with suggestions about decision-making strategies to enhance efficiency or facilitate their working practices. Moreover, we designed evaluation strategies to understand how users can accept conversational agent (CA) support in future activities and how good the usability and communicability level of the CA is in its interaction. By using these case studies, the paper aims to reply to two main research questions:

1. What key design principles should be considered when developing conversational agents (CAs) to support workers in their professional tasks?
2. What methods can be employed to assess the effectiveness of CA support in facilitating and enhancing the working experiences of workers?

Based on these considerations, in the next Section, we present an overview of relevant studies we used to motivate adopting conversational agents in working activities. Then, we present the two case studies. The first one aims to combine a CA in a learning management system to assist teachers in creating digital courses. A second case study focuses on integrating CA into a dashboard that geriatric professionals use to develop new exercises for older users. Section 2 describes the common strategy based on EUD techniques we adopted in designing our CAs, illustrating related opportunities, strengths, weaknesses, and threats. Furthermore, we suggest strategies for designing evaluation methodologies aimed at comprehensively assessing users' acceptance of CA support in forthcoming activities and gauging the usability and communicability levels of the CA during its interactions. Finally, Section 6 sums up conclusions and future works.

2. Overview of Conversational Agents to Support Working Practices

Conversational agents are computer programs that simulate human-like conversation through text or speech-based interactions. They utilise natural language processing (NLP), machine learning, and other artificial intelligence (AI) techniques to understand user queries, provide relevant responses, and perform tasks autonomously. These agents can range from simple chatbots offering predefined responses to sophisticated virtual assistants capable of understanding complex commands and executing various tasks.

The benefits of using conversational agents in workplaces concern their enhanced efficiency. They can automate routine tasks, such as scheduling meetings, managing emails, and retrieving information, allowing employees to focus on more strategic activities[15, 16]. Moreover, unlike human assistants, CAs can operate round the clock, providing support and assistance to workers irrespective of time zones or working hours. They can offer personalised assistance through data-driven insights and user profiling, giving personalised recommendations according to past interactions to anticipate users' needs and preferences [17,18]. This solution empowers employees by providing instant access to information, resources, and support, improving their decision-making capabilities. Furthermore, CAs are highly scalable solutions that can handle multiple conversations simultaneously, making them suitable for organisations of all sizes [17,18]. Finally, in the context of employee training and onboarding, CAs provide interactive guidance, answer frequently asked questions, and deliver learning materials in a user-friendly manner. The reviews presented in [19-21] examine the evolution of chatbot technology, its applications across different industries, and the potential benefits and challenges associated with its implementation in the workplace. Other works, such as in [19], explore strategies for designing, deploying, and evaluating chatbots to maximise their effectiveness and user acceptance.

Despite numerous strengths, CAs also exhibit some weaknesses. One notable limitation is that the initial investment required to implement conversational agents can be substantial, encompassing development, integration, and training costs. Over-reliance on these agents may also lead to reduced human interaction and dependency on technology, which could impact employee morale and interpersonal relationships [22]. Moreover, privacy and data security concerns can arise from storing and processing sensitive workplace information [23]. Ethical concerns surrounding data privacy, algorithmic bias, and misuse of CAs pose regulatory and reputational risks for organisations deploying these technologies. Based on this overview, we can say, to our knowledge, that no system has yet been designed that helps workers with strategies to integrate their feedback and working experiences in the agents' recommendations or how to prioritise their work, providing reminders on when to switch tasks or get back on task, take breaks, and reflect on how much they accomplished at the end of the day. Starting from these considerations in the following sections, we present the conversational agents redesigned to reply to these research questions partially.

3. Design of Conversational Agents for Specific Context Domains

3.1. Conversational agent in education

The literature presents many studies regarding using chatbots in the educational domain [3-5]. According to the review [5], chatbots are mainly applied for teaching and learning (66%). However, to our knowledge, chatbots are rarely used to assist teachers in creating new digital courses. In this field, they assume the role of prompters to assist teachers in finding and selecting proper learning materials available on the internet. The proposed idea is to employ a chatbot to find existing Learning Objects (LOs) [24-26] and suggest them to teachers for course creation. These LOs serve as building blocks for quickly assembling courses. The chatbot interacts with teachers to gather course information and then suggests LOs based on topics, difficulty, type, and duration. We use visualisation aids and strategies like those in Figure 1-A to present information transparently to teachers, facilitating their understanding and decision-making process.

Additionally, the chatbot assists in sequencing LOs according to prerequisites and student evaluations, providing suggestions for different learning paths. Once the teacher selects an LO, the chatbot suggests a list of LOs that can be used in the following lesson according to their prerequisites. In Figure 1-B, the teacher can see the suggested LOs in the first line at the top of the dashboard. The white dashed rectangles represent the suggested LOs the teacher has not selected but that the system provides because they relate to the other LOs. The teacher can select them in a second moment. In the Figure, the teacher has chosen LOs that are coloured, and the colours allow her/him to discriminate the type of learning content (video lesson, exercise, document and quiz). Finally, the teacher can sequence the LOs by dragging and dropping them on the third line of the screenshot.

Another important suggestion is present in the second line of the screenshot in Figure 1-B. In this case, the recommendation system suggests combining the LOs in different learning paths. The branches depend on the output of the previous LO. If the LO ends with a test, the choice of the next LO depends on the obtained result. Without a test, the choice depends on the student's evaluation. The system aims to streamline course creation and enhance teaching efficiency.

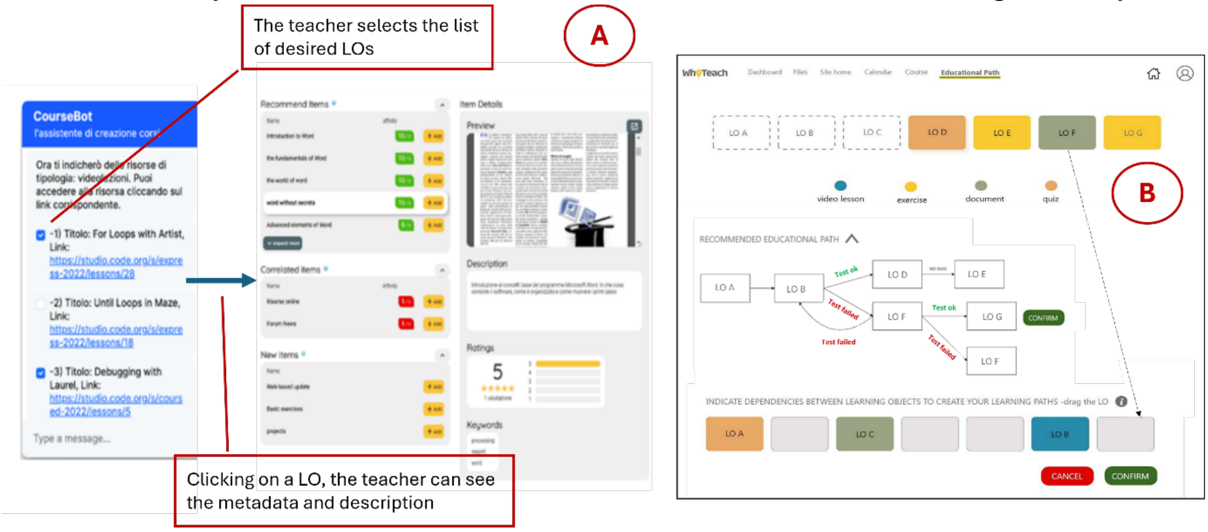

Figure 1: In the first screenshot (A) on the left, the chatbot asks the teacher to select the LOs to insert into the final course. Clicking on a LO on the right allows the teacher to see further information about it: the topics the LO covers, a description, the rating and its keywords. In the second screenshot (B), the CA lists suggested LO at the top of the web page. The teacher does not specify the white dashed LOs. The teacher can sequence the LOs by dragging and dropping them on the third line of the screenshot. Finally, as depicted in the second line of the screenshot, the RS can suggest a possible combination of LOs presented in the first list showing different learning paths. As explained in the text, the branches depend on the output of the previous LO.

3.2. Conversational Agent for Active Ageing

Senile dementia represents one of the healthcare emergencies of the near future [27]. Several studies highlight that currently available pharmacological methodologies cannot definitively halt degenerative processes. In support of these treatments, cognitive stimulation for patients experiencing cognitive decline is gaining traction. However, professionals in this field often have to independently devise exercises for their patients, relying on their theoretical and clinical knowledge and experience. To help senior doctors and nurses (now called geriatric professionals) in their activities, we introduced an innovative web-based dashboard designed to address the challenges associated with detecting and managing cognitive decline in elderly individuals. This dashboard is a comprehensive toolkit, readily accessible via the internet, that offers a complete suite of features, including patient profiling, treatment planning, and real-time cognitive capacity monitoring according to a predefined schedule.

An innovative aspect is integrating an AI service, particularly a conversational agent powered by OpenAI's API[2], to assist in generating cognitive exercises. Since creating exercises can be time-consuming for these professionals, who often lack the necessary time for this task, a CA enables them to develop exercises tailored to the patient's needs, which are then reviewed and modified by the user. In detail (see Figure 2), upon receiving a request, the CA initiates a call to the OpenAI API, specifying the type of exercise desired and prompting the API engine to return a formatted JSON object for convenient data interpretation. After validating the returned JSON object, the agent populates a web form with the data generated by OpenAI. Subsequently, the user can review the proposed exercise and choose whether to retain, modify, or discard it. If the user opts to keep the proposed exercise, they can formulate the evaluation model for the new exercise to enhance future interactions with the OpenAI engine. Because the generated output is not entirely controlled, user validation is required before it is accessible to the CA. Figure 2 illustrates an example of generation via the dashboard interface. Finally, an endpoint is utilised to maintain conversation context to prevent duplicate exercises from previous responses, enabling the model to avoid reproducing answers already provided in earlier calls.

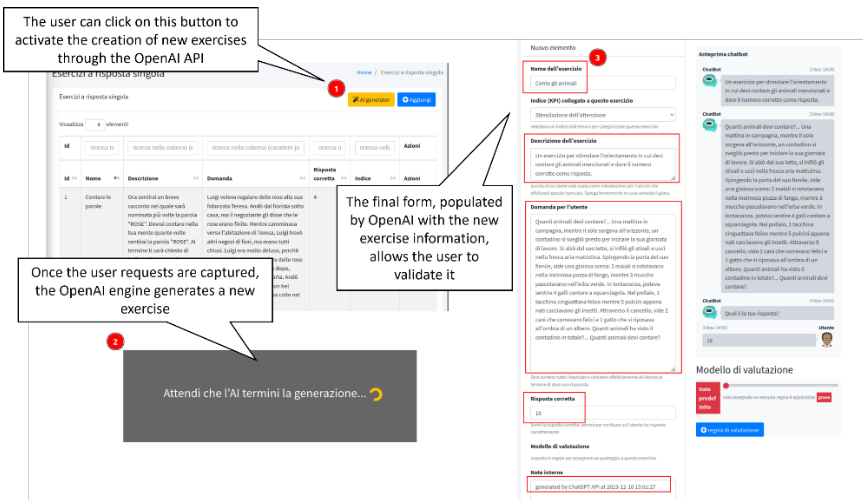

Figure 2: The screenshot illustrates the flow of API usage in OpenAI. The user can activate the creation of a new exercise through the AI generator button (step 1). Once the user's requests are captured, the OpenAI engine generates a new exercise (step 2). Finally, the system utilises the OpenAI reply to populate the form with further exercise information, enabling the user to validate it (step 3).

4. A Strategy for Designing CA in Working Environments

Designing a CA for working environments involves creating virtual assistants or chatbots to assist users in their tasks and workflows effectively. EUD [28-31] strategies can enhance this process by enabling us to design, customise and tailor the conversation agent to suit workers' needs better. EUD provides end users with strategies, methods, techniques, and tools to act as non-professional software developers and create, modify, or extend software artefacts. The term End-User Development is not new. It stems from the field of End-User Programming [35]. The shift from "programming" to "development" reflects the emerging awareness that, while adapting a computer to a user's needs may include some form of programming, it certainly is not limited to it. EUD is relevant to a potentially large population segment, including most end users of

[2] https://openai.com/blog/openai-api

traditional computer applications. We aim to adapt EUD strategies by integrating the working platforms with functionalities to facilitate users' decision-making processes and working practices with the help of CA.

In these terms, we can redefine the concept of EUD as the process whereby end-users (in our case, the workers) develop their working practices through the assistance of conversational agents. Within this framework, for the development of all conversational agents outlined in the preceding Section, we have implemented a design strategy based on three key points:

1. The CA should deliver straightforward and well-justified suggestions, enabling the user to comprehend the rationale behind each recommendation provided.
2. The worker should remain central to the decision-making process. Utilising the agent's suggestions, the user should have the autonomy to make personalised decisions that best align with their needs and requirements without being constrained by the chatbot's recommendations.
3. Whether positive or negative, the user's feedback must be integrated to enhance the agent's suggestions in subsequent interactions. This iterative process ensures continual improvement in the agent's assistance.

An example of the application of the first principle is depicted in Figure 1. The screenshot shows how the teachers can communicate the desired LOs and the resources they want to include in the digital course to the CA by selecting the related checkboxes. To maintain users' trust and acceptance and transparently explain the motivation behind a suggestion, we adopted a subset of the guidelines as stated in [33]. These 18 practical design guidelines aim to improve the interaction between humans and AI. To enhance transparency and aid user understanding, teachers can utilise a taxonomy of topics proposed by previous users. This taxonomy aims to provide insights into learning objective (LO) content and enhance transparency, acceptance, and trust in recommendations.

Additionally, the system reports evaluations inferred by the CA based on the user's history and profile for each topic. Two further lists accompany the main topics: "Correlated items" display LOs for which the user missed to provide information but can be helpful for the course, and "New items" include less relevant or unexplored topics aimed at addressing the cold start problem as proposed by Wilkinson in [34]. Finally, the LO explanation contains a detailed description, preview, keywords, and teacher ratings. Another example is depicted in Figure 2, where the geriatric professional can see the exercise generated by the CA and how it will be visualised to the patient on her/his smartphone/table (the image further to the right in Figure 2).

Examples of applying the second principle are present in all CAs we designed. In the first case study, the CA allows teachers to combine the suggested LOs in a sequence of lessons the students must follow. The CA for geriatric professionals asks them to validate the generated exercise.

In each case study, the worker is at the centre of the decision-making process in all these examples. While utilising the CA's suggestions, users can make personalised decisions that align best with their needs and requirements without being constrained by the chatbot's recommendations. Furthermore, the validation process proposed for each CA exemplifies the application of the final principle. Whether positive or negative, user feedback is integrated to refine the agent's suggestions in subsequent interactions. This iterative approach guarantees ongoing enhancement in the agent's assistance.

5. Evaluation of CA Interaction in Working Environments

Besides designing the design principles at the base of each CA, we are currently testing and defining different models and methods to evaluate the efficacy of using CA in working environments. The first objective is to use a model to assess the workers' computational thinking level and the EUDability of an EUD environment. The first idea we are investigating is to combine the EUDability model [34], which is composed of a 15-item checklist to measure Concreteness, Modularity, Structuredness, Reusability, and Testability of a system, with the Computational Thinking Scale (CTS) by Tsai et al. [35]. This scale, validated in computer programming education, assesses problem-solving attitudes. We used this model to evaluate the geriatric professionists' activities in the project described in Section 3.2 as reported in [37]. This study seeks to illustrate the effectiveness of employing the EUDability checklist and CTS questionnaire in preliminarily assessing the appropriateness of an EUD environment within a particular work setting, focusing on its intended users. The outcomes of this evaluation can serve as a basis for refining the working environment to enhance its usability for end users. A second model we are testing to evaluate our CAs is based on the Bot Usability Scale (BUS) [38, 39] as a standardised tool for assessing user satisfaction after interacting with chatbots, aiding in developing user-friendly conversational systems. We used this model to evaluate the CAs of the projects in Sections 3.2. The introduction of BUS-11 aims to streamline chatbot evaluation, enabling practitioners to compare and benchmark performances during product assessment. This tool can potentially standardise and enhance comparability in human-conversational agent interaction.

Finally, we are studying how to integrate the two previous models by a method we studied to evaluate the CA's communicability skills and the level of acceptance of a CA from the workers we adopted in the project described in Section 3.1. In [40], to assess the impact of the CA on the teachers' activity, we adopted an extended version of the UTAUT model [41] to study its acceptance and intention to use it. As discussed in the paper, the final results of our tests demonstrate sound effects for concerns about the acceptance of the CA. Specifically, good values concern the quality of the assistant's ability to communicate effectively, the level of perceived trust in its suggestions and finally, how the teachers' experience affects their perception of the ease of use of the assistant. In conclusion, we are studying a holistic approach to evaluating CAs in workplace environments, emphasising the importance of considering technical aspects, user attitudes, usability metrics, and overall impact. By adopting such a comprehensive evaluation strategy, researchers can provide valuable insights for developing and implementing CAs tailored to the needs of diverse work environments and user groups.

6. Future works

Future research could focus on refining and validating evaluation models to provide more accurate assessments of CA effectiveness and user satisfaction in diverse working environments. Additionally, studies could explore the long-term impact of CAs on workers' productivity, satisfaction, and overall well-being across various industries and professions. Moreover, investigating the ethical and societal implications of integrating CAs into workplace environments is crucial. Future research could examine privacy, data security, algorithmic bias, and the potential impact of automation on job roles and employment dynamics. Considering the global nature of workplaces, there is a need to examine how cultural differences influence the design, adoption, and effectiveness of CAs. Comparative studies across diverse cultural contexts can provide valuable insights into tailoring CAs for global workforces. Encouraging interdisciplinary collaboration between computer science, psychology, human-computer interaction, and other relevant fields can enrich CA design and evaluation research. This multidisciplinary approach can foster innovation and address complex challenges in creating effective CAs for working environments.

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