What Can You Do? Studying Social-Agent Orientation and Agent Proactive Interactions with an Agent for Employees

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ABSTRACT
Personal agent software is now in daily use in personal devices and in some organizational settings. While many advocate an *agent sociality* design paradigm that incorporates human-like features and social dialogues, it is unclear whether this is a good match for professionals who seek productivity instead of leisurely use. We conducted a 17-day field study of a prototype of a personal AI agent that helps employees find work-related information. Using log data, surveys, and interviews, we found individual differences in the preference for humanized social interactions (*social-agent orientation*), which led to different user needs and requirements for agent design. We also explored the effect of agent proactive interactions and found that they carried the risk of interruption, especially for users who were generally averse to interruptions at work. Further, we found that user differences in social-agent orientation and aversion to agent proactive interactions can be inferred from behavioral signals. Our results inform research into social agent design, proactive agent interaction, and personalization of AI agents.

Author Keywords
Agent; personalization; social-agent orientation; agent proactive interaction; enterprise personal agent.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Half a century after the introduction of first-generation chatbots like ELIZA [47], conversational agent interfaces have become increasingly common, as demonstrated by popular applications such as Apple Siri, Google Now and Microsoft Cortona. Many of these agents act as a new interface paradigm for *information-finding*, which incorporates or aims to replace the traditional interfaces such as search engines and recommender systems [12]. In addition to handling natural conversational interactions, scholars argue that the advantage of the agent inter-face lies in its social capabilities [1, 6, 7, 16, 21]. The social aspect of the agent interface not only provides potentially more engaging user experiences, but also engenders new technologies and designs that leverage a human metaphor and social context. For example, many systems utilize a "personal assistant" metaphor that makes users more receptive to functions such as reminders and task delegation [20, 31, 50]. Some embrace the opportunities for personalization by continuously learning about the user through social and relational conversations [16].

However, questions remain as to whether *agent sociality*, the incorporation of humanized social features, is favored for an information-finding application, the evaluation of which is often based on task performance such as accuracy and relevance of the information retrieved. The necessity of sociality may be especially questionable for users with high productivity versus leisurely needs, such as users in organizational settings. Moreover, we argue that there could be individual differences in preference for the level of agent sociality, potentially shaped by individual experiences with both the increasingly popular commercial agent applications and conventional information-finding applications such as search engines.

Another potential of the agent interface, as some argue [5, 24, 52], is to initiate proactive interactions in a manner similar to how a person initiates conversations. Proactive interactions may serve a variety of purposes such as recommending, reminding [52], facilitating learning [24], or persuading [5]. However, proactive interactions may risk interrupting users. Especially for employees with busy schedules and thus scarce attention resources, interruption by agent proactive interactions may result in low responsiveness, and even worse, undermine the overall experience with the agent system.

To explore these topics, we conducted a 17-day field study with a prototype of an enterprise personal agent that aims to help employees find work-related information in a large-size international company. We contribute to the human-agent interaction literature with a rare opportunity to study the social interactions and proactive interactions of agents

DIS 2016, June 04 - 08, 2016, Brisbane, QLD, Australia

ACM 978-1-4503-4031-1/16/06 $15.00
DOI: http://dx.doi.org/10.1145/2901790.2901842

in a real user context for an extended period. The majority of user studies for agent systems rely on lab experiments (e.g. [17, 24, 48, 49]). Such a controlled environment and limited timeframe may not allow full exploration of the social aspects of human-agent interactions. Meanwhile, a few field studies documented that users exhibit anthropomorphic behaviors such as asking "how are you?" as well as flaming behaviors such as typing random letters [25, 46], which are not often observed in lab studies. Therefore, we believed a field study would be more suitable for studying agent sociality. Also, we studied an agent specialized in the enterprise context. While there is a growing interest in developing personal agents for the work environments [1, 18, 20, 52], there have been few field studies for these systems to the best of our knowledge.

In this paper, we focused on studying individual differences in *social-agent orientation,* defined as the preference for humanized social interactions with an agent interface, such as having natural conversations and social dialogues. We explored how the individual differences led to differences in user requirements for agent system design and user behaviors that can be used to infer such orientation. By testing a variety of agent proactive interaction designs, including initiating social dialogue and crowdsourcing user questions, we also examined how users reacted to agent proactive interactions. Our study highlights that agent sociality designs are crucial for some users' experience, but may not fit others, at least for a performance-driven, non-leisure context. We also underline the importance of considering user aversion to unsolicited proactive interactions in a work environment, especially for users with busy schedules and frequent social contacts. In the following section, we introduce the background of the study before discussing hypotheses and research questions.

BACKGROUND

Agent Sociality

The development of AI agents could be dated back to the 1960s [47]. In the last two decades, we see an increasing number of studies focused on improving the design of agent systems. Among others, one direction is to introduce and improve the human-like attributes of agents. Earlier studies focused on the appearance of agents, including using humanized images [37], facial expression [11], gesture, and movement [27]. Recent research explored incorporating common human conversational and social strategies, including storytelling, reciprocal appreciation, being socially conscious, expressing empathy, humor, and many others [4, 8, 41]. Rich evidence suggests that *agent sociality* (the presence of human attributes in agent design) can elicit more cooperative behaviors from users, and lead to heightened engagement and more positive user opinions about the system. Emerging recently is the concept of the "relational agent", to build long-term relationships through continuous social interactions [6, 16]. Relational agent is considered to have great potential in many domains such as healthcare, education, and personal task management.

Another line of research on agent sociality explores personalization. Many explored the design of personalities built into agent dialogues [17, 26]. Studies consistently found that users favor agent personalities matching their own [17, 33, 45], or matching the task context (e.g., seriousness versus playfulness [22]). Another type of personalization aim to individualize the interactions such as by recognizing returning users or remembering information from previous conversations [21, 29]. Personalization was found to improve rapport, cooperation, and engagement with robots and agents.

Social-Agent Orientation

Many of the anthropomorphism efforts in agent designs recognize following the Computers are Social Actors (CASA) paradigm proposed by Nass et al. [34]. They demonstrated that social rules and expectations guiding human-human interaction can be applied to human-computer interaction, including using social categories and exhibiting social behaviors such as politeness and reciprocity. The CASA paradigm suggests users can behave *as if* computers warrant human considerations. This implies that computer interface should accommodate these social aspects of user needs, a point further addressed by scholars in the field of affective computing [40].

While agent interfaces are well suited to cater to social interactions, evidence suggests that there are individual differences in the tendency to exhibit social behaviors when interacting with agents or robots. Lee et al. find that, when interacting with a robot, some users appear to be more social, with more relational conversations, politeness, attention to the robot, and self-disclosure. Interestingly, such tendency can be predicted by whether the user greets the robot at the first encounter [28]. Ogan et al. looked at how children interact with a teachable agent, and found that some tend to use the pronouns "we" and "you" while others use "it," where the former predicts better learning outcomes [28]. These results point to possible individual differences in mental model of the systems, as repeatedly suggested by the observation that when interacting with a robot or an agent, some users report viewing it more as a social entity while others treat it as a technological entity [19].

By pointing out "individual differences in the strength of social response" as a future research agenda for CASA paradigm [34], Nass et al. suggested a key predictor could be the extent to which the users focus on the task and ignore task-irrelevant dimensions of the system. We consider it especially relevant to agent systems that target important *utilitarian needs*. In contrast to chatbots for hedonic use (e.g. ELIZA, Microsoft XiaoIce), the agent in our study was developed to address employees' serious information needs. So it is possible that some users would primarily seek to satisfy utilitarian needs. The co-presence of utilitarian and social needs is manifested in the observation that users' subjective evaluations of an agent, including satisfaction and likability, were often not strongly associated with objective measurements such as task completion and agent mistakes, and are impacted by the presentation and conversational design of the agent [42, 48].

Based on these previous findings, we studied *social-agent orientation*, defined as the individual preference for humanlike social interactions with agent interfaces. Partly, we are inspired by observing the large variances in the extent of sociality designs in information-finding agents, ranging from embodied conversational agents that attempt to faithfully mimic human [9], to popular personal assistant systems that work solely with a text or voice input window and little anthropomorphic conversations (e.g., Google Now). With these systems becoming commonplace, they could potentially shape the differences in users' general mental model of agent interfaces. Other factors could also contribute to the individual difference. For example, a study on human-robot interactions showed that parasocial interaction tendency, which media scholars use to explain individuals' tendency to have illusionary reciprocal relationships with media persona, predicts positive user attitude towards hedonic robots [30]. However, in this paper, we leave the investigation of the potential causes of social-agent orientation to future studies, but focus on understanding *how varied social-agent orientation leads to differences in user needs and preferences for agent interface design*.

Agent Proactive Interactions

A few recent studies explored agent-initiated proactive interactions as technological interventions to influence users, for instance, to enhance learning [24] or to improve health regimen adherence [5]. While they provide evidence that users generally welcome such interactions, they also point out that a major challenge is to deliver information that users can immediately apply [48]. Some also suggest a mismatch between an agent's message and the delivery context can undermine user trust and compliance with the agent [14]. While these studies reveal the problem of context matching in message content, a less-studied topic is the problem of interruption by proactive interactions, which we note might be more difficult to investigate in lab studies than in real user contexts. Meanwhile, the HCI community has a long history of studying the negative influence of interruptions on task performance and user emotions [2], and especially giving it crucial consideration for technology design in enterprise [15, 38]. By conducting a field study with an enterprise information-finding agent, we studied whether perceived interruption of agent-initiated interactions is associated with negative user opinions of the system, and we explored what factors may affect such perception, including the design of proactive interactions.

RESEARCH HYPOTHESES AND QUESTIONS

We start by investigating how social-agent orientation impacts user preference by studying user attitudes toward the system. Using the metaphor of an office assistant, the prototype was designed to be consistent with such a role in both representation (e.g. with a common English name and a professional image) and conversational style (e.g. with polite and professional tone). It was also built with the capability to handle basic social conversations such as greetings and answering common "small talk" questions such as "what are you up to?" Given the high sociality design of the tool, we hypothesize:

> **RH1:** Users with higher social-agent orientation will have more positive opinions of the agent system.

We expect that users with high social-agent orientation may gain satisfaction from social interactions with agents, and thus may place less emphasis on their utilitarian needs, which in the context means getting the correct information from the agent. We therefore hypothesize:

> **RH2:** Users with higher social-agent orientation will be more tolerant of agent mistakes.

To identify user categories to deliver personalized design solutions, we are interested in how to infer individual differences based on users' behavioral signals. We ask:

> **RQ1:** How can social-agent orientation be inferred from behavioral signals?

Furthermore, to inform the personalization design to accommodate the preferences of users with high or low social-agent orientation, we ask:

> **RQ2:** How do design requirements for information-finding agents differ for users with high or low social-agent orientation?

In the professional context, those who perceive agent proactive interactions to be interruptive may form negative opinions of the application. We hypothesize:

> **RH3:** Users who perceive agent proactive interactions as interruptive will have less positive opinions of the agent system.

We are also interested in predicting aversion to the interruption of agent proactive interactions. We ask:

> **RQ3:** What factors influence perceived interruption of agent proactive interactions? How can it be inferred?

In the rest of the paper, we first introduce the agent prototype and discuss the study design. We present quantitative analyses to test RH1- RH3, and explore RQ1 and RQ3. By identifying individuals with varied social-agent orientation, we conducted interview studies to explore answers to RQ2.

SYSTEM DESCRIPTION

We introduced a prototype of a personal agent named "Ella Jones". The agent could be installed on the enterprise instant messaging (IM) tool. Users could initiate a conversation with the agent from a chat window (Figure 1). The agent was designed with a professional-looking cartoon of a female face.

Using an AI agent dialog development platform [53], we built knowledge nodes and pattern-matching rules for the agent's conversational output. For example, we could create a knowledge node that links to information about the enterprise's timesheet policy, and specify matching to the node when users ask questions mentioning "timesheet" or its variations. When matching fails, the agent asks "do you mean any of the following?" with a list of potentially related questions. If no related question is found, the agent says "sorry, I don't know the answer" or its variations.

Figure 1. Ella interface

To create the knowledge nodes for the agent to answer work-related questions, we relied on existing internal repository of frequent employee questions provided by the Human Resource department. In addition, we asked 8 employees to intensively interact with the agent for 1-2 weeks to collect common questions they had at work.

We also built around 200 knowledge nodes to handle common social dialogues such as "thank you", "how are you?," "what do you do for fun?" (a single node may cover many variations of a statement using regular expression). They were partly from an existing repository included with the AI dialogue development platform, collected from previous deployment. Two researchers work on adapting the agent's answers to fit the persona of a professional office assistant. Moreover, to handle questions inquiring about the agent system, we built nodes for the agent to introduce itself, including its functions (e.g. a prototype system to navigate enterprise internal knowledge), and personal stories (e.g. "I'm new to the company…").

Although the system was a prototype with limited capacity, it was able to provide answers to about half of the questions users asked. Currently, commercial general-purpose AI agents like Siri often only reach similar success rate [1] and most agent technologies can only handle knowledge in very specific domains. The limited capacity of the prototype served to study user tolerance towards agent mistakes (RH2), which is especially important to consider given the current limitations of agent systems.

Introducing New Features

To encourage user engagement with the agent, we introduced several new features throughout the study. These new features included: 1) an option to "crowdsource" user questions to their peers if the agent could not find an answer; 2) an option to anonymously crowdsource; 3) an invitation for the user to teach the answer to a question the agent had failed to answer; and 4) an invitation to use the "person lookup" function, with which the user could ask the agent to retrieve the profile information of coworkers. These features were designed to be small additions to the agent's primary Q&A function that would not significantly alter the way users interact with the agent.

METHODOLOGY

Participants

We recruited 30 volunteers from the enterprise, with a mix of full-time employees and interns (38.1% are female and the average age is 28.8, SD=8.5). We selected mostly participants employed for less than a year, as they are likely to have higher needs for information-finding tasks.

Study Design and Procedure

Participants were invited to a briefing meeting, where they were instructed on how to install the personal agent in the enterprise IM tool. The agent was introduced as an "AI agent that answers questions you have at work… just like with a coworker, you can chat with her on the IM tool anytime if you have questions about corporate knowledge and process." To collect data in naturalistic setting, participants were given no further instruction on how to use the tool and were told to freely interact with the agent. We informed participants that the system would log all the contents and time stamps of their interactions for analysis.

After the study, all participants were invited to participate in a survey. Active participants with interaction frequencies above the median value were invited to participate in a 20-min interview. We chose active participants because they were more likely to have formed good understanding of the system and thus more suitable for inquiring about design requirements. The response rate was 70% for the survey and 50% for the interview. We discuss the details of the survey and interview study in later sections.

Proactive Interactions

One goal of the study was to understand how users react to proactive interactions initiated by the agent in an office environment. To this end, we designed three types of proactive messages: *new feature self-introductions*, *crowdsourcing requests,* and *social messages.*

In the "introducing new feature" section, we mentioned that we introduced four new features during the testing period. Importantly, the agent's self-introduction of these new features served as the first type of proactive interaction. These are messages like *"Starting from today, I can ask around for you if I cannot find an answer…"*. We set the introduction messages to be delivered to all participants on the same day when they signed onto the IM tool, if they did. Otherwise, it was delivered at the next sign-on.

The crowdsourcing feature was introduced on the 6th day of the study. When the agent could not answer a question, it offered the option to direct it to other participants of the study. To coworkers who were available on the IM tool, the agent then sent a proactive message asking *"Hi [name], can you answer this question for your colleague?"*

The last type of proactive interaction was social messaging, asking, "*Hi* [name], *what's the most exciting thing about work today?"* or its variations. We were particularly interested in this type of message because it would allow us to test how users respond to *proactive social interactions*—an agent that exhibits relational, "caring" behaviors. Therefore, we introduced this type of message as a between-subjects variable – we randomly selected half of the participants to receive a greeting message from the agent everyday if they signed onto the tool in the morning.

Measurements

System Performance

Given that the objective of the information-finding agent system is to answer participants' questions, we considered the success rate of answering user questions as the measurement of system performance. We anonymized the askers and labeled whether each question received a reasonable answer. Using the results, we calculated the agent success rate for each participant.

Behavioral Measurements

To answer RQ1, we looked at the association of user behaviors and self-reported social-agent orientation. We coded relevant behaviors from the conversational interactions, including socializing, politeness, and agent-grounding behaviors (defined as follow-up attempts such as rephrasing in order to obtain a desired answer). We will discuss the coding schema in details in the "inferring social-agent orientation" section.

Subjective Measurements: Survey Design

One week after the field study, we conducted a survey to collect users' opinions of the agent and users' social-agent orientation with conversational agent systems. We also collected demographic information including age, gender, self-reported experience with conversational agent systems, as well as their usage of the enterprise IM tool, including how often they send messages and how often they feel they are interrupted by others' messages.

User Opinions: Users' opinions on the agent system were measured by averaging the following three items, all on 7-point Likert scale (Cronbach alpha=0.86).

- *Satisfaction*: How would you rate your overall experience with Ella? ("Not satisfied at all" to "very satisfied")
- *Ease of use*: How would you rate your interactions with Ella ("Very difficult to talk to" to "very easy to talk to")
- *Likability*: How much do you like Ella? ("Not at all" to "a lot")

We measured *perceived interruption* by asking participants to rate "in general, how interruptive was it when Ella tried to start a conversation with you?" and *perceived friendliness* by asking "please rate how friendly Ella is."

Social-agent orientation: At the end of the survey, after asking about demographic information (in order to be separated from Ella specific questions), we asked each

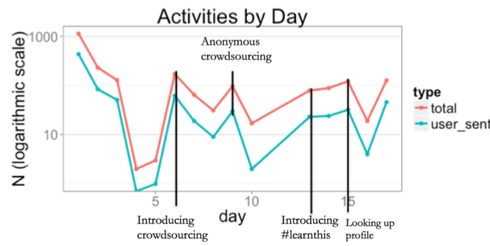

Figure 2. Number of interactions by day

participant to rate his or her social-agent orientation. The social-agent orientation was measured by averaging the following two items with a 7-point Likert scale from "completely disagree" to "completely agree" (Cronbach alpha=0.86):

- *"I think "small talks" with an AI agent or chatbot is enjoyable."*
- *"I like chatting with an AI agent or chatbot."*

Although the interactions with Ella may potentially impact the self-reported social-agent orientation, thus present a potential limitation of the study, we note that measuring it before the study would likely bias users behaviors. We therefore chose to survey it a week after the study, and emphasized that participants should rate based on their general preference, not specifically towards Ella.

RESULTS: QUANTITATIVE ANALYSIS

During the 17 days, the 30 participants on average sent 27.4 messages (SD=33.3, median=14) to, and received 49.8 messages (SD=50.3, median=36.5) from Ella. Figure 2 shows the total number of interactions per day. User interactions peaked in the beginning, indicating strong interest at the initial encounter with the agent. While the interest dropped after the first couple of days (Note, day 4, 5, 11, 12 were weekends, so the interactions were close to 0), the proactive interactions to introduce new features effectively increased usage.

Table 1 shows the number of each form of proactive interactions delivered and the total response rate for each. Response was defined to be any immediate reaction, e.g. trying out the new feature, answering a crowdsourced question, or replying "got it." The response rate suggested that these interruptions had low responsiveness and were potentially not well received. We will further explore the topic of perceived interruption in the rest of the paper.

Effects on user opinions

In this section, we examine which factors impacted user opinions of the agent system. In particular, we tested whether high social-agent orientation led to more positive user opinions on Ella, which was designed to have high sociality (RH1), whether it moderated the impact of system

Type	N	Response rate
Introducing features	86	26.7%
Crowdsourcing requests	75	28%
Social messages	104	45.2%

Table 1. Descriptive statistics for proactive interactions

performance on user opinions (RH2), and whether the perceived interruption of agent proactive interaction is negatively associated with user opinion (RH3).

To test these hypotheses, we used the user opinion measured in the survey (see description in the "Measurement" section) as the dependent variable. We built a linear regression model of user opinions as a function of self-reported social-agent orientation, perceived interruption of proactive interaction collected from the survey, and our rating of the question success rate for each participant, controlling for age, gender, and self-rated experience with conversational agents. To test RH2, we included the interaction between social-agent orientation and success rate as an independent variable.

The results of the regression model are shown in Table 2. We found that, perhaps not surprisingly, the strongest predictor of user opinions is the system performance, i.e., success rate. The significant positive effect of social-agent orientation shows that users with high social-agent orientation tended to have more positive opinions of the system (RH1 confirmed). Moreover, the significant negative interaction between social-agent orientation and system success rate indicated that users with high social-agent orientation were also more tolerant of negative system performance (RH2 confirmed). We also found that perceived interruption of agent proactive interactions was associated with less positive opinions (RH3 confirmed).

Among the control variables, we found that age had a positive effect on user opinions, implying that older users in our sample (correlated with work experience) had more positive opinions. General experience with conversational agents was associated with more critical opinions of the agent. We did not find any gender differences.

To summarize, consistent with the predictions, we identified that individual differences in social-agent orientation had significant impact on user opinions. High social-agent orientation not only led to more positive user

	β	SE	p-value
Intercept	-0.59	0.84	0.49
Success rate	3.75	1.16	<0.01**
Social-agent orientation	0.50	0.16	<0.01**
Success * Social-agent orientation	-0.83	0.31	0.02*
Perceived interruption	-0.18	0.07	0.02*
Control variables			
Gender (female baseline)	0.14	0.29	0.63
Age	0.09	0.02	<0.001**
Experience	-0.22	0.09	0.02*
Adjusted R^2=0.72, $F(8,12)$=7.55, p=0.001			

Table 2. Linear regression model predicting user opinions.

opinions on the high-sociality agent, but also made the opinions more robust and less impaired by suboptimal system performance. It may imply that users with high social-agent orientation did not judge the system solely by its utilitarian value, but also appreciated its sociality designs. We also found that participants who perceived the proactive interactions to be interruptive had less positive opinions of the system. It is noteworthy that the perceived interruption was a stronger predictor of user opinions than perceived friendliness of the agent (β=0.06, p=0.66), suggesting that, at least in the professional context, interruption could be a more crucial design consideration than agent personality. In the next two sections, we will explore how to infer social-agent orientation and aversion to proactive interaction from users' behavioral signals.

Inferring Social-Agent Orientation

In human-agent interaction literature, content analyses of users' conversational interactions are often performed to infer user status or attributes [10, 36]. Identifying the indication of conversational signals for the underlying user attributes is an important step towards user profiling and user modeling, which may enable personalization and development of adaptive systems. Based on this view, we are interested in identifying users' behavioral signals that can be used to infer social-agent interaction (RQ1).

Behavioral Measurements

After carefully reviewing user conversational behaviors, and inspired by Lee et al.'s work on users' exhibition of social behaviors towards a robot [28], we chose to explore if the following three behavioral measures can be used to infer social-agent orientation.

Socializing questions are questions that directly address the agent, such as *"what is your favorite color?" or, "what do you do for fun?"* These questions are unrelated to the intended system function of finding enterprise information, but are typical of human interactions. We coded and counted how many socializing questions each participant asked, normalized by the total number of questions the user asked, to create the *socializing index*.

Politeness reflects how politely the user treated the agent. We chose to code *polite behaviors* by including greetings (e.g. *"Good morning"*), appreciation (e.g. *"Thank you"*), apology, farewell, and other kinds of courtesy. We coded *impolite behaviors* by including explicit insult (e.g. *"You are dumb"*) and flaming behaviors (e.g. repeating a question within a short period). For each participant, we calculated the number of polite behaviors, minus the number of impolite behaviors, and normalized it by the total number of questions asked, to create the *politeness index*.

Agent-grounding questions are intended to obtain a desired answer from the agent. We were inspired by, but wanted to differentiate from, the original term "grounding behavior" in communication research, which refers to people trying to reach common ground during conversing [13]. Agent-

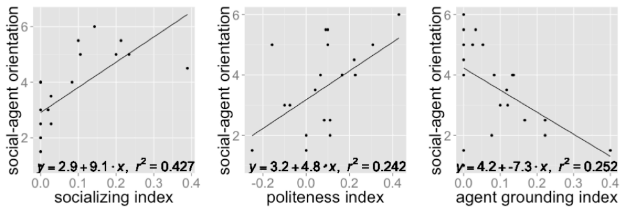

Figure 3. Inferring social-agent orientation based on behavioral measures

grounding questions happened when the agent failed in a user's initial attempt, and the user asked follow-up questions. They include *rephrasing* (e.g. from "*What does PMOM mean?*" to "*Define PMOM*"), and *changing granularity* (e.g. from *"Does the company give discounts to Disney world?"* to *"Are there employees discounts at theme parks?"* to *"What employee discounts do we have?")* We coded and counted the number of agent-grounding questions for each participant, and normalized it by the total number of questions to create the *agent-grounding index*.

We studied the inference power of these behavioral signals on users' self-reported social-agent orientation by studying their correlations. The results are presented in Figure 3. We found that all three measures are significantly correlated with social-agent orientation. Specifically, asking socializing questions has the strongest correlation with social-agent orientation (β=9.1, t (19)=3.76, p=0.001). Being polite to the agent also positively correlates with one's social-agent orientation (β=4.8, t (19)=2.46, p=0.02). Interestingly, we found that asking agent-grounding questions negatively correlates with one's social orientation (β=-7.3, t (19)=-2.53, p=0.02).

We argue that the agent grounding behaviors reflected a process of attempting to identify and fit an input model that the system can process and respond. These resemble user behaviors using search engines, iteratively generating new queries to locate the desired information. We also highlight that these behaviors signal the *high utilitarian needs* of low social-orientation users. They used the system for its functional goal of finding information, and adapted their usage to better satisfy such needs. Indeed, as evidenced, we found that the *agent-grounding index* significantly correlates with the question success rate for participants (r^2=0.33, β=1.29, t (28)=3.72, p<0.001).

To summarize, we found that users with high social-agent orientation could be identified from behavioral signals, including asking socializing questions, being polite, and engaging less in asking agent-grounding questions intended to retrieve desirable answers. We suggest these behavioral signals could be easily detected with NLP techniques for user profiling. These results echoed findings in Lee et al. [28], where they found that user exhibition of social and relational behaviors with robots are correlated, including asking socializing questions and showing politeness. Using self-reported measures of social-agent orientation, we further prove that these correlated behaviors may result from an underlying user attribute of desiring to engage in humanized social interactions with agent systems. In the "interview study" section, we will further explore whether and how this orientation is associated with different mental models of the agent, as well as differences in user requirements for agent system design.

Understanding Perceived Interruption

In previous analysis, we found that those who perceived the proactive interactions to be interruptive tended to have less positive opinions about the system. This suggests that another personalization opportunity would be to personalize the proactive interactions. An important question is what factors impact the perceived interruption (RQ3). For example, the frequency or the type of proactive message could make differences, or perhaps it is driven by a general user attribute of aversion to unsolicited messages at work. Such knowledge may help us identify appropriate personalization strategies for proactive interactions.

We examined the predictive power of three variables on self-reported perceived interruption: frequency of receiving proactive messages from the agent (since users were not always logged onto the IM tool, this frequency largely varied), type of interruption (receiving vs. not receiving social messages), and general interruptibility, which was measured by a 7-point scale self-reported rating how often one feels being interrupted by messages from the enterprise IM tools. We found no significant effect of the frequency of receiving proactive messages (β=0.04, t (19)=0.68, p=0.50), nor whether one received social messages (β=0.08, t (19)=0.10, p=0.92). However, we found significant effect of the general tendency of perceiving IM messages to be interruptive (β=0.60, t (19)=2.46, p=0.02) (Figure 4 left).

The results suggest that perceived interruption is likely associated with users' general aversion to unsolicited IM messages at work, regardless of whether it is from an agent or colleagues. It implies that the perceived interruption may not be alleviated by simply reducing message frequency or modifying message contents of proactive interactions. We also note that such an attribute could be related to how often one uses the enterprise IM tools, as we found a correlation between the general interruptibility and self-claimed usage frequency of the IM tool (Pearson's r(19) = 0.53, p <0.01). It implies that given the context of office environment, professionals who have busy schedules and frequent social contacts may be especially intolerant of the interruption from agent proactive interactions.

We also attempted to infer the user attribute of aversion to proactive interactions based on behavioral signals. By hypothesizing that people considering the proactive interaction to be interruptive were likely to be less responsive, we calculated the response rate for each user. As expected, we found that the response rate is negatively correlated with the extent one found agent proactive interactions to be interruptive (β=-3.9, t (19)=-2.36, p=0.03) (Figure 4 right).

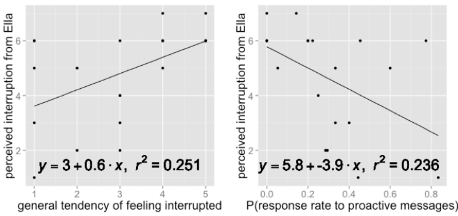

Figure 4. Predicting perceived interruption from proactive interaction based on (left) general tendency of feeling interrupted by IM messages and (right) response rate.

In summary, our study highlighted that, in the enterprise context, proactive agent interactions may risk disrupting some users and harming their overall user experience. We found that the individual aversion to agent proactive interaction is likely associated with the general user aversion to unsolicited messages at work. This tendency is at least partially associated to the user's busy work routine, which could be related to users' positions in the enterprise and/or their work patterns. To avoid interruption, it may be necessary to turn off proactive interactions for targeted users, who can be identified from low or decreasing response rate to proactive messages.

INTERVIEW STUDY: UNDERSTANDING USER MENTAL MODELS AND PREFERENCES

We conducted post-study interviews to further understand whether the varied levels of social-agent orientation are associated with different mental modals of agent interfaces, and how the varied orientation leads to different user requirements for designing information-finding agents (RQ2). We interviewed 7 of the most active users. Among them, three rated their self-rated social-agent orientation below the median (4), the rest were equal or above median.

The interview was semi-structured and focused on understanding: 1) user's mental model of the system, for which we asked participants to describe their expectations at the encounter of the agent, their general view of the agent, and their experiences; 2) user requirements, for which we asked them how they wish to *improve* the system.

All interviews were conducted through audio conferencing software and were recorded and transcribed. We analyzed the transcripts based on grounded theory [44], following an iterative open-coding process. We focused on comparing the responses between the two clusters of participants (social-agent orientation below or above/equal median). While our interview sample was relatively small, we were able to identify some consistent themes across most, if not all, participants. We will first discuss their mental models, then the emerging themes from their descriptions of requirements for an enterprise information-finding agent.

Differences in Mental Models

By finding that higher social-agent orientation led to more social behaviors towards the agent, we hypothesize that they could be mediated by a mental model of a social, instead of technological, entity. To concretely learn about these mental models, in Table 3, we present some representative quotes describing the mental models of Ella from interviewees with varied social-agent orientation scores. We observe that users with low social-agent orientation consistently viewed the agent as an *interface for information access,* and emphasized the *utilitarian value* of the system. In contrast, users with high social-agent orientation viewed the agent as a *humanized assistant* and described it using human-specific treats. The striking differences in their descriptions of mental model again highlighted that users with low social-agent orientation were primarily seeking the utilitarian value of the system, while those with high orientation also valued engaging in social interactions with the agent.

Based on the results, it is necessary to consider personalization of agent systems to adapt to these mental models. To this end, in the next two sections, we focus on examining differences in user requirements described by the participants with high and low social-agent orientation. The goal is to identify design considerations for information-finding agents with high or low sociality, allowing personalization for different classes of users.

User Requirements: High Social-Agent Orientation

When analyzing user requirements (i.e. how they wish to improve the agent), we identified two themes that were mentioned repeatedly, but exclusively by users with higher social-agent orientation. The first theme is *improving conversations*. Examples include improving the capability of handling continuity and turn-taking, awareness of user status, having more variations in answers, and also tailor the granularity of answers, e.g. giving more general or specific answers depending on the asker's intention.

Another prominent theme high social-agent orientation users expressed was to *present a personality*, including

ID	SO score	Quotes
P5	2	*"I see it as a way to access the vast amount of company information and infrastructure ... So being able to access that kind of information directly..."*
P8	2.5	*"[It] integrates and helps users make sense of all the different repositories within the company."*
P3	3	*"I am using a chat-bot interface to find information…."*
P11	4	*"I was thinking of her as a way of augmenting search…. but part of the mental model is what are the things I want to talk to people on [the IM tool]"*
P12	4.5	*"She has a personality. I like her, more on her friendliness, instead of a tool".*
P17	5.5	*"The metaphor I have in mind, who is like a lovable colleague, but kind of cool colleague, that most of our conversations are kind of one-sided..."*
P26	6	*"I want to talk to her like a human, but she still feels robotic. I wish she would have more personality."*

Table 3. User quotes describing mental model of the system

providing more subjective and opinionated answers instead of solely retrieving facts, presenting relational behaviors, memorizing previous conversations, and initiating meaningful proactive interactions. In general, they desired to have conversations beyond the functional goals, and to engage in more social dialogues. Such needs are exemplified in the following quote:

"I think humor, subjective thing, personality… I think if there is, like, humorous reply, it is like Easter Eggs that would reward the 'necessary interactions', I think people tend to enjoy more. So even if the tool does not work, but if it gives you funny answers, it adds to my delight. I think it may attract people to interact more." (P12)

User Preference: Low Social-agent orientation

We found three distinct themes from users with lower social-agent orientation. The first theme is *including features from conventional information-search tools*. By viewing the personal agent as an interface for information access, they naturally related it to familiar information-finding technologies. They particularly mentioned features that could improve its capability for providing desired information with less required user input, such as better processing of (non-conversational) input, giving multiple potential answers, suggesting or automatically correcting input, providing context aware recommendation, and handling ill-defined information finding tasks, as exemplified in the following quotes:

"It is very hard to get the keywords, and you have to fully understand the whole protocol of asking the particular chat-bot the way it wants to be asked. There is a lot of friction trying to use it…So, how do I ask something I don't know about. And a chat-bot never does it for me…But a search engine might just give you a bunch of semi-close results. It will get me to where I want." (P3)

We contrast these responses to the "improving conversation" theme identified among people with high social-agent orientation: while both express needs for improving the information-finding process, those with high social-agent orientation placed emphasis on having an easy, natural, or even "intelligent" conversation, while people with low social-agent orientation preferred more machine-like solutions that could reduce the required user input.

The second theme also made a strong contrast. Users with low social-agent orientation explicitly stated the *unnecessity of humanized features*. P3 mentioned that even though in the beginning he had some social conversations with the agent, he was "testing the system", and he would not do that in the long run. P5 also commented that he preferred a non-humanized, especially neutral interface that avoids any stereotypical human features like gender or profession.

The last theme identified from users with low social-agent orientation was to *improve the transparency and affordance of the system*. P5 had confusion when first encountering agent system: *"I never really understand what the functionality is. Like what Ella can do or cannot do."* P3 and P8 both expressed preference for a more transparent system, for example by knowing from which repository the agent gets the information. We note that such needs are consistent with the mental model of search-engine like system, and are to improve the information-finding process.

As a core interface design concept introduced by Don Norman, affordance refers to *communicating what user action is possible in design* [35]. It is, however, challenging to realize in agent systems as they are mostly single-modal (conversation) and typically present limited cues without user initiation (e.g. just a chat window). Interestingly, we identified *affordance-understanding* behaviors from the interaction data. The most typical one was to ask *"what can you do?"* when initially encountering the agent. We found 8 out of the 30 users asked such a question within the first three interactions with the agent. Consistent with the qualitative finding of higher needs for affordance, 75% of them are people who self-identified to have low social-agent orientation (below median). In responding to the question, the agent explained her functionality — to answer enterprise-wide questions, and also provided examples of questions. By simply asking this question to form a better understanding of the system affordance, we found that it significantly improved the success rate of using the agent system, compared to those who didn't ask these questions (β=0.156, t (28)=2.180, p=0.04). The results underline the importance of *designing affordances* in agent systems, especially for users with high utilitarian needs, and suggest that one way to do so is to carefully embed the explanation and instruction on how to use the system into the dialogue.

DESIGN IMPLICATIONS AND DISCUSSIONS

Individual Differences in Social-Agent Orientation

Our study demonstrated that there are individual differences in social-agent orientation. When using an information-search agent, some users value sociality designs and prefer engaging in human-like social interactions, while others may care less about this, focusing primarily on task performance. Such differences are found to be associated with different mental models of the system and lead to distinctive design requirements. The results recommend developing personalized agent interfaces. For example, we envision a customizable agent that allows users to choose the levels of social attributes. Those with high social-agent orientation may favor the availability of choosing agent look and persona, even if it means investing time. Those with low social-agent orientation can skip these steps and use a non-humanized interface such as an input box. This initialization would already differentiate these two user groups for further personalization.

For the high social-orientation user group, we recommend designs that imitate human-human interactions. There is a rich body of research that explores relevant techniques inspired by communication and linguistic literature [4, 16, 17]. By conducting a field study, we found that, somewhat surprisingly, 18% of the questions were "socializing questions" that are typical of social dialogues and irrelevant to the system's intended function. We also found that those with higher social-agent orientation were more likely to ask socializing questions. We consider some of these questions as natural, subconscious responses when a user deemed the agent as a social entity (e.g. asking "how are you going to learn?"). Some other questions appeared to be simply for the enjoyment of social dialogues or to explore the agent's social capabilities (e.g. asking "what is your favorite color?"). When developing a personal agent, especially more social versions, it is important to ensure handling of these types of questions. We also recommend having variations and more opinionated responses to create natural and engaging social dialogues, which could be enabled by having adaptive and individualized conversation models.

The low social-orientation group place less emphasis on the conversational design but more on the utility of the system to find information easily and quickly, and may consider standard conversational interactions as burdensome. We recommend designs consistent with the mental model of *"an interface for information access"* and to focus on smoothing the information finding process and reducing required user input, which may not resemble human-human conversations. To keep this group of users engaged with agent interfaces, it is also necessary to consider what advantages agent interfaces could offer over those of the conventional information finding tools in improving task performance. For example, agent's conversational model may facilitate mixed-initiative automation by increasing user input and integrating knowledge about the user from different contexts. We also consider agent mediated information-finding a potential paradigm for *collaborative search*, which is an emerging research topic with many novel interaction techniques being developed [32].

Lastly, we note the evolving nature of the user differences in mental models. Almost all the participants reported having had some experience with conversational agent systems. Although our sample from a technology company is potentially biased towards tech-savvy users, we note the increasing availability of popular agent applications is shaping user perceptions of, and expectations for, agent systems. For example, P3, who reported to have low social-agent orientation, repeatedly referred to his preference for Google Now, which is designed to be an extension of a search service with rather limited sociality designs. So these mental models are "learned" and can possibly evolve in the future. We also point out that much of the friction in conversational interactions, deemed as unfavorable by users with low social-agent orientation, is constrained by current language processing techniques. Once we have overcome these challenges, it may be worth revisiting the topic of user differences in utilitarian and social orientation.

Agent Proactive Interactions

While we found evidence that agent proactive interactions may carry the risk of interruption, we by no means intend to reject proactive features. Instead, we urge consideration on how to improve the reception of proactive interactions by reducing its interruption cost and increasing its value.

To reduce the potential interruption costs, we can learn from the large body of HCI literature on interruption, including predicting the cost of interruption and improving interruption strategies by considering the context, activity, and emotional status of the user, as well as the format of the interruption (see review in [23]). In addition to the awareness of delivery context, our study suggests *user attribute awareness* by identifying user groups that are more or less susceptible to interruption, potentially based on demographics or social status. An agent system could also easily learn about such attribute from users' previous responses. Moreover, advanced context-aware and user-attribute aware techniques can be developed by accessing users' schedule-related information from sources such as email or calendar tools.

Research also suggests that the aversion to interruption could be reduced through increasing its perceived utility. During our interview, when asking participants why they did not respond to social messages they repeatedly answered things like *"I did not see anything happened after I replied the first time… I was expecting it to come back with help for what I said I was going to do"(P8)*. When we asked why they did not respond to messages introducing the crowdsourcing feature, they replied: *"We are already using Slack…I don't know how Ella would be better (p 26)"*. These answers suggest that if proactive messages can explicitly communicate the value it creates, users may be less resistant to their interruption. Future research is needed to explore these possibilities.

CONCLUSION

By studying human-agent interactions in a natural, but special context – enterprise information-finding, our study shows that there are individual differences in the preference for engaging in human-like social interactions and agent sociality designs. Such individual differences are associated with the extent one focuses on satisfying utilitarian needs and may be particularly important to consider for agent systems intended for productivity versus leisurely use. Our study also illustrates that user's general preference for a design paradigm can have profound implications for system design, impacting how users interact with, expect from and evaluate the system. Our findings can be used to inform the development of personalized agent interfaces for user groups with high or low social-agent orientation. We also highlight the potential risk of interruptions from agent initiated proactive interactions in the work environment and suggest not only context awareness but also user-attribute awareness for personalizing agent proactive interactions.

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