Co-Performing Agent: Design for Building User–Agent Partnership in Learning and Adaptive Services

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ABSTRACT
Intelligent agents have become prevalent in everyday IT products and services. To improve an agent's knowledge of a user and the quality of personalized service experience, it is important for the agent to cooperate with the user (e.g., asking users to provide their information and feedback). However, few works inform how to support such user-agent *co-performance* from a human-centered perspective. To fill this gap, we devised Co-Performing Agent, a Wizard-of-Oz-based research probe of an agent that cooperates with a user to learn by helping users to have a partnership mindset. By incorporating the probe, we conducted a two-month exploratory study, aiming to understand how users experience co-performing with their agent over time. Based on the findings, this paper presents the factors that affected users' co-performing behaviors and discusses design implications for supporting constructive co-performance and building a resilient user–agent partnership over time.

CCS CONCEPTS
• **Human-centered computing → Empirical studies in HCI; User centered design.**

KEYWORDS:
Co-performance; Intelligent agents; Adaptive services; Personalization

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1 INTRODUCTION
Intelligent agents, which leverage user data to personalize system behaviors for individual needs, are becoming increasingly prevalent in everyday IT products and services. For instance, intelligent agents for mail prioritization, news filtering, and content recommendations [22,24,25] have been widely adopted in mobile services to effectively manage information overload. Also, recent examples, such as smart thermostats and wearables, provide personalized support for diverse activities in users' daily lives (e.g., automatic temperature control of a home based on a household's lifestyle and personalized feedback and suggestions for health management).

User–system interaction in the era intelligent services becomes reciprocal transactions of data rather than simple input–output interactions. The quality of user experience in learning and adaptive services depends on how a user and an agent *co-perform* to improve the agent's knowledge of the user. Users have to perform their roles, from sharing personal data with systems to giving their feedback on how a system behaves. However, there are several limitations in supporting such co-performance in current learning and adaptive services. First, while it has become increasingly important for users to understand their roles to enable them to fully benefit from this technology, current systems rarely support users in building a partnership mental model with the systems. Also, current systems do not provide a proper channel for users to control the ways in which the systems learn. Thus, the systems are still opaque to users. Lastly, while these are ongoing transactions, the systems do not clearly communicate how the reciprocal interactions work after the initial interactions, and this often leads to negative consequences to users' experiences.

Given this situation, helping users have *a partnership mindset* that positions users themselves as the co-creators of the service with intelligent agents rather than as passive receivers of the services given by a system, would be an important starting point at which to support the co-performance over time. From this motivation, we devised a Wizard-of-Oz-based research probe called Co-Performing Agent, which co-performs with users by incorporating several approaches to build a partnership mindset for users. By conducting a two-month exploratory study with the probe and several participatory design activities [26], we investigated how users co-perform and develop a relationship with their own agent over time. By doing this, we expect to contribute to providing some clues for improving the limited designs for co-performance in learning and adaptive services.

2 BACKGROUND & RELATED WORKS

In this section, we review previous studies to provide an understanding of the importance of co-performance and the potential of our partnership-building approach in supporting co-performing experiences.

UX Issues in Learning and Adaptive Services

While the potential of intelligent agents in providing personalized supports for people's lives is ever growing as technologies advance, previous research has shown several user experience issues of autonomously adaptive behaviors of intelligent agents. First, it is difficult for users to understand how a system works (e.g., what it knows, how it knows the information, and what it does with the information), as intelligent systems are not often designed to be intelligible and transparent to users [2]. Studies in intelligent systems also highlighted that autonomously adaptive and proactive system behaviors can confuse people, resulting in users' decreased sense of control [10,29,32]. For example, a study of learning thermostats [31] reported how the changes made by Nest based on its own assumptions about user needs annoyed users and gave the sense of losing control over the changes.

HCI researchers have investigated ways to overcome these issues of *transparency* and *controllability.* For example, Cramer et al. [4] revealed that providing an explanation of why certain contents are recommended can increase the trust and acceptance of recommendations. In addition, Kulesza et al. [17] suggested educating users about the underlying mechanisms of recommendations so that they can better understand the systems and manually control the factors that contribute to recommendation results. More recently, the transparency issue arose even in the context of social media newsfeed algorithms. To address these issues, Eslami et al. [8] developed FeedViz, which visualizes both filtered and unfiltered newsfeeds so that users can compare the results and control the priority of newsfeed content.

These attempts suggest potential ways to increase the visibility of the black-box processes of intelligent system personalization. However, it becomes challenging to explain the ever-increasing complexity of intelligent systems to users. Also, providing users too much control over systems might violate the very purpose of intelligent systems in supporting users with less cognitive overload [10]. In this regard, increasing discourse in HCI [6,21] raises the question of how to provide the proper level of transparency and controllability to users in the emerging types of intelligent systems. Responding to this ongoing discussion, this study investigates how a partnership mindset building approach could contribute to address existing UX issues.

The Co-Performance Perspective in Cooperating with Users in Learning and Adaptive Services

There has been research that proposed and investigated ways to incorporate user input into improving system intelligence for personalization. For example, the notion of *programming by demonstration* or *programming by examples* [5,20] has been incorporated in designing interface agents to make systems learn the ways users perform a repetitive task *over the shoulder* so that systems can automate some procedural tasks. In addition, previous research on recommender systems has investigated how user feedback (e.g., ratings and evaluation) can improve the quality of recommendations [9,25]. While previous works contribute to demonstrating the technical feasibility of incorporating user inputs in learning systems, few works investigated how *users* might experience intelligent agents or the systems that attempt to cooperate with users for personalization and what they would expect from cooperating with systems over time.

In overcoming the technology-centered perspective, the notion of co-performance [16] suggests ways to rethink user–system relationships. The notion of co-performance emphasizes the process of shaping the role of artificial agency *together with users,* instead of understanding artificial agency as the one that are *"scripted at design time."* [16] Aligning with this theoretical notion, previous research in personalized services also has pursued a similar perspective. Researchers in this line of work argued the importance understanding users not just as passive recipients of the service, but more as active agents who can take a role in adjusting the service experience [7,11,16,19]. In this regard, Lee et al. [19], for example, proposed a way to help people reflect more deeply on their needs to better personalize health services. Also, researchers like Huang et al. [11] investigated design spaces for eco-coaching thermostats which aim to provide users thermal comforts not just by assuming users are mere receivers of comfort given by the systems, but rather as independent agents who can take energy-saving actions by themselves.

As these previous works imply, investigating the ways to support user–agent co-performance is considered worthwhile to study, not just to provide users more personally relevant support for their lives, but also to empower users in the experience of learning and adaptive services. Building on these initial works, we investigate how users experience co-performance in the wild, aiming to suggest design implications for supporting users' co-performing experience over time.

Social and Relational Strategies for Agent Design

Previous research has investigated how social and relational factors could affect user–agent relationship and their cooperation. For example, conversational strategies, such as personalized small talk, have shown to improve rapport, cooperation, and engagement with computational agents [3,18]. Also, a body of work in line with the 'Computers are Social Actors' paradigm has shown that how users perceive computers differently depending on the social strategies they incorporate, such as personality and humor [23]. In spite of this potential, social and relational strategies have rarely been addressed for empowering users as cooperators in improving agent intelligence and improving the quality of personalized service experiences. With this gap in mind, this paper explores users' co-performing experience and investigates ways to help users build a sound partnership with agents as co-creators of the personalized services. By doing so, we expect that this study will also contribute to the emerging discussions on the cooperative relationship between users and intelligent technologies [1].

3 METHOD

To investigate users' co-performing experiences from a user-centered perspective, we took an exploratory approach rather than simulating users' experience within existing intelligent systems, which already have defined functions and ways of co-performing. To investigate users' reactions and expectations in a more flexible manner, we devised an exploratory study by combining various designerly research methods, including a research probe, the Wizard-of-Oz method, and participatory design activities.

Co-Performing Agent: A Wizard-of-Oz-based Probe to Simulate Co-Performing Experiences

We first devised a Wizard-of-Oz-based research probe, called Co-Performing Agent to simulate co-performing experience (Figure 1). Since the fundamental goal of co-performing with the agent is to improve the service for a user's personal needs and preferences, setting up the Co-Performing Agent probe with each participant's personal service needs in mind was important to understand their genuine co-performing experiences. Thus, we planned to ask study participants to create a fictional service that they actually need in their lives. In addition, to help them readily come up with ideas for the service, we specified our research context as a user-created fictional service in a car environment, as this provides a promising environment where people expect personalized services while moving between diverse places that are closely related to users' personal lives (e.g., home, office, and social places).

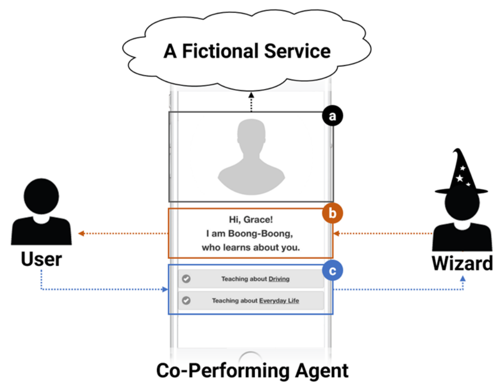

Figure 1. Co-Performing Agent: (a) an agent profile, (b) an agent's message, (c) a teaching information panel

We devised Co-Performing Agent as a web-based mobile application in order to enable users to access it whenever they want. The probe consisted of three parts (Figure 1): an agent profile, an agent's message, and a teaching information panel. To support users in having a partnership mindset for co-performance, we designed Co-Performing Agent to embody three partnership-building elements, namely, *First Encounter Interaction*, a *Teaching Channel* for a user, and an agent's *Learning Messages.* Although the probe was devised only for our research purpose, and the ways we designed the probe might not be the only ways to build a user–agent partnership, we hoped this probe would provide a setting for initiating our investigations of users' co-performing experiences.

First Encounter Interaction. Building a partnership mindset should start from the initial phase of interaction with the agent, because users often set an unreasonably high expectation of intelligent systems and such misled initial expectations increase the potential of users' disappointment and early abandonment of the systems even before the systems acquire the knowledge of users [13,30,31]. Thus, we designed Co-Performing Agent to communicate its immature knowledge of a user during its first encounter with the user (Figure 2). In designing this initial interaction, we were inspired by how people introduce themselves when they first meet each other. People exchange basic information to explore each other and to experiment whether they would like to continue developing the relationship. Utilizing this exploratory conversation, we designed Co-Performing Agent to communicate its ability and to simulate its reciprocal information exchanges with a user and its learning through simple example conversations (e.g., asking a user's name and utilizing the information in the subsequent conversation).

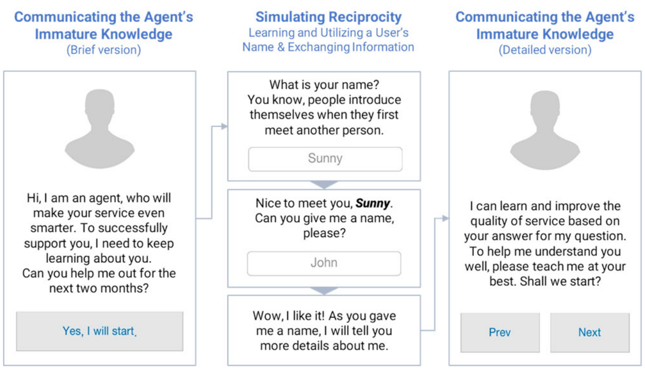

Figure 2. The Script for First Encounter Interaction

A Teaching Channel for Users. To simulate the actual co-performing experience, we also devised Co-Performing Agent to provide users an explicit channel to teach their agent (Figure 3). For instance, if a user selects an information category to teach from a teaching information panel, the user will be taken to a page where s/he can answer the questions asked by Co-Performing Agent. If a user enters an answer, Co-Performing Agent will show text that says, "Thanks for teaching. I got your answer well," to reassure users that the agent is learning. The answer data was sent to and stored on the Co-Performing Agent database, which will be utilized by the Wizard to create an agent's learning messages (see the following section).

We intentionally designed the contents of this teaching channel to be empty at first and asked participants to decide what and how their agent would learn by themselves through a participatory design activity (see the following section). This was because that the automated data collection that are prevalent in current systems cannot consider the information a user feels comfortable to share with the system and many other types of information exist that cannot be detected by sensors but can be given by a user if they want. Thus, by allowing users to freely choose what they want to teach and how they teach it, we aimed to enable users to have control over the agent's learning.

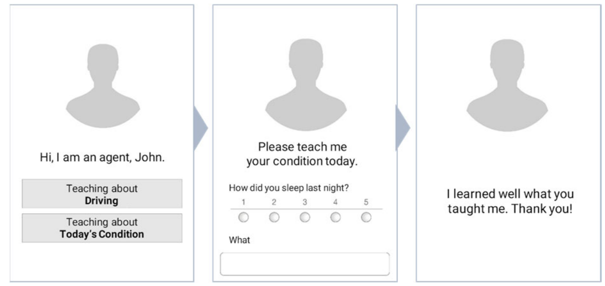

Figure 3. The Script for Learning Interaction

Agent's Learning Messages. We designed Co-Performing Agent to provide an agent's learning messages to enable a user to know the growth of agent's ability over time. This was because that users often expect such reciprocal information transactions with the systems that leverage user's personal data. For example, a study of self-tracking devices showed that users expected more personal nuance in the health-related recommendations, as they accumulated their activity data over time [13]. Such users' expectations of data-leveraging services are quite aligned with the notion of social reciprocity [14,28], a social norm whereby of people try to repay what others have provided to them (e.g., goods, information, and favors). According to social exchange theories, reciprocity plays an important role in maintaining relationships [14,28]. Given previous research findings and theories, reciprocity was deemed an important notion for supporting users in building a partnership mindset over time.

From this motivation, we developed three levels of the agent's learning messages, as a feedback for a user's teaching, by gradually improving the quality of inferences and recommendations: i) a fact-level learning message that only repeats the collected data, showing users that the agent *is* actually learning what users teach it, ii) an inference-level learning message that shows some of the inference that an agent discovered from the collected data, representing the growth of the agent's intelligence; and iii) an action-level learning message that provides proactive suggestions based on the agent's understanding of the user. This three-level learning messages may not be the only way to simulate the growing reciprocity, but we expected that this setting would at least enable users to think about how their co-performance works by showing them how the quality of the agent's knowledge of a user can be improved over time.

Participants

Through an online screening survey that inquired about applicants' driving patterns and purposes, we recruited eight regular drivers who were aware of agent-based interfaces but did not have much experience with them. As they regularly drove their own cars, we expected that they would have their own service needs for our research context and a motivation to start co-performing with the agent probe to improve the fiction service they would create for the study. Participants were in their 20s or 30s and most of them were graduate students, except one housewife, who was on maternity leave. While their apparent occupation was similar, they all had different life patterns and personal purposes for driving, which was the most important recruitment condition for this research. For example, most participants usually drove for commuting purposes on weekdays, but they drove for different purposes on the weekends (e.g., for traveling, dating, shopping, etc.). Also, six of the participants had regular fellow passengers (e.g., a romantic partner, children, and colleagues), whereas the other two usually drove alone. We expected these differences would provide opportunities to observe how co-performing with the agent probe would be experienced in each participant's different service needs and life contexts. All the participants consented to the study under the approval of Institutional Review Board (IRB).

Study Design

The study consisted of a **pre-session** to set up the Co-Performing Agent probe for each user's own service needs, a two-month **in-the-wild deployment** to simulate co-performing experience in a user's real-world life, and **weekly sessions** to inquire whether and how users' perceptions of and attitudes toward co-performance changed over time.

Pre-Session. Participants visited the lab prior to the study and had an individual pre-session to create their own fictional service and to set up the Co-Performing Agent probe for that specific service needs. First, we asked each participant to create a fictional service in a car that they need in their daily lives. By reflecting on their driving experience and daily life, each participant came up with major features of the fictional service they needed (Table 1) and drew those features on a blank mobile screen template (Figure 4-a), which we provided to help them concretely imagine their fictional service.

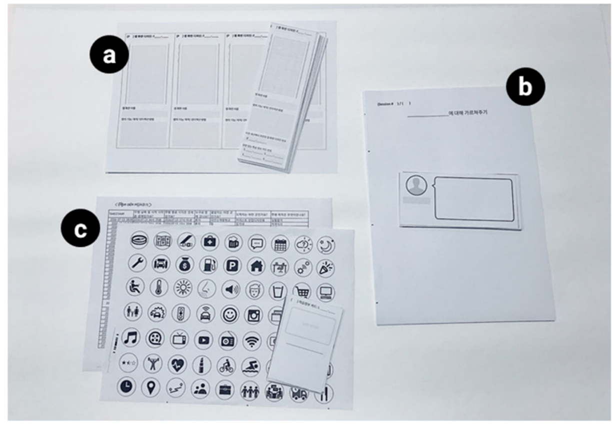

Figure 4. Materials for Participatory Design Activities

Then, we gave an individual access link for Co-Performing Agent to each participant, which took each user to the interactive web pages for the First Encounter Interaction. Following the interaction script, each participant read the agent's introduction of its immature ability and experienced the simple simulations of reciprocity (i.e., teaching the agent his or her name and giving the name of his or her agent). We further asked participants to decide the agent's appearance and ways of speaking, if they wanted, which allowed us to inquire their initial perception toward the agent. As the last step to set up the Co-Performing Agent, we asked each participant to create a list of questions to teach the agent by filling out a blank question and answer template (Figure 4-b). The template guided participants to decide what questions their agent would ask them to improve the fictional service and how they would answer the question (e.g., free text, options, scale, etc.). We guided participants to list similar questions under a category and to specify the name of the category. We used this material to create the list of teaching information on Co-Performing Agent. By allowing participants to select only the category of information they want to teach the agent at a given time, we aimed to enable users to teach the agent more effectively.

Regarding all the features and contents created by participants, we inquired why each participant created such a fictional service and why he or she decided to teach such questions to understand the users' initial perceptions of and expectations toward Co-Performing Agent. Based on the outcomes of participatory design pre-session, each participant's Co-Performing Agent was updated, and all the materials created by participants were filed to use in their upcoming participatory design sessions.

Table 1. Each Participant's Initial Fictional Service

Participant	Major Features of a Fictional Service
P1	**Daily Briefing service** that provides today's briefing of P1's health condition based on the sleep patterns and the amount of physical activities.
P2	**Dining Mate service** that provides restaurant information on the way to a destination based on P2's dining patterns.
P3	**Personal Reminder service** that reminds things to do and where to go based on P3's driving patterns.
P4	**Hangout Mate service** that provides the top 3 restaurants'/activities'/places' information based on P4's leisure time driving patterns.
P5	**Personalized Navigation service** that provides real-time information for P5's frequent hangouts before heading to the place (e.g., on-going promotion, crowdedness, and open–close day and time).
P6	**Personalized Shopper service** that reminds the user of a grocery shopping list and provides the price information at nearby markets based on P6's necessity and stock information.
P7	**Driving Mate service** that visualizes and analyzes the places that P7 has visited and P7's driving habits.
P8	**Personal Jockey service** that automatically plays audio content based on P8's own driving modes (e.g., playing cheerful music when driving back home and playing English news when driving to his second language class).

In-the-Wild Deployment of the Co-Performing Agent Probe. To simulate co-performing experiences, we deployed the customized Co-Performing Agent for eight weeks in the wild. We guided participants to teach their agent through the teaching information panel by answering the questions that they devised during the pre-session, thinking that the information they teach would be the source of learning by the agent. To observe participants' natural engagement with the agent, we allowed them to decide when and how frequently they would teach.

During this two-month deployment, we provided the learning messages by utilizing the collected user data (Table 2). We decided not to provide a learning message in week 1 to simulate a situation in which the collected information is not enough to build a knowledge of user. From week 2 to week 8, two researchers, as a Wizard, changed the default greeting message on the probe into the learning messages they developed by interpreting the actual user data collected on the Co-Performing Agent database: the fact-level learning messages for week 2 and 3, the inference-level learning messages for week 4 and 5, and the action-level learning messages for week 6 to 8. Intentionally, learning messages for week 7 were designed to violate the reciprocity (e.g., attempting to over-interpret) to investigate how such misbehaviors of Co-Performing Agent affect users' perceptions of and attitudes toward co-performance. The personalized learning message was given to each participant twice a week, and participants were able to give their own feedback to the agent regarding its messages by teaching it (during W1–W5) or by rating the agent's recommendations (during W6–W8). To ensure that participants did not evaluate their experience of Co-Performing Agent based on groundless assumptions on the agent's capability, we consistently emphasized that the agent provided the learning messages purely based on how participants had taught their agent.

Table 2. The Examples of Learning Messages for P4's Fictional Service (i.e., Hangout Mate Service)

Week	Learning Message	Examples
W1	Default	"Hi, I'm your agent, OO."
W2	Fact Level	"You've been to OO last week. How was the trip?"
W3		
W4	Inference Level	"I think you may feel tired after a long-distance trip during holidays!"
W5		
W6	Action Level	"You seem to love sushi. How about going to a new sushi café near your office next time?"
W7		(W7-intended mistake) "You may like to drink a beer with your wife, since you haven't gone out for beer lately. How about OO pub on this Friday?"
W8		(W7-recovery) "Sorry, I gave you the wrong recommendation. For your health condition, how about going to OO juice café for a drink?"

We deployed Co-Performing Agent for two months, considering the time required for technology adoption and the agent's learning. In relation to the time required for technology adoption, the researchers suggested that two months would be enough time to observe stable interaction with the artifacts without the novelty effect [12,27]. Regarding the time for the agents' learning, the two-month period was expected to provide the possibility to learn repetitive behavioral patterns in life, as participants can teach their daily, weekly, and monthly behaviors at least twice. Although it may not be sufficient to observe the entire trajectory of co-performance over time, a two-month duration was expected to provide participants the time to adopt a new artifact and to provide the likelihood of actual learning during the study.

Weekly In-Depth Inquiry Sessions. To inquire whether and how users' perceptions of and attitudes toward co-performance change over time, we conducted an in-depth inquiry session every week in person. During each session, we first conducted a de-briefing interview of users' thoughts, feelings, and any challenges users had while interacting with Co-Performing Agent. Then, we asked them to do three participatory design activities by reflecting on their experiences: i) the *agent profile revising activity*, ii) the *service revising activity*, and iii) the *learning question revising activity*.

The agent profile revising activity was to inquire about users' changed perception of the relationship with the agent. Reflecting on their co-performing experience, we asked participants to describe their relationship using an analogy. If they thought it was necessary, participants were allowed to change the given properties of Co-Performing Agent (e.g., appearance, the ways of speaking, etc.) so that we could provide the updated version of the Co-Performing Agent probe in the following week.

The service revising activity was to inquire about users' perception of their agent's ability. For this purpose, we first asked participants to create *inferred information cards* (Figure 4-c), on which they were asked to write down the information that they thought their Co-Performing Agent had learned or discovered from what they had taught it. This was to enable participants to think of the perceived knowledge of the agent more easily and concretely. For this activity, each participant was given the raw data they had taught to their Co-Performing Agent up until the session. Then, we asked participants to add, delete, or modify the features of their Co-Performing Agent service as a way to express how they thought their agent could improve its service, given the inferred information that they thought that their agent had acquired. Participants modified the features only when they thought that their Co-Performing Agent had learned a reasonable amount of information necessary for the service evolution. Otherwise, participants were guided to hold off on modifying the features and teach their Co-Performing Agent more until it acquires the enough amount of information. In this way, we aimed to investigate users' perceptions of their agent's ability with more rationale.

Lastly, we conducted the learning question revising activity to inquire about the users' attitude toward further co-performing behaviors. For this activity, we asked participants to modify the ways that they taught the Co-Performing Agent, considering the agent's current ability and their expectation of service evolution.

Each weekly in-depth session lasted about an hour. All the collected data were used to understand how participants' perceptions of the agent's ability and their relationship changed over time and to gain insight on the ways to improve the support for building user–agent partnerships. After each weekly session, the probe was modified based on the outcomes from the session (i.e., modified agent's name, profile image, and learning contents) and participants resumed to teach their agent with the updated questions.

Data Collection and Analysis

To understand participants' co-performing behaviors and their partnership development with their agent over time, all the relevant data from the pre-session and weekly sessions were audio-recorded and transcribed (e.g., participants' in-the-wild co-performing experiences, feelings and thoughts toward their agent, the relationship analogies, and all the rationales of participatory design activities). Over 72 hours of interview transcripts were re-organized with the related participatory design outcomes from the offline sessions. After each weekly session, preliminary analysis was conducted by five researchers searching for emergent themes and patterns with regard to user–agent partnership and co-performing behaviors. After finishing all the sessions, we conducted a more holistic analysis by analyzing how users' co-performing experiences in a given week affected their perceptions of their partnerships and the co-performing practice in the subsequent weeks. We iterated this analysis process to identify the underlying reasons and factors for their co-performing behaviors and perception of their partnership that were commonly observed across participants.

4 FACTORS AFFECTING CO-PERFORMING BEHAVIORS

From the analysis, we found three factors that affected users' co-performing behaviors: i) users' initial mental model toward an agent's capability, ii) confirming experiences, and iii) changes in the styles of learning.

Users' Initial Mental Model toward an Agent

The first factor that affected users' co-performing behaviors was users' initial mental models about agent's potential capability. Although all participants went through the same introduction to Co-Performing Agent, they had different initial mental models about the agent's potential capability, namely *Getting-Things-Done (GTD) Agent* model and *Companion Agent* model.

Getting-Things-Done Agent Mental Model. Participants with GTD Agent model (P3, P5, P6, and P8) tended to think that the agent's capability to improve the service was limited to machinery optimizations (e.g., automating and streamlining). Thus, these participants thought their agent would provide *efficiency-related value* to users through the co-performance. For instance, P3 thought that his agent would improve his Personal Reminder service by providing prediction-based navigations (e.g., automatically setting a predicted destination where he should go at a given time) so that he can reduce time for navigating. Also, P8 expected that his agent would improve the Personal Jockey service by learning which music it should play depending on his pre-defined driving contexts and automatically playing the content even without him manually selecting music time after time (e.g., playing cheerful music when driving back home, English news when driving to his second language class, and podcasts when driving for long distances).

Since they had such expectations, they wanted their agent to quickly develop simple service features through a short period of co-performance. For this reason, they taught their agent focusing on a *single aspect of their lives*, mostly just about driving history. In addition, they tended to teach the aforementioned information at a *factual level* (e.g., when and where they have been, what the purpose was, and whom they were with) and expected these data to be analyzed in a *statistical way* (e.g., the three most frequently visited places (P5), the average time of daily workout (P6)).

Companion Agent Mental Model. Unlike the participants with the GTD Agent mental model, participants with the Companion Agent mental model (P1, P2, P4, and P7) thought that the agent had the capability to acquire a deeper understanding of its user and to improve the service not only for machinery optimization, but also for more personally nuanced supports (e.g., personalization based on user's state and taste). Thus, these participants thought that their agent would provide *more integrated* and *high-level supports* as companions, enabling users to gain better self-knowledge and inspiring them to be their desired selves. For instance, P7 expected his agent to improve its Driving Mate service not just at the level that it quantifies his travel history and suggests the most preferable place, but to the level that it suggests new places where he might have not thought to visit but would be nice to visit so as to enable him to explore new areas.

With such expectation of the agent's capability, these participants thought that a *longer-term co-performance* is necessary and taught their agent about *multiple aspects* of their lives, even though it might take more time to help their agent build a truly deeper understanding of the user. For instance, P1 taught her agent not just about her commuting pattern, but also about her health-related data (e.g., workout and sleep), interest-related data (e.g., interests toward stock information) and personal driving habit data as well, expecting her agent to improve the Daily Briefing service to take care of her daily lives. Also, Companion model participants tended to teach the aforementioned information at a *subjective level* and expected to be analyzed with *semantic interpretations.* For instance, while P3 (GTD model) expected that his agent would infer the *frequency* of the places he visited from his driving data, P7 (Companion model) expected that his agent would infer his *favorite places* and *lifestyle* from his driving data.

As these differences show, the mental model that participants initially had toward agent-based services shaped different overall attitudes toward co-performance (e.g., the quantity and quality of information that each participant decided to teach in the first week and the eagerness to teach over time).

Iterative Confirming Experience

Another important factor that affected users' co-performing behaviors was *confirming experience*, an experience through which a user can confirm that an agent is learning with the help of the user. We found that whether and how participants experience such confirmation in the earlier weeks affected participants' willingness to continue teaching their agent in the later weeks, resulting in *the virtuous cycle of enhancing user–agent partnership* or *the vicious cycle of deteriorating user–agent partnership.* Meanwhile, it was interesting to note that the vicious cycle was observed more frequently from the participants with the GTD Agent mental model. In what follows, we describe how confirming experiences affected users' co-performing behaviors and the relations between initial mental model and the resulting user–agent partnership.

The Virtuous Cycle of Enhancing User–Agent Partnership. In this study, the confirming experiences mainly happened through the learning messages our wizard researchers provided to each participant. When we provided a learning message that was reasonably improved based on what participants had taught, participants could be sure that their agent was learning as they expected, and this confirming experience enabled participants to realize their roles and the value of their inputs for service evolution: *"Although it (his agent) said that it would learn what I teach [in the first encounter interactions], it was a bit ambiguous to me. However, when it reacted to what I taught, I realized that it actually* *utilizes what it learned from me. I think I should teach more carefully."* –P7 (Companion model)

Like the case of P7, such confirming experiences motivated participants to provide quality information to their agent. P1, for example, decided to increase the amount of information she was teaching about her favorite stock items from one item per day to three items per day (P1-W2). Also, P2, P3, and P4 decided to teach more concrete and detailed information instead of abstract information. For instance, P2 decided to teach her agent the specific name of a passenger rather than just teaching 'a friend' (P2-W3) so that her agent could improve its Dining Mate service based on P2's dining pattern with that friend. By learning additional details about the information that it had learned previously, these participants' agent could provide more concrete learning messages over the following weeks, and this *reinforced* those participants' continued willingness to co-perform with their agent. As this example shows, when the agent repeatedly provided confirming learning messages showing its *growth*, the virtuous cycle of teaching-confirming-teaching was iterated over time. By doing so, these participants were able to build trust toward their agent's knowledge of the user gradually and to develop stable relationships with their agent. Thus, P1 (Companion model), who had built a resilient partnership with the agent, said her agent was like *"another me who takes care of my life,"* highlighting the strong trust toward her agent's knowledge of her.

The Vicious Cycle of Deteriorating User–Agent Partnership. In contrast, we also found situations in which the learning messages did not properly provide confirming experiences and de-motivated the continued co-performing behaviors. There were two major causes for failures in providing proper confirming experiences. The first reason had to do with users' initial mental models that we discussed in the earlier section. Two types of users reacted differently, even though they were given the same level of learning messages. For instance, when Companion model participants received the fact-level and inference-level learning messages, they easily confirmed the value of their inputs and tried to explore ways to help their agents improve their knowledge of the user more meaningfully (e.g., teaching enriched contextual information about their daily driving and lives). However, GTD model participants were not clearly aware of their role in co-performance, even though they were given the same quality of learning messages as the Companion model participants. Thus, they tended to put less effort into teaching, which resulted in the users teaching too shallow and unstructured information to allow the agents to infer meaningful information from the data.

In addition, while the participants with Companion model were satisfied with the gradual learning pace of Co-Performing Agent, the participants with GTD model tended not to appreciate the prolonged learning process. They thought that what their agent had to learn for service evolution (e.g., the repetitive behavioral patterns) should not require much time to learn. Thus, they expected action-level feedback from the agent much earlier than the participants with Companion Agent mental model. However, in this study, action-level learning messages were given after a month of learning; this postponed-evolution model made the GTD model participants difficult to confirm the value of their inputs in a timely manner. In consequence, these not-rewarding experience demotivated these participants to put their efforts into teaching over time. For example, P6 wanted to sync all data from third party applications without her manually teaching her agent: *"I don't like to teach health information by myself, because it is so much of a burden for me and I don't even believe the agent has the intelligence to learn. I just want the agent to automatically collect necessary data from the related applications on my phone and provide service smartly."* (P6-W3)

The second reason was the learning messages that showed mis-interpretations of what users taught and overly supportive actions that they did not expect from their agent. For instance, P5, who wanted Personalized Navigation service and had the GTD mental model, received a movie recommendation from his agent (e.g., "You've done a lot of work this week. How about going to a weekend movie date? The latest movie, 'Mechanic,' is now playing at your favorite movie theater."). While this recommendation was based on his driving history to a movie theater with his girlfriend, P5 thought that inferring the specific type of movie to recommend was excessive given that the information he had taught was only the fact that he went to the theater once.

P8, who also had the GTD mental model, experienced the failures in confirming experiences for both reasons. After he taught where he drove, he received the inference-level learning message saying, *"You visited Jokbal (the name of Korean dish) restaurant last week. You seem to like Jokbal!"* This learning message was neither tightly related to the initial service he wanted, i.e., Personal Jockey service, nor aligned with his GTD mental model. He said, *"I hated when it said that last week. It was uncomfortable to talk about FOOD with an agent for a CAR service. It was like, for example, talking about my romantic partner with the car agent. It would have been much better if it just said that I visited some restaurant, which is the fact I taught."* (P8-W4) P8 said his agent *"exceeded"* its authority and he felt frustration in sharing detailed information with his agent: *"I got a tendency not to teach too many details of my destination after the agent 'crossed the line' last time. I used to write the exact name of the place in the past, but now I try not to do so and just write something like 'a restaurant' or 'a cafe'. I don't want to give too much detail to this agent, because I realized that it could THINK by itself."* (P8-W6)

As this example shows, when users were not able to have confirming experience in a timely manner, the teaching-confirming-teaching cycle was not iterated properly. In consequence, these participants were not able to build trust toward their agent' knowledge of the user and a stable relationship with the agent. For example, P3 (GTD model), who had an unstable partnership with the agent, said his agent was like "an intimate, but annoying friend," because he was somewhat bored of helping his agent after eight-week co-performance.

Influences on User Experience of Adaptive Services. Confirming experiences seemed important not only for users' continued co-performing behaviors, but also for users' actual service experiences. As participants with Companion agent model went through the virtuous cycle of teaching-confirming-teaching iteratively, their sense of control over the system was enhanced over time as well. Thus, even when their agent made the (intended) mistakes we planned for this study, they showed more accepting responses to their agent. For instance, P4 (Companion model) thought that the mistake was *"a part of the learning process,"* through which his agent *"attempts to extend the knowledge by itself."* In the case of P7 (Companion model), he was even able to analyze why his agent made such mistakes, although he had not provided information that was relative to the incorrect inference of the agent. Thus, he tried to think of what he could do to amend the incorrect knowledge of his agent. This user-empowered reaction was contrary to the reactions from P6 (GTD model), who regarded the mistake as a limitation of machines and thought there was not much she could do about this technical flaw. In addition, when the agent provided more proactive suggestions in the later weeks, the participants who went through iterative confirming experiences tended to accept their agents' recommendations and showed more generosity, thinking that they could control the system, even if it made mistakes. This seemed to be because they had a clear understanding of how their input could change the agents' behaviors. As these examples show, confirming experiences were important to develop more stable and resilient partnerships with the agent.

Changes in the Styles of Learning over Time

Regardless of the initial mental models and confirming experiences, changes in the agent's styles of learning were important for all participants to co-perform over time, as the changes affected users' perception of their agents' activeness in learning. For instance, in the case of participants who continued teaching the same contents in the same ways for several weeks, they were in *"doubt about whether the agent is learning correctly or not"* (P2) and thought that the agents *"do not have the willingness to learn."* (P8) In a similar vein, participants appreciated when the agent started to get user feedback on what it recommended instead of just continuously learning the raw data over time. When the agent provided more satisfying learning messages in the following weeks by reflecting on the collected user feedback, participants said that this kind of ping-pong interaction for learning gave them more *"communicative"* (P3), *"cooperative"* (P5), and *"diligently learning and ever-growing"* (P4) impressions of the agent.

From the analysis of the data gathered from the learning question revising activities, we found several qualities of learning questions that participants considered as important in the changes of agent's learning styles. Firstly, participants cared the efficiency of the co-performance. For instance, while participants thought that they need to answer the agents' questions by manually entering the answers in the beginning, they expected that their agents would create the predicted user answers based on a user's answering patterns in the later interactions, for example, by automatically showing the names of frequent destinations of a user when asking the user to teach driving history. By doing so, participants expected to teach more efficiently over time.

Also, participants cared to change the level of information they teach over time. For instance, in the beginning, participants tried to teach as much information about their daily lives as they could even in a bit abstract level, because they thought that their agent had little knowledge of the user and had learn the user's representative profiles as quickly as possible. However, over time, participants became to think that their agent had collected enough mundane and superficial information about their lives and tried to focus on providing more unusual and deeper information that their agents might not know unless users teach that information. For instance, after a week of teaching, P1 decided to reduce her efforts to teach regular behavioral information (e.g., commuting information) and decided put more effort into teaching subjective and contextual information that her agent could consider in improving the Daily Briefing service (e.g., her physical condition including the self-evaluation of the sleep quality in five-star rating, the reasons she could not sleep well, and her know-how to improve her sleep quality).

In addition, as the agents' knowledge of the user grow and participants' perceived relationships with their agents became closer over time, participants expected some proactive questions from the agent. For instance, P2 expected that her agent would be *"curious"* if she drove far away to have a rice dish because her agent knew that she prefers flour-based foods. Thus, she expected that her agent would ask questions like, "Why are you going far away to have rice dishes on weekdays?" While these proactive questions should be designed carefully, this kind of conversation would enhance the potential for service personalization.

5 DESIGN IMPLICATIONS FOR CONSTRUCTIVE CO-PERFORMANCE OVER TIME

The findings of this study suggest three factors that should be considered in designing for users' co-performing experiences. Reflecting on these findings, we discuss further design implications for supporting constructive co-performance and building a resilient user–agent partnership over time as follows.

Supporting Co-Performance Based on Users' Mental Model toward Agents

Reflecting on our findings, supporting users' co-performance with an understanding of a user's mental model of agent-based services would be important to enable constructive co-performance over time. In doing so, two types of initial user mental model we found from the study (i.e. the GTD and Companion Agent mental models) can be used to inquire as to how a user would like to co-perform with the agent and what s/he might expect from co-performance. For example, if an intelligent agent provides users the option to choose one of the co-performing journeys in the first encounter interaction (e.g., a short-term and focused co-performance for GTD Agent mental model vs. a long-term and multi-faceted co-performance for Companion Agent mental model), the agent would be able to adjust its methods of co-performance to be more suitable to the chosen mental model. While Kulesza et al. [17] also classified users' mental models depending on the degree of understanding of how systems work (i.e. functional vs. structural), our classification of users' mental models provides a more actionable taxonomy to reduce the conceptual gap between users' expectations and actual system behaviors.

Meanwhile, we also observed potential changes of a user's initial mental model over time. For example, one of our participants with a GTD mental model (P5) changed his mind to teach diverse tidbits of his daily life rather than teaching factual-level information after he realized that his agent might not learn additional information if he continued teaching repetitive daily activities. While the willingness to teach multi-faceted information represents the co-performing behaviors of users with Companion Agent mental model, P5 still showed the characteristics of GTD mental model, showing less accepting reactions when his agent provided a learning message that actually utilized the life tidbits information. This mixed expectation in co-performance raises a further research question regarding how such a transitional phase should be supported by a system to continue the co-performance without deteriorating users' partnerships with their agent.

Explicitly Designing for a Learning Period before Providing Proactive Support

From the findings of this study, we also found that a resilient user–agent partnership and trust are not ones that can be built immediately. Instead, it could be built through the iterative cycles of confirming experiences over an expanded period of time. However, most current learning and adaptive systems do not explicitly consider these iterative and time-taking nature of building a user's trust and partnership toward intelligent agents. Rather, those systems tend to attempt to provide proactive supports as quickly as possible without considering users' perceived ability of and trust toward the systems. This collapsed interaction phase for co-performing and confirming experiences might have caused early abandonment of these intelligent systems. In this sense, explicitly designing for a learning period before providing proactive supports would create opportunities for users to build a partnership mental model by allowing both users and agents to simulate co-performance and recover their partnership more easily beforehand.

Careful Considerations for Applying Human-Likeness in Co-Performing Agent Interface

One of the interesting findings of this study is that the human-likeness and rapport building interaction of Co-Performing Agents were not a primary factor for their co-performing experience, although it seemed influential in user–agent interactions. Some of the participants (P4-Companion model, P3-GTD model) even felt uncomfortable when the agents' learning messages included casual ways of speaking in the beginning, because they thought that trying to build an intimacy even before completing its original purpose (i.e., building a knowledge of users) was inappropriate and unnecessary. Rather, such user–agent intimacy was naturally built though the iterative confirming experiences that enabled users to realize that the agent had a quality understanding of their lives. Thus, applying human-likeness in co-performing agent interfaces should be carefully considered and if necessary, interactions for building rapport would be better in the later interactions.

6 DISCUSSION

In-the-wild deployment of Co-Performing Agent also revealed several issues around collecting users' behavioral traces in the real-world context. These issues suggest some challenges and opportunities for future research.

Users' Concerns on Privacy and Controllability of Personal Data Collection and Inference

As participants continuously taught their personal information, revealing traces of their daily lives, participants' privacy concerns became salient over time. For example, there were participants who had concerns about continuous data tracking for agents' learning, considering whether they should share their behavioral traces even when they did not want to. P2 was especially concerned about the potential embarrassment of unexpectedly revealing sensitive information in a social context: *"Let's suppose that I want to dine out with my new boyfriend and what if it (her agent) tactlessly suggests the restaurants that my ex-boyfriend and I used to go to? Considering such situations, I am not sure whether it would be still okay to give all of my information to the agent."* (P2-W4) As P2's perceived privacy concern increased over time, she wanted her agent to ask her whether she wanted to mark given behavioral data as a *"secret."* Based on that secret marking, she wanted her agent to pretend not to know secret events when she was with someone else.

This kind of privacy concern may happen as the amount of collected data gets bigger and the potential of inferring personally-related traits becomes more feasible over time. Moreover, this is already prevalent in everyday online services: the traces of what a user liked on Facebook could infer a lot of traits of a user [15]. Although sharing personal data to get personalized service might be inevitable, more research should be conducted to investigate the ways to build a sound user–agent partnership with a proper controllability for users.

Temporal/Permanent Expiration of User Profile

During the two-month study, participants came to face the changes in their lives and they expected the ways their agent provided the service to be reoriented in response to such life changes. For instance, P4, who wanted to receive restaurant recommendations for dining with his wife, wanted to rule out raw seafood for a while from the recommendations, as the couple started to prepare for pregnancy. Thus, he created a new set of questions to teach the changed situations and taught his agent to avoid sushi restaurants that he and his wife used to visit, during the time they were preparing the pregnancy. Also, P1, who expected an agent's service for reviewing her daily exercise, was getting busier due to her tasks at work and did not have time to exercise at all. Thus, she wanted her agent to recommend exercises that she could do during the short breaks in a day, rather than the ones that require significant time and effort: *"How I lived in this week was quite different from the previous four weeks in many senses. My commuting time was shifted, and I couldn't exercise even once this week. Given the information Ryan [her agent] has learned so far, I thought that Ryan could notice the changes and I expected some feedback related to the changed life patterns."*

These examples show that how the considerations on these kinds of temporal or permanent changes of a user's profile could enhance personalized service experiences. Thus, this suggests further research on how to support users in helping their agents re-learn their profiles and how to support them in managing the expired profiles, which would extend our understandings on supporting user–agent co-performance over time.

7 CONCLUSION

In this paper, we presented a two-month exploratory study that investigated how users' perceptions and attitudes toward Co-Performing Agent changed over time. The findings of this study contribute to providing empirically grounded design implications for supporting user–agent co-performance by highlighting the factors affecting users' co-performing behaviors; *users' initial mental models, confirming experiences,* and *changes in the styles of agents' learning*. Investigating users' co-performing experiences by manipulating these factors would uncover further implications for supporting constructive co-performance over time. As an initial work that investigated human-centered ways to support user–agent co-performance, we hope this study inspires future research into creating personally-relevant services *together with users* and empowering users in their experience of intelligent IT services over time.

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