Insights for Proactive Agents: Design Considerations, Challenges, and Recommendations

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Abstract

Proactivity of intelligent agents, a central concept in human-centered AI, poses significant challenges for their design, technical implementation, and deployment. Based on the authors' experience in the Hybrid Living project, this position paper focuses on how to achieve proactive behavior in smart home assistants and robots that assist individuals with daily tasks in their homes. The paper highlights the interdisciplinary nature of the domain along with the need for a unified ontology and robust frameworks to define proactive behavior. Based on their insights, the authors propose a set of design considerations for modeling proactive behavior within agents. Finally, the paper highlights some emerging challenges while providing recommendations to help with future research and development of proactive agents to enable human-centered experiences.

Keywords

human-centered AI, proactive behavior, intelligent agents, service robots, design considerations

1. Introduction

Advances in technology have enabled interactive artificial agents, such as smart home assistants or service robots, to become increasingly adept at performing tasks autonomously. They are becoming more sophisticated and can use multimodal input to understand user needs and communicate with them about the tasks to be performed. With these advances in capabilities, critical questions have been raised about the need for a more human-centered design that takes into account the user's needs and context. A central emerging concept is that agents should be able to act proactively, which requires them to recognize or even anticipate user wants and needs, thus fostering a human-centered experience throughout the interaction.

This position paper is based on our experience in the 'Hybrid Living' project, which focuses on the use of intelligent agents in the home environment. This project investigates the role of intelligent agents, particularly service robots, in assisting individuals with everyday household tasks. These tasks include managing tableware (from setting the table to clearing it), loading and unloading the dishwasher, and interacting with home appliances and smart storage units. While these challenges are already complex from a robotics standpoint, our primary focus is on enabling seamless multimodal interaction between the intelligent agent and the people it coexists with. A key aspect of our research is developing proactive behaviors in the agents, which presents a significant interdisciplinary challenge due to the highly diverse and deeply private nature of the home environment. Throughout the course of this research project, collaborating with partners from various disciplines has provided valuable insights into the complexities of integrating intelligent agents into household environments. These collaborations have highlighted critical challenges and opportunities, shaping our understanding of human-agent interaction (HAI), proactive agent behavior, and the social and technical factors influencing adoption. The perspectives presented in this paper are drawn from first-hand experience and interdisciplinary discussions, offering considerations that we believe are essential for future research.

This paper focuses on the various aspects related to achieving proactive behavior in agents. We first emphasize the interdisciplinary nature of the field along with the need for a unified ontology

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and robust frameworks for implementing proactive behavior. Based on our insights, we outline what we consider central issues in designing proactive agents. Additionally, we shed light on some of the challenges associated with modeling proactive behavior in agents. Finally, we conclude with some recommendations to guide future research and development of proactive agents to create human-centered experiences. However, we do not claim to have fully solved these challenges; rather, our recommendations serve as a foundation for further exploration and refinement in this domain.

2. Creating human-centered experiences

Designing the perfect framework for human-agent interaction (HAI) has been the subject of debates and discussions for several decades. The topics of these intellectual endeavors for a long time were largely concentrated around the degree of control/automation offered to agents while performing different tasks [1, 2, 3].

With rapid advancements occurring in the field of Artificial intelligence (AI) and Deep Learning in the last decade [4], there has been a considerable rise in different applications where agents have become extremely complex yet more competent at performing autonomously [5]. This can be attributed to both the algorithmic and computing advancements that have taken place in recent years [6].

The field of HAI has also experienced a major shift due to these advancements. The interactions have become richer as agents are able to utilize multiple modalities such as text [7], speech [8], visual [9], and physiological signals [10] among others, to infer user requirements [11] and communicate with them to achieve their tasks [12]. The possible applications for interactive agents have expanded [13] with use cases ranging from the domains of healthcare [14], education [15], and household [16] to business [17], industries [18], and the workplace [19]. This also reflects in the increased usage of certain terms such as intelligent, smart, autonomous, and social/sociable among others, in product descriptions, advertisements, research proposals, and publications.

As the field has made significant progress, concerns have also grown, particularly regarding the role of humans in interactions with such agents. The concept of Human-centered AI (HCAI) has gained attention among researchers in the field [20, 21]. According to the HCAI framework proposed by Shneiderman [21], the goal should be to design systems that balance high levels of human control with computer automation to enhance human performance. Furthermore, it becomes crucial to identify situations where either full human control or full computer control is required, while mitigating the risks associated with excessive control by either humans or computers.

One potential approach to enhancing human performance is by equipping agents with proactive-anticipatory behavior to foster a human-centered experience [22, 23]. This can improve the system's helpfulness, safety, and reliability, while also boosting user trust and satisfaction [24, 25].

2.1. Proactive interaction

In today's world, we can see large-scale utilization of large language models for designing interactive agents. Even though the models show impressive language-generation capabilities since they are trained on large amounts of language data, they prove to be insufficient on their own for creating a rich human experience of interaction. One of the most obvious drawbacks is that a majority of systems are reactive in nature [7]. They only generate necessary responses based on the input given (prompt/command). Even conventional interactive agents (such as home-assistants, robots, and virtual agents) usually operate reactively, in response to certain stimuli or commands. The tasks are generally performed by using utterances or text as input, prompting a passive response behavior. Therefore, they only respond after receiving these inputs, leading to delays and frustration among users during problem resolution. Consequently, they may prove to be unsatisfactory for tasks requiring sociable interaction [25].

Proactive interaction can help address the limitations of traditional reactive approaches. Nothdurft et al. [26] define proactive behavior in dialogue systems as "an autonomous, anticipatory system-initiated behavior, with the purpose to act in advance of a future situation, rather than only reacting to it". It can improve the user experience, especially with agents providing assistance after anticipating and assessing the information relevant to the user [27]. Furthermore, it can provide uninterrupted assistance leading to faster problem resolution while preventing escalation. This can help in developing reliable relationships, while fostering higher satisfaction and trust from humans towards agents [28, 29].

However, it is important to recognize that proactive behavior within agents must be carefully balanced and should have specific design considerations while being integrated within HCAI frameworks. Otherwise, they can end up as nuisance/counter-productive to their design objectives and negatively impact user experience [26, 30, 31].

2.2. Interdisciplinary nature

The discussion about designing proactive agents can only begin with the understanding that is an extremely interdisciplinary field where sophisticated technological systems interact with complex human elements [32]. Therefore, it draws from various fields ranging from technological ones, such as computer science, engineering, embedded systems, mechatronics, robotics, etc. to those that explain human behavior, such as neuroscience, psychology, sociology, linguistics, anthropology, among others.

This makes interdisciplinary collaboration a pre-requisite in the process of design, development, and evaluation of human-centered proactive agents [33, 34]. However, this is often not the case as the expertise from non-technological fields, focusing on human-centered experience, is often ignored during the initial stages of design and development [21, 35]. This is arguably one of the primary reasons why technology has disruptive, rather than adaptive, real-world impacts for its users and society at large. Disruption, which has long been positively held as one of the cornerstones of modern technological progress, must be critically examined. Without careful consideration, disruption can go beyond replacing systems with efficient or novel alternatives. It can have unforeseen, negative consequences with significant long-term social, cultural, and environmental impacts [36, 37].

2.3. Unified ontology and framework

There is a need for clear design frameworks along with unified expanding ontology for proactive behavior [38]. In interdisciplinary fields, the definitions and interpretations may often vary across disciplines. Research within individual fields tends to focus on a singular discipline perspective, primarily providing explanations within a specific context, while overlooking the interdisciplinary elements of the findings. This results in ambiguous terminologies and perspectives. Furthermore, the findings are typically not transferable between fields, limiting their broader applicability and reproducibility [34].

3. Design considerations

In this section, we describe the factors that we consider are important for implementation of proactive agents. Although our descriptions of these factors are brief, it is important to note that they represent distinct sub-fields that can be/have been the focus of extensive research on their own. They encompass intricacies relevant to the broader context and need to be explored more in-depth as part of a larger design framework.

3.1. Initiation and engagement

The first set of impressions towards the agent follows from the manner in which the agents are introduced to initiate and further engage in interaction with a human user [39, 40] The design of this phase becomes especially important in the case of proactive behavior, where the agent interacts based on an anticipated stimulus or recognized need that has not been explicitly communicated by the user [41, 42].

If implemented well, these can prove to be extremely helpful for user experience and help in increasing the trust and reliability of the system. However, on the flip side, it can also reflect on the system poorly as users may find it unhelpful and in the worst case an irritation or distraction [30]. In some cases, anticipatory behavior might also feel intrusive to the user [26, 43].

3.2. Context awareness

A major difference between a reactive and a proactive agent is context awareness. The grasp of context allows the agent to display helpful anticipatory behavior according to different situations [43]. Context awareness can also help agents to resolve problems and avoid escalation when undesired events occur.

The context of proactive behavior will differ significantly according to the task requirements of the user, the environment, and sensory modalities available at the disposal of the agent (speech, visual, physiological, etc.) [44, 45]. Although having multiple modalities may be advantageous for additional information, the computational resources required can prove to be a major constraint for context modeling. Furthermore, context modeling should also consider the privacy concerns of its users.

3.3. Task

Perhaps the most significant factor to consider for the design framework has to be the task and application itself. The nature of the task and the level of assistance required from the agent play a fundamental role in determining the set of actions [46], which determines the protocols for proactive behavior.

If the task demands a high level of intervention, the agent must have sophisticated levels of context awareness to perceive the different stages involved in the process of task completion [45]. This can be beneficial for recovery specifically when failures or errors occur. Moreover, in the case of agents, such as robots, that perform physical movements along with communicative acts, special attention is also required on architectures to flexibly combine physical and conversational acts to display appropriate behavior while performing the tasks [47].

3.4. Explainability

Explainability is another key factor to consider when designing proactive agents. The system design should consist of functionalities that communicate the reasoning of the agent to the user along with explanations about the decision-making process [48].

This may be accomplished by creating triggers for proactive explanations to minimize surprise, especially when the agent deviates from expected behavior. This can help agents avoid perceived faulty behavior while aiding users in failure detection [49]. Lastly, it will allow users to adapt to the unforeseen situations created by the agents while establishing trust and confidence in them.

3.5. Human traits

Detecting and/or showcasing human traits, such as emotions [50], politeness [51], humor [52], and personality [53], is a critical factor in designing proactive agents for creating “natural” and relatable interactions.

Accommodating these traits can enable agents to deal with social expectations and make the experience more engaging to users. For example, emotional awareness allows agents to respond empathetically, while politeness and humor can build rapport. Additionally, when it comes to verbal interactions, traits such as voice characteristics (natural/synthetic, gender, affect, personality, vocal-fillers, etc.) [54], language, and cultural norms [55] are also important to consider when designing protocols for interaction. However, the importance of these traits is subjective and largely depends on the users as well as the tasks that require sociable interactions. As preferences for these traits vary among users, tailoring them to specific tasks and demographics is key to enhancing the agent’s effectiveness.

3.6. Safety

Ensuring the safety of users along with the system is crucial in all applications involving agents. Considering proactive agents can be expected to interact with humans and operate dynamically in their environments, they must have mechanisms to prevent accidents or malfunctions that pose risks to both the system and those around it [56, 57]. Furthermore, the agents need to be perceived as safe, in addition to actually being safe [58]. This adds another layer of complexity to the system's design, requiring attention to user expectations, fail-safe protocols, and safety testing.

3.7. Privacy and security

Users are frequently reluctant to embrace technologies that involve social agents due to privacy and security concerns [16]. The gathering and handling of personal data — such as routines, preferences, or sensitive interactions — raises apprehensions about data breaches and the potential misuse of information [59]. This may prove to be an obstacle for generating proactive behavior in agents in deeply private settings, such as in the domestic, business, or healthcare context. Therefore, the privacy and security issues associated with agents must be carefully addressed in the design process to develop trust and encourage their adoption. The design measures should also empower users to have more control over the collection and processing of their personal data, as well as safeguard their personal space [60].

3.8. Platform

The platform of the agent, whether a robot, smart home device, or any other embodied AI system, plays a pivotal role in shaping its design and functionality [61]. The platform's inherent capabilities, architecture, and constraints directly impact the nature of assistance the agent can offer and determine the effective actions it can perform [62]. Designing for proactive behavior requires careful alignment with the platform's strengths and limitations to ensure seamless, meaningful, and contextually appropriate interactions.

4. Challenges

In this section, we outline issues and limitations that we encountered in the Hybrid Living project while planning the development of proactive behavior within agents. To provide clarity, we have categorized the issues into three distinct groups, each addressing different aspects of the development process. The insights presented here are drawn from our own experiences. While they highlight some common obstacles, it is important to note that other challenges may arise depending on the specific task or project [63].

4.1. Technical

Proactive agents, particularly sophisticated systems such as robots, rely on a combination of intricately designed mechanical, electronic, and software components for performing specific tasks. One of the major hurdles that these systems encounter is error-recovery and diagnosis. When a malfunction or deviation occurs, identifying the issue quickly becomes crucial. The failure could stem from mechanical/electronic breakdowns, software glitches, or communication issues between components. Consequently, creating a robust system architecture to handle these errors while aiding in diagnosis proves to be a major challenge [47, 64].

Another concern is the computing power available on the platform. Sophisticated agents might require substantial computational resources to process complex data in real-time for their decision-making components. With higher computing resources, the system can process faster and reduce latency (the time it takes for the system to respond). High latency can result in delayed responses and undermine the agent's ability to perform tasks effectively. Latency-related issues are largely attributed to heavy software components, code inefficiencies, inefficient network infrastructure, and/or insufficient computing resources available on the platform.

4.2. Collaboration

As previously discussed, interdisciplinary collaboration is a crucial prerequisite for designing proactive behavior within agents for human-centered experiences [33, 34]. However, there is a notable absence of established frameworks or methodologies that promote meaningful collaboration across diverse disciplines. While engineers, designers, and developers often work together to create products, the contribution of non-technical disciplines is frequently undervalued in the design process. Despite their critical role, the lack of clear guidelines undermines the effectiveness of these collaborations, often leading to suboptimal design outcomes. Even when multidisciplinary teams are in place, their potential remains underutilized due to this gap.

4.3. Evaluation

Understanding user expectations by carrying out evaluations and having user involvement throughout the development process proves to be a significant challenge [21]. One significant issue is the reliance on convenience sampling or improper sampling techniques, which often leads to biased demographics. This often leads to findings that may not be applicable or transferable to broader user groups, ultimately diminishing the effectiveness of evaluation [65].

Additionally, early-phase testing and user evaluation with prototypes can be inefficient due to various factors such as resource constraints, environment, and system limitations. These challenges hinder the ability to gather accurate user feedback. Furthermore, due to the complexity of integrating several intricate components into a unified design, evaluating the impact of different components on the overall system also proves to be challenging.

5. Recommendations

The previous section outlined various design considerations and challenges involved in modeling proactive behavior within agents. In this section, we provide our recommendations based on our insights to help with future research and development.

5.1. Interdisciplinary team

First and foremost, we recommend an interdisciplinary team to design proactive agents. To ensure they are effective and aligned with user needs at every stage, we need relevant experts from both technical and non-technical fields.

In the first stage, we should begin by assessing the agent's necessity and defining the specific tasks it will address for improving human experiences. This ensures that the agent is tailored to the real-world needs. Next, the level of proactivity required from the agent must be determined. Experts from different disciplines, such as cognitive sciences, behavioral sciences, and engineering, can determine a balanced behavior to ensure that agents are helpful and improve the user experience. It is also essential to define clear limitations of the agent and possible scenarios for inducing failure. Understanding the points at which the agent may fail or perform undesired actions is crucial for system robustness. Even with the best efforts, failures and errors are inevitable in complex systems, making the development of safety protocols and error recovery strategies indispensable. These safety protocols ensure that when failure occurs, the agent behavior can be reconfigured or stopped altogether without causing damage to users, the environment, or the system itself. Lastly, in the case of commercial production, impact assessments throughout the entire life cycle, from conception to post-deployment maintenance, are also a requirement.

In short, an interdisciplinary approach is not just a benefit but a necessity for creating proactive agents that are efficient, safe, and capable of meeting real-world challenges in an ever-evolving technological landscape.

5.2. User understanding

When designing proactive agents, one of the most crucial aspects to ensure success is a deep understanding of user experience and expectations. Often, convenient sampling is conducted for such purposes, where feedback is gathered from easily accessible individuals, often leading to biased or unrepresentative data. Instead, we recommend a purposive sampling to ensure that the right users are involved in the design process. Purposive sampling targets specific groups for intended user profiles, based on factors such as demographics, behavior, task complexity, or technological familiarity. This approach helps to gather information about actual potential users, their real-world environments, and broader use cases.

Additionally, we recommend that user involvement in the entire life cycle, rather than as a final feedback mechanism during testing or post-deployment. Conducting purposive sampling along with involving users throughout the development cycle ensures that the proactive agent is genuinely designed with its users in mind. This will also help improve the adoption, satisfaction, and long-term success of the system.

5.3. Modularity

We strongly recommend creating modularity as a key principle in the research and development of proactive agents. This approach offers numerous advantages for improving efficiency, scalability, and extending the applicability of the technology.

First, modularity promotes reuse rather than reinvention. Research groups can avoid duplication of efforts by building agents with interchangeable modules, such as AI models, decision-making algorithms, data processing systems, electronic/mechanical components, and different platforms. A modular framework allows for faster development while reducing the wastage of resources. High-quality results can be obtained by leveraging existing components, instead of creating completely new solutions every time.

Beyond technology, modularity in knowledge plays a vital role in ensuring transferability. In non-technical disciplines, the concept of modularity can be applied to concepts as well. They can be broken down into discrete modules that can be adapted to the unique challenges across disciplines. This broadens the applicability of findings and allows experts from different backgrounds to integrate the concepts into their workflow. For instance, based on prior HRI, socio-psychological, and linguistic studies on user expectations, observed results can be applied to designing effective interaction strategies. This can help in leveraging existing knowledge across disciplines, enabling efficient interdisciplinary collaboration without requiring each field to start from scratch.

Moreover, modularity fosters greater cooperation between industry and research. It will allow researchers to develop core innovations and for industries to apply them in real-world settings. This collaboration ensures that academic research is quickly translated into practical applications, while the insights from the industry help refine the technology.

6. Conclusion

With significant progress taking place in the technological landscape, interactive agents have become increasingly complex yet more competent at performing autonomous tasks. Due to rapid advancements in the domain of HAI, interactions have become richer as agents can utilize different modalities to infer user requirements while communicating with them for different tasks. Along with these advancements, there has been increasing attention on HCAI frameworks, which suggest designing systems balancing high levels of human control with computer automation to enhance human performances. Equipping agents with proactive behavior can help with realizing the philosophy of HCAI to foster human-centered experiences.

In this position paper, we discuss the various aspects related to proactive behavior within agents that can provide a human-centered experience. We discuss about the interdisciplinary nature of the domain and the need for unified ontology along with frameworks for defining proactive behavior. Based on our work and experience in the Hybrid Living project, we outline various design considerations along with the challenges involved in modeling proactive behavior within agents. We conclude this paper by providing some recommendations based on our insights to help with future research and development.

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