Toward Better, Proactive, Adaptable and Symbiotic Conversational Agents for Digital Accessibility

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Abstract

Conversational Artificial Intelligence (AI) holds significant promise for promoting digital inclusion, offering natural language access to information and services for citizens who face barriers with traditional, visually oriented web interfaces. Yet current chatbots often stop at retrieving or displaying content, providing little support for interpretation, comparison, or decision-making. This position paper, developed within the context of the PROTECT project (imPROving ciTizEn inClusivity Through Conversational AI), argues that future conversational agents must go beyond basic information delivery to become better, proactive, and symbiotic. Building on recent work on Explanation User Interfaces (XUIs) and Human-Centered AI, we explore how explanations can be integrated into dialogue to foster trust, transparency, and collaboration. We outline opportunities for conversational explanation interfaces (ConvXUIs), identify research challenges—including evaluation metrics, cognitive load, personalization, integration with web architectures, and ethical regulation—and discuss how symbiotic interaction can empower users as active participants in digital life. By advancing conversational agents that explain, justify, and co-construct meaning, we envision a path toward more inclusive, trustworthy, and effective digital accessibility.

Keywords

Conversational Agents, Accessibility, Explanation User Interfaces, Conversational Explanations, Symbiotic AI

1. Introduction

Digital inclusion is increasingly recognized as a fundamental right, enshrined in the EU Directive (UE) 2019/882, which requires full and effective participation in society for all citizens, including people with disabilities [1]. Yet, significant digital barriers remain: in Italy, four out of ten people still do not use the Internet regularly, and more than half of the population lacks basic digital skills [2]. These gaps prevent equal access to knowledge, services, and opportunities.

Conversational Artificial Intelligence (AI) has emerged as a promising solution to bridge these barriers [3]. Chatbots and voice-based agents can mediate access to digital services, supporting citizens with visual impairments, elderly users, and other fragile populations who struggle with traditional, visually-centric web interfaces. The PROTECT project (imPROving ciTizEn inClusivity Through Conversational AI) tackles this challenge by envisioning a paradigm of Conversational Web Browsing, enabling users to access, navigate, and understand the Web through natural language interaction [3].

However, conversational agents for digital accessibility currently face several limitations. They often stop after retrieving or opening a website, leaving users without guidance to interpret, compare, or act upon the information presented. Moreover, their reasoning processes remain opaque, risking mistrust and exclusion rather than empowerment.

This position paper argues that overcoming these challenges requires rethinking the *role* of chatbots for digital accessibility. They should not only deliver information but also explain, justify, and *collaborate* with their users. We propose that chatbots need to become adaptable [4], proactive [5], and symbiotic [6]. They should follow human-centered principles, anticipate when explanations are needed, and

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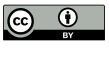

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engage in forms of collaboration that help users achieve their goals of accessing digital content. To do this, they must incorporate lessons from the literature on Explanation User Interfaces (XUIs) and align with the broader perspective of Human-Centered AI, where explainability and trust are essential for meaningful interaction.

The rest of the paper is organized as follows. Section 2 reviews related work on Explanation User Interfaces (XUIs) and places them in the context of Human-Centered AI, with particular attention to the role of explainability in fostering trust and trustworthiness. Section 3 considers the application of these ideas to conversational agents, outlining the opportunities and challenges of embedding explanations into dialogue. Section 4 develops the main position of the paper, presenting three design imperatives for the next generation of chatbots: they should be better, proactive, and symbiotic. Section 5 highlights research challenges and open questions, including evaluation methods, adaptivity, and ethical considerations. Finally, Section 6 concludes by summarizing the contribution and reflecting on how the PROTECT project can contribute to the development of inclusive conversational systems.

2. Background: Explanation User Interfaces and Human-Centered AI

The need for AI systems to provide meaningful explanations has become a central topic in recent years [7, 8]. Explanations help users understand why a system behaves in a certain way and, more importantly, whether its suggestions can be trusted.

Explainability has emerged as a central concern in the development of artificial intelligence, particularly in systems that support decision-making or where users must critically evaluate the information provided [9]. The field of explainable AI (XAI) has gradually shifted from a purely technical endeavor, focused on generating explanations, to a more user-centered perspective, where the focus is on how explanations are received, interpreted, and acted upon by humans [10].

A central finding by Cappuccio et al. [8] is that effective explanations are not only about transparency, but about helpfulness, interactivity, and personalization. XUIs that allow users to explore explanations, ask follow-up questions, and adapt content to their needs foster higher trust and adoption. This aligns with the broader vision of Human-Centered Artificial Intelligence (HCAI), which reframes AI not as a replacement for human intelligence, but as an augmentation tool [11, 12, 13]. Within HCAI, explanations are a form of dialogue: they sustain trust, calibrate reliance, and enable informed human agency.

In this respect, recent work has stressed the need for what Ehsan and Riedl [14] call human-centered explainable AI (HCXAI), a reflective socio-technical approach that places end users and their values at the core of explanation design. Similarly, Schoonderwoerd et al. [15] argue for the development of design patterns that link explanation techniques to user needs, demonstrating that a single explanation format rarely works for all situations or all users.

A key reason for this shift is the recognition that explainability and trust are deeply intertwined. Explanations are not merely descriptions of an algorithm's reasoning: they play a crucial role in shaping whether users choose to rely on a system, and in what way [16, 17, 10, 9]. Empirical studies confirm this connection. For instance, experiments in decision-making tasks have shown that explanations improve not only user performance but also the calibration of trust, helping people to distinguish when reliance on AI is appropriate and when it is not [18]. A broader review of decision support systems has also identified trust and transparency as recurring evaluation criteria across domains such as healthcare and finance [19].

However, the relationship between explainability and trust is not straightforward. Meta-analyses show that while there is a positive correlation between the two, the effect is moderate and highly dependent on contextual factors, such as usability, accuracy, and perceived fairness of the system [20]. Philosophical work adds nuance by distinguishing between different kinds of trust: some forms of trust may indeed require explanations, while others rest on broader judgments about competence, integrity, or benevolence. As Baron [21] notes, explainability may contribute to—but cannot fully determine—trustworthiness. This distinction highlights that trust in AI is not only about the system's internal workings but also about the intentions and accountability of its designers and maintainers.

The implications for HCAI and HCXAI are clear [8]: Explanations must be accessible, context-sensitive, and aligned with user goals. Poorly designed or overly technical explanations can easily backfire, either overwhelming users or creating misplaced confidence. Incremental and adaptive strategies, which reveal just enough information at the right time, are often more effective than exhaustive technical transparency. Moreover, evaluation of explanations must take into account not only subjective perceptions of trust but also behavioral measures of reliance and performance, since these may diverge.

While most studies of explanation user interfaces (XUIs) have focused on static or visual domains such as expert dashboards or healthcare applications [8], their findings are directly relevant to conversational agents. In dialogue, explanations unfold dynamically, and their effectiveness depends not only on content but also on delivery—timing, phrasing, tone, and the agent's responsiveness all matter. Trust in chatbots is therefore shaped by the conversational process as much as by the information disclosed [22]. In inclusive contexts such as PROTECT, where users may face barriers of literacy, vision, or confidence, explanations become not only mechanisms of transparency but also instruments of reassurance and empowerment. The challenge, then, is to adapt the principles of XUIs and HCAI to conversational interaction, designing explanations that sustain trust while remaining accessible, concise, and meaningful.

3. From Explanation Interfaces to Conversational Agents

Most of the work on explanation user interfaces has so far concentrated on static or visually oriented contexts [8]. Domains such as healthcare, finance, and recommendation systems have been the testing ground for many explanation techniques, from visualizations of feature importance to counterfactual examples that show how outcomes would change under different conditions. These applications typically assume that users engage with explanations through dashboards, charts, or other visual means. While valuable, this focus leaves relatively unexplored the possibilities that arise when explanations are embedded in conversations.

Conversational agents, such as chatbots and voice-based assistants, differ from static interfaces in one fundamental respect: they are inherently dialogical [23]. Instead of presenting information in a single, fixed form, they support ongoing interaction where users can ask questions, request clarifications, and shift direction as the dialogue unfolds. This interactive nature makes conversational agents a particularly promising frontier for explainability. Explanations are no longer stand-alone artifacts but become part of a dynamic exchange that can adapt to user needs in real time. This makes them ideal candidates for embedding explanations into natural language conversations, creating *Conversational Explanation User Interfaces (ConvXUI)*.

Embedding explanations into conversation opens up several opportunities. One is the possibility of providing explanations that are seamlessly integrated into dialogue. Rather than requiring users to interpret graphs or technical terms, the system can state in plain language why it suggested a resource, or how it prioritized one option over another. For example, instead of passively presenting a list of links, a chatbot might add: "I suggested this page because it contains the official information you asked for, and it is maintained by a government agency." Such conversational explanations situate transparency directly within the user's natural flow of interaction.

Another opportunity lies in the proactive nature of dialogue. Unlike static UIs, conversational agents are able to anticipate potential points of confusion and intervene before misunderstanding arises. A chatbot could, for instance, notify the user if a suggested page does not meet accessibility standards, or explain the confidence level it assigns to a recommendation. By offering clarifications unprompted, the agent reduces cognitive load and reassures users that the system is not only functional but also attentive to their needs.

Dialogue also makes follow-up interactivity natural. If a user is dissatisfied with an explanation or wants to compare alternatives, they can simply ask questions such as "why not another source?" or "show me a different option." This ability to engage in back-and-forth negotiation distinguishes conversational

explanations from the static disclosures found in traditional XUIs. In effect, the explanation process itself becomes a collaborative activity, rather than a one-way transmission of information. Dialogue-based explanations are even more relevant in the context of education, where they can be either employed to implement gradual machine teaching [24, 25] or to foster trust [26]. Intuitively, this is particularly relevant in the context of digital accessibility, where users do not have access to the source of information.

Finally, conversational explanations can be adapted to different modalities, making them particularly relevant for inclusive contexts. While textual or spoken explanations may suffice for many, agents can also be designed to integrate with assistive technologies, ensuring that explanations are perceivable by users with visual or auditory impairments. This multimodal adaptability strengthens the potential of conversational agents to act as mediators of digital inclusion.

Taken together, these characteristics suggest that chatbots can operationalize the principles of explanation user interfaces in ways that go beyond traditional approaches. Explanations in this setting are not fixed objects but evolving parts of a dialogue, tailored to user goals, responsive to situational needs, and capable of building trust through transparency and responsiveness. In this sense, conversational agents offer an underexplored but highly promising space for advancing the design of explainable and trustworthy AI systems. Additionally, this embodies the two-way interaction that is at the core of *Symbiotic AI* [27, 11]: on one hand, through ConvXAI, humans are empowered in learning new aspects of the websites they interact with, and their capabilities are augmented by overcoming the difficulties that limit content accessibility; on the other hand, AI agents continously learn new patterns of use and continously improve themselves by interacting with their users [11].

4. Towards Better, Proactive, and Symbiotic Chatbots

The limitations of current conversational agents highlight the need for a new design orientation. If chatbots are to support digital inclusion in meaningful ways, they cannot remain tools that simply retrieve information. Instead, they must evolve into agents that explain, clarify, and collaborate with their users [3]. We argue that three imperatives are particularly important: chatbots must be better, proactive, and symbiotic.

4.1. Better: Human-Centered by Design

To be effective, chatbots must begin from the principles of human-centered design [23, 28]. This means not only creating interfaces that are technically functional, but also ensuring that interactions are aligned with the abilities, needs, and expectations of diverse users. In practice, this requires explanations that are accessible and adaptable. A visually impaired person may need a short, clear verbal summary of why a page was recommended, while a more digitally literate user might want a detailed account of the selection criteria. Providing multi-level explanations—simple justifications for some, more detailed reasoning for others—ensures that chatbots can serve a broad population without overwhelming or underserving particular groups. Importantly, explanations should avoid jargon and remain anchored to what is relevant for the task at hand, so that they enhance rather than hinder understanding.

4.2. Proactive: Anticipating Needs and Clarifying Decisions

A second imperative is that chatbots should not wait for users to request explanations but should offer them proactively when they are likely to be needed [5]. In the context of explanation user interfaces, trust has been shown to be one of the most frequently studied outcomes. However, trust cannot be imposed; it must be calibrated. Proactive explanations can help in this process. For instance, a chatbot that highlights potential limitations—such as a source being outdated or a webpage not complying with accessibility standards—signals to users that it is attentive, reliable, and aligned with their interests. Similarly, disclosing confidence levels or the rationale for prioritizing one result over another allows users to make informed decisions about whether to rely on the system. These acts of

proactive explanation are not simply usability features; they are mechanisms through which the chatbot demonstrates trustworthiness and invites appropriate reliance.

4.3. Symbiotic: Co-Constructing Meaning with Users

Beyond being human-centered and proactive, chatbots should also aim for a form of interaction that can be described as symbiotic [6]. Symbiosis implies a relationship in which human and machine capabilities complement one another [11]. In this model, the chatbot is not merely a tool that delivers answers, but a partner in a collaborative process of sense-making. Explanations become part of an ongoing negotiation: the system proposes, justifies, and adapts its reasoning, while users refine their questions, adjust their goals, and provide feedback [29]. Over time, this back-and-forth builds not only better outcomes for specific tasks but also greater confidence in the agent as a reliable collaborator. Additionally, explanations may also serve as a mean to enable adaptability (i.e., customization explicitly triggered by the users, for example through end-user development techniques [4, 30]) of the conversational agent, allowing human users to guide the system in preferring some kinds of information with respect to others [29]. In the context of the PROTECT project, such a symbiotic partnership directly supports the broader goal of enabling dignified and active participation in digital life, where users are not passive recipients of information but active participants in shaping their own interactions with technology.

5. Research Challenges and Future Directions

Reimagining chatbots as better, proactive, and symbiotic agents raises a number of research challenges that need to be addressed if this vision is to become reality. These challenges are not only technical but also methodological and ethical, reflecting the complexity of designing systems that both explain themselves and support diverse populations.

Need for Evaluation Metrics While existing work on explanation user interfaces has frequently assessed trust, usability, and satisfaction, conversational settings demand a richer set of measures. Dialogue-specific aspects such as flow, responsiveness, and perceived empathy play an important role in how users experience explanations. In addition, proactive explanations require us to assess not just whether trust increases, but whether it is calibrated—whether users rely on the system appropriately, neither too little nor too much. Developing robust methods for measuring calibrated trust in conversational contexts is therefore an important step forward.

Explainability vs. Cognitive Load Explanations are most useful when they clarify, but they risk becoming counterproductive if they are too detailed, too frequent, or too technical. For users with limited digital literacy, overwhelming explanations may cause disengagement rather than empowerment. Incremental disclosure strategies, in which information is revealed gradually and on demand, may help strike the right balance. Future work needs to explore how such strategies can be implemented in conversation without disrupting the natural flow of dialogue.

Personalization and Adaptivity Users differ in terms of expertise, preferences, and cognitive capacities, and explanations must reflect this diversity. A system that treats all users identically risks alienating some while underserving others. Adaptive conversational strategies that adjust the depth, style, and timing of explanations to individual users are therefore a priority. Yet personalization also raises questions about privacy, fairness, and the risk of overfitting explanations to perceived user profiles, which will require careful study.

Integration with Web Architectures To realize the PROTECT vision of conversational web browsing, chatbots must be able to interact seamlessly with web content, extract relevant information, and present it in accessible ways. This requires coupling dialogue systems with web accessibility layers in

a manner that preserves fidelity while still allowing for adaptation and explanation. Research at this intersection is still limited and will be crucial for scaling inclusive solutions.

Ethics and Regulation Explanations shape how users perceive and rely on AI systems, and thus have consequences for fairness, autonomy, and accountability. As the EU AI Act [31] begins to take effect, developers will need to ensure that conversational agents meet legal requirements for transparency while also respecting the dignity and agency of their users. A key part of this is ensuring that explanations do not encourage blind trust or mask limitations, but instead foster a balanced understanding of what the system can and cannot do.

Trust Calibration in Dialogue Trust in chatbots cannot be imposed; it must be calibrated. Explanations must strike a balance between revealing system strengths and exposing limitations. Over-explaining risks overwhelming users, while under-explaining risks fostering blind trust. Developing conversational strategies for calibrated trust is an open challenge, particularly in inclusive contexts where users may be vulnerable to over-reliance.

Addressing these challenges will require contributions from multiple disciplines: computer science to develop robust techniques, human-computer interaction to study usability and adaptivity, and social sciences and philosophy to interrogate issues of trust, responsibility, and fairness. Taken together, these lines of inquiry will help shape the next generation of conversational agents that are not only technically proficient but also genuinely inclusive and trustworthy.

6. Conclusions

The PROTECT project takes as its starting point a simple but pressing reality: large groups of citizens remain excluded from the benefits of digital services, either because of disabilities, situational limitations, or gaps in digital literacy [3]. Conversational AI offers a promising path toward addressing these barriers, but current systems fall short [3]. They often provide access to information in a narrow sense—retrieving or displaying content—without supporting the deeper processes of understanding, comparison, and decision-making that genuine inclusion requires.

This position paper has argued that to meet these challenges, chatbots must evolve into *better, proactive, and symbiotic agents*. Drawing on the literature on explanation user interfaces and human-centered AI, we have suggested that explanations are not just technical add-ons but integral to building trust, enabling informed use, and fostering collaboration. Explanations delivered through conversation can be tailored to user needs, offered proactively to prevent confusion, and shaped through dialogue to support joint sense-making. Additionally, explanations allow interventions, allowing users to customize and adapt the conversational agent to their own specific needs [32, 29].

Realizing this vision will not be without difficulties. Research is still needed to develop evaluation methods that capture calibrated trust in conversational contexts, to design adaptive explanations that respect users' cognitive capacities, and to ensure technical integration with web architectures. Equally important are the ethical and regulatory dimensions: as conversational systems mediate access to public information, they must remain transparent, accountable, and aligned with societal values.

Despite these challenges, the potential benefits are considerable. If designed with care, chatbots can move beyond their current role as information retrievers and become genuine partners in interaction, supporting citizens in accessing, understanding, and acting upon online resources. In doing so, they can contribute directly to the goals of digital inclusion, ensuring that participation in the digital sphere is not a privilege for the few but a right accessible to all.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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