박 사 학 위 논 문

Ph.D. Dissertation

지능형 IT 서비스의 개인화를 위한 상호 호혜적 협력 경험 디자인

Co-Performing Experience Design for Personalization in Intelligent IT Services

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한 국 과 학 기 술 원

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Co-Performing Experience Design
for Personalization in Intelligent IT Services

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Advisor: Youn-kyung Lim

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초 록

사용자의 데이터를 수집하고 분석하는 기술의 발전으로 인하여 사용자 개인에게 맞춤화 된 서포트를 제공하는 지능형 IT 서비스의 가능성이 계속해서 높아지고 있다. 기술이 고도화됨에 따라 지능형 IT 서비스에서의 맞춤화는 시스템에 의해 점차 자동화되는 방향으로 나아가고 있지만, 그러한 시스템 주도적 방식으로 인하여 사용자는 지능형 IT 서비스를 경험함에 있어 점차 주도권을 잃게 되는 사용자 경험 측면의 이슈가 계속해서 제기되고 있다. 이러한 맥락 속에서 본 연구는 사용자가 수동적인 서비스 수용자로서가 아닌 적극적인 협력자로서 시스템이 사용자에 대해 학습하는 과정에 협력하는 방식으로 서비스를 경험할 수 있게 돕기 위해서는 지능형 IT 서비스와 유저 간의 상호작용이 어떻게 디자인되어야 하는가를 시간적 관점에서 탐색하고 디자인 가이드를 제시하는 것을 목표로 한다. 이를 위하여 지능형 IT 서비스를 사용하는 사용자의 전반적 경험 및 사용자의 실제 상호 호혜적 협력 경험을 이해하기 위한 사용자 중심적 연구가 진행되었으며, 그 결과를 바탕으로 상호 호혜적 협력 경험 디자인을 위한 프레임워크를 개발하고 이를 활용하여 진행된 워크샵 기반 전문가 인터뷰를 통해 그 효용성 및 역할에 대해 탐색하였다. 본 연구가 사용자 경험 디자인 연구 및 실무에 기여하는 바는 다음과 같다. 첫째, 사용자와 지능형 IT 서비스 시스템 간의 협력을 상호 호혜적인 관계 형성 과정으로 바라보는 관점을 제시하였다. 이는 시스템의 학습 과정에 사용자가 참여하는 것을 단발적이며 태스크 중심적으로 바라보았던 기존의 관점과는 차별된다. 둘째, 사용자의 상호 호혜적 협력 경험을 서포트 하기 위해서 고려해야하는 사용자-시스템 간의 관계 단계 및 파트너십 영향 요소를 발견하였다. 셋째, 이를 프레임워크화 하고 검증함으로써 디자이너가 상호 호혜적 협력 경험을 디자인하기 위해 고려해야하는 생각의 틀을 제안하고 상호 호혜적 협력 경험의 각 단계에서 고려할 디자인 가이드를 제안하였다. 본 연구의 결과는 사용자가 진정한 협력자로서 자신의 역할을 이해하고 시스템과 협력할 수 있도록 서포트하기 위한 디자인 가이드를 제시함으로써 보다 인간 중심적인 맞춤화 서비스 및 지능형 IT 서비스 경험을 제공하는데에 기여할 것으로 기대된다.

핵심 낱말: 상호 호혜적 협력, 개인화, 지능형 IT 서비스, 시간에 따른 사용자 경험, 인터랙션 디자인

Abstract

With the development of technology for collecting and analyzing user data, the possibility of intelligent IT services that provide personalized support to individual users is continuously increasing. As technology becomes more sophisticated, personalization in intelligent IT services is increasingly being automated by the systems. However, system-driven approach raises the issues in user experience as users often lose their controls over the systems' behaviors in the experience of intelligent IT services. In this context, this research aims to investigate the ways to support users' experience of intelligent IT services, not just as a passive service recipient, but more as a co-creator who actively participates in the process that systems learn about the users over time. To do so, user-centered studies were conducted to understand users' overall experience of intelligent IT service and their co-performing experience over time in the wild. Based on the results, a framework for designing co-performing experience was developed and its role and value in the design practice was investigated through a workshop-based expert interview. This research contributes to user experience design research and design practice as follows. First, this research proposed a perspective for understanding users' participation in systems' learning as a process of building the relationship with intelligent IT services through reciprocal interactions between users and systems. This is different from the existing approach that considers users' participation in a system's learning process as task-oriented and fragmented interactions. Second, this research identified important phases and factors that should be considered in supporting users co-performing experience over time. Third, this research proposed co-performing experience design framework, which would provide a thought framework for designing co-performing experience in intelligent IT services. By providing design guidelines for supporting users to understand their role and to co-perform with the systems, the results of this research are expected to contribute to inform the design of intelligent IT services that provide personalized service experience in a more human-centered way.

Keywords: Co-Performance, Personalization, Intelligent IT Services, User Experience over Time, Interaction Design

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CHAPTER 1.

Introduction

Chapter 1.
Introduction

This dissertation investigates the ways to improve users' co-performing experiences for personalization of intelligent IT services. This introductory chapter provides an overview of this dissertation, including background, aims, methodology, and overall structure of this research.

1.1 Research Background

As technology advances, the potential to provide personalized IT services to users is ever-growing by leveraging data about users collected through personal and mobile devices. The advances in activity sensing technologies created huge resources for understanding people by digitalizing their behaviors, and the advances in user modeling technologies have enhanced the possibility of service personalization by enabling to infer the characteristics of users (e.g., physical states, routines, preferences, interests, emotion, etc.) from the collected user data in unprecedented ways. In addition, the emerging smart consumer devices and environments (e.g., smart phones, wearables, smart home appliances, and connected cars) provide diverse channels to offer the personalized service even closer to people's everyday lives in the real world.

While these technological advances accelerate the trends for developing intelligent systems that automatically personalize the services for individual users, previous research around intelligent and autonomous systems in the field of Human-Computer Interaction (HCI) have continuously emphasized the importance of empowering users to have controls over how systems learn about users and personalize the services (Lee et al., 2015; Churchill, 2013; Lustig et al., 2016). The primary reasons for this are due to two user experience issues around intelligent and autonomous systems: Transparency and Controllability. First, the ways that autonomous intelligent systems behave (e.g., what it knows, how it knows the information, and what it is doing with the information) are not often designed to be intelligible and transparent to users (Bellotti and Edwards, 2001). Thus, users often feel difficulties in developing a proper mental model of system capability due to the lack of system feedback and transparency (Luger and Sellen, 2016). Second, intelligent systems often decrease users' sense of control over the systems as the systems automatically change theirs behaviors (Höök, 2000; Montague, Hanson and Cobley, 2011; Zimmerman et al., 2007). In addition, as the systems can be seen as if they behave on its own assumptions, people often experience negative feelings from those systems' proactive supports (Yang and Newman, 2013, 2012, Eslami et al., 2015a; b).

In this regard, emerging research have argued the importance and value of designing intelligent systems in a way that adjust the intelligent and personalized services *together with users*, rather than making the systems decide by themselves (Lee et al., 2015; Kuijer and Giaccardi, 2018; Huang et al., 2017; Eslami et al., 2015b). This way of empowering users in the experience of intelligent IT services is theoretically conceptualized as *co-performance* (Kuijer and Giaccardi, 2018), highlighting the perspective of understanding artificial agency not as the one that are scripted at design time, but as the one that can be acquired and adjusted next to people. As everyday IT products and services are increasingly becoming intelligent, it is regarded to be important to support co-performance between users and systems in intelligent IT services to improve users' experience in those services over time. Indeed, emerging smart products and services request users to take an active role in helping the systems' learning process (e.g., asking users to share personal data with systems and asking users to giving feedback on how a system behaves), aiming to provide more personally-relevant service experiences for individual users.

While this implies the shift in the role of users from a passive service recipient to an active co-creator of the service, it is still unclear how users would experience co-performance and how the systems should be designed to support their co-performing experience over time. Due to this lack of understanding, current system designs have several limitations in supporting co-performance from a user-centered perspective. 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 co-performance can be taken place over the course of using the services, 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 these limitations, this research investigates the ways to support users' co-performing experiences for personalization of intelligent IT services. Indeed, the increasing discourses around intelligent, algorithmic, and autonomous systems emphasize the importance of exploring and supporting a new form of interaction between users and emerging technologies (Emanuel et al., 2016; Lustig et al., 2016). Building on these initial discourses, this research investigates the ways to support co-performance from a user-centered perspective. By doing so, this research aims to contribute to empowering users in the experience of intelligent IT services.

1.2 Research Aims

The fundamental research questions of this research are:

"How do users experience personalization and co-performance in intelligent IT services over time?"

"What do users expect from intelligent IT services by co-performing with the systems over time?"

"How intelligent IT services should be designed to support users' co-performing experiences over time?"

To answer these questions, this research pursues following aims:

Aim 1: To establish a theoretical background for the notion of co-performance as a theoretical lens toward empowering users in the experience of intelligent IT services

Aim 2: To understand users' perception and expectation of personalization and co-performance in intelligent IT services and to investigate design requirements for supporting co-performing experiences over time

Aim 3: To examine the impact of considering the design requirements in designing personalization and co-performing experiences in intelligent IT services

Aim 4: To add to the understandings of human-centered ways of supporting co-performing experiences in intelligent IT services

1.3 Research Methodology

1.3.1 Research Context

To investigate the research questions, the research context for empirical studies was further specified in terms of the service scope and the targeted users.

Service: On-the-Go Personal Assistant Services

Among many types of intelligent IT services, this research focuses on personal assistant services delivered through personal and mobile devices that continuously collect users' activity data throughout their daily lives and thus, have potential to leverage those data as a source of providing personalized support for users on the go, namely, **on-the-go personal assistant services** (Figure 1-1).

Figure 1-1. Example Scenarios of On-the-Go Personal Assistant Services (Self-Learning Intelligent Vehicle by Land Rover, 2014)

The reason to focus on on-the-go personal assistant services is that this type of services provides a representative service context, where co-performance is expected to be highly important to properly build a system's knowledge of a user and to provide personally meaningful supports to users. Also, as illustrated in the envisioning scenarios of personal assistant services in industries (Figure 1-1), this type of service aims to support users in a very close proximity to individual users' personal and social lives. Thus, investigating the ways to empower users to have control over this type of service was regarded to be a worthwhile starting point for designing co-performing experience.

Depending on the aims of this research, the instances of on-the-go personal assistant services were either selected from existing services or devised for the context of study. To investigate users' experience of personalization in intelligent IT services, an existing personal assistant service—a health assistant service delivered through commercial wearable activity tracking devices—was studied. While it provides basic forms of personalized services, it was selected because users are able to have a clear perception of what types of user data are collected through the system, unlike other types of personal assistant services (e.g., mobile AI assistants) of which mechanisms for data-driven personalization are often opaque to users. To investigate users' co-performing experiences, a research probe that simulates co-performing experience was devised and situated in the context of a user-created fictional personal assistant service in a car environment. The reason for asking study participants to create the own fictional service for this research was to naturally engage the participants to co-perform with the service with which they have genuine needs for personalization. The reason for selecting a car environment as a context of the fictional on-the-go personal assistant service was that it is expected as one of the promising environments where people expect personalized services while moving between diverse physical spaces (e.g., home, office, and social places) that are tightly related to users' personal lives.

Participants: Novice Users in their Young Adulthood

In terms of the target users, this research focuses on co-performing experiences of **novice users**, who are in their **young adulthood** (from 20 to 35 years old). As young adults have strong needs to manage their lives due to the radical transitions in their life contexts (Erik Erikson, 1980), they are expected to be benefited greatly from the personalized supports by on-the-go personal assistant services. The reason to focus on novice users was because that co-performing with the services is a relatively new experience for end-users and thus, it was expected to important to understand novice users' perception and expectation in interacting and co-performing with on-the-go personal assistant services in order to design the emerging technology-based services in a more acceptable and adoptable ways for current consumers.

1.3.2 Research Methodology

To investigate the ways to support users' co-performing experience, this research was conducted by utilizing qualitative research methods. This research was conducted in four phases (Figure 1-2): i) **a theoretical phase** for conducting a critical review of literature to build a theoretical background of this research and to identify the potential of co-performance perspective in empowering users in the experience of personalization in intelligent IT services (Aim 1), ii) **an empirical phase** for conducting two in-the-wild user studies to investigate design requirements for supporting co-performing experiences over time (Aim 2), iii) **an evaluative phase** for conducting a workshop-based expert interview to examine how the design requirements discovered from the research carried for Aim 2 inform the practice of designing personalization and co-performing experiences in intelligent IT services (Aim 3), and iv) **a synthesis phase** to add to the understandings on supporting users' co-performing experience (Aim 4).

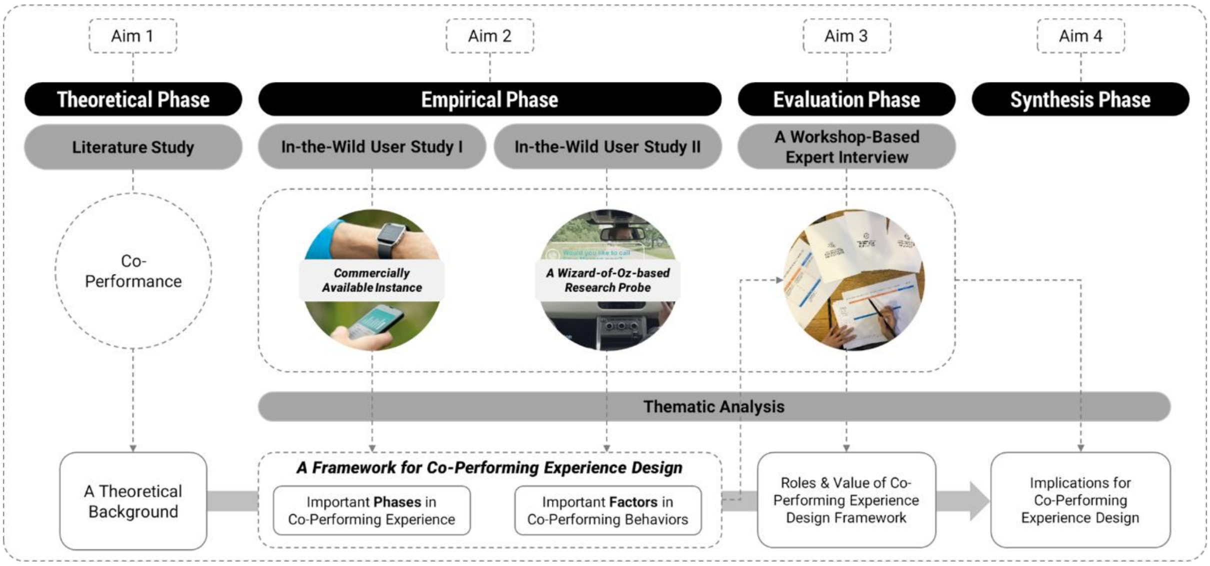

Figure 1-2. Research Overview

The Theoretical Phase (Aim 1)

To build a theoretical background for the necessity of co-performance perspective in designing for personalized service experiences, **literature study** was intensively conducted. The critical literature review was conducted focusing on the three major areas of research in the field of Human-Computer Interaction (HCI), Design, and User Experience design research: i) research on personalization in technology-based services and users' experiences in intelligent systems, introducing two major UX issues: transparency and controllability, ii) research on empowering users in the experience of intelligent IT services, and iii) research the notion of co-performance. By reflecting on the conceptual limitations in current approaches to cooperating with users, the notion of co-performance was proposed as a theoretical lens toward designing for personalization in intelligent IT services.

The Empirical Phase (Aim 2)

The empirical phase aims to investigate design requirements for supporting co-performing experiences over time (Aim 2). In order to investigate the requirements from a human-centered perspective, understanding users' genuine thoughts and expectations toward intelligent IT services and co-performing experiences is particularly important. For this aim, two different user studies were conducted *in the wild*: i) a three-week user study that investigated users' lived experiences of commercially available intelligent IT services in their own life context, and ii) a two-month iterative participatory design study, which utilized a Wizard-of-Oz-based research probe devised for this research purpose, in order to investigate users' actual co-performing experience in the wild and their expectations toward co-performance through iterative participatory design activities.

Study I: A Three-Week User Study to Investigate Users' Lived Experience of Intelligent IT Services

The first user study investigated user perception and expectation of on-the-go personal assistant services through a three-week deployment of wearable activity tracking services. To capture user perception and expectation of on-the-go personal assistant services, three research methods were utilized: i) **weekly semi-structured interviews** to understand how users experienced wearable activity tracking services and how such experience affected their perception and expectation of the service and further interactions with the health assistant service system, ii) **a diary** to collect more nuanced and vivid experiences (thoughts, feelings, and/or episodes related to the use of the given health assistant service.), and iii) **a redesign session**, which asked participants to redesign the system in terms of functions, visualizations, and interactions based on the three-week experience of the activity tracker, to further investigate participants' expectation on the tracker systems in a more explicit way. Regarding the collected, **thematic analysis** (Braun and Clarke, 2006) was conducted to discover the overall design directions for supporting co-performing experiences.

Study II: A Two-Month Iterative Participatory Design Study to Investigate Users' Co-Performing Experiences

The second user study aimed to investigate users' actual co-performing experiences. To simulate co-performing experience, a Wizard-of-Oz-based research probe, called Co-Performing Agent, was devised and deployed for two months. The probe was designed in a way that users can teach their everyday activity information for personalizing a fictional in-car assistant service and can experience the growth of the system's intelligence through a Wizard-of-Oz technique. In this sense, the purpose of devising the probe is well aligned with *experience prototyping* (Buchenau and Suri, 2000) and *user enactment* (Odom et al., 2012). To capture how users think of co-performing experiences, **semi-structured interviews** were conducted every week. Also, to inquire users' expectation of co-performing experiences, the probe was iteratively modified through weekly **generative sessions,** through which participants were able to modify what they teach and how they teach. Regarding the interview transcript and the outcomes from the generative sessions, **thematic analysis** (Braun and Clarke, 2006) was conducted to elicit important factors that should be considered in supporting co-performing experiences.

The Evaluation Phase (Aim 3)

The evaluation phase of this research aims to investigate the impact of considering the design requirements identified from the empirical phase in the practice of co-performing experience design.

Study III: A Workshop-Based Expert Interview

For this aim, a framework for co-performing experience design was developed by integrating the design requirements identified from the empirical phase as the elements of the framework. To examine the genuine value and roles of the framework in design, professional designers' reflection and evaluation were critical, because only those of who have experiences in designing personalization for actual end-user services can discuss how the framework affect their design approach, reflecting on their current practices. For this purpose, **a workshop-based expert interview** was conducted with eight professional designers individually. This in-depth expert interview was designed to compare designers' design approach to co-performance before and after utilizing the framework to examine the value and roles of the framework in designing co-performing experiences and intelligent IT services. To do so, designers' current practices for co-performance design was firstly investigated through semi-structured interviews. Then, designers were introduced to the framework through a tutorial and asked to redesign co-performing experiences in their current service by reflecting on the co-performing design framework. To investigate the changes in the designers' design approach before and after utilizing the framework, an in-depth debriefing interview was followed. By incorporating redesign activities with in-depth discussions, qualitative evaluation of the framework was conducted.

The Synthesis Phase (Aim 4)

The last phase of this research aims to add to the understandings of human-centered ways of supporting co-performing experiences in intelligent IT services (Aim 4). To do so, the relationships among the elements of the framework was furthered defined. In addition, by reflecting on the findings and insights, design principles for each stage of the framework were suggested. Lastly, to inform the ways to pursue human-centered personalization in intelligent IT services, which is the eventual purpose of co-performance, this research also suggests potential contents of co-performance by reflecting on users' expectation toward co-performing agents' knowledge of users.

1.4 Dissertation Outline

This dissertation consists of seven chapters as shown in Figure 1-3. Following describes the focus and outcome of each chapter.

Chapter 1 outlines this dissertation. It illustrates the motivation and research background of this dissertation. It presents four research aims that structure this research and the methodology used for this research. The four research aims are i) to establish the potential of co-performance in personalization of intelligent IT services, ii) to investigate design requirements for supporting co-performing experiences over time, iii) to examine the impact of considering the design requirements in designing personalization and co-performing experiences in intelligent IT services, and iv) to add to the understandings of human-centered ways of supporting co-performing experiences in intelligent IT services.

Chapter 2 establishes the notion of co-performance for personalization in intelligent IT services. This chapter reviews a critical literature review on the existing works in designing personalization and co-performance in technology-based services. This chapter introduces two major UX issues in intelligent systems: transparency and controllability and existing solutions to resolve the issues. By discussing the current approach to two UX issues, this chapter presents the notion of co-performance as a theoretical lens toward designing personalization in intelligent IT services.

Chapter 3 presents the three-week study, which investigated users' lived experience of intelligent IT services. This chapter presents how users' perception and expectation of intelligent IT service changed over time in three stages of user-system relationship development. Reflecting on the underlying reasons for the findings, this chapter suggests an overall direction to design for co-performance, i.e. a partnership mindset approach, and an initial set of implications for each stage of co-performing experience.

Chapter 4 presents the two-month participatory design study, which simulated and investigated users' actual co-performing experiences through a partnership mindset building approach. This chapter presents the factors that affect users' co-performing behaviors and their partnership with Co-Performing Agents.

Chapter 5 integrates the findings from the chapter 3 and the chapter 4 as a co-performing experience design framework. To examine the value and roles of the framework, this chapters presents the workshop-based expert interview. This chapter presents five design patterns that show how professional designers were informed by the framework and discusses how the framework contributes to overcome the challenges designers are currently facing in the practice of designing for co-performance in their services.

Based on the results of the three empirical studies, *Chapter 6* provides a broader reflection on the findings of this research. This chapter discusses the further relationships among the elements of the framework and suggest design principles for co-performing experience design based on the interpretation of the three empirical studies.

Lastly, *Chapter 7* concludes this dissertation by summarizing the major findings of this research and highlighting the contributions of this dissertation. This chapter also discusses the limitation of this research, suggesting future research directions.

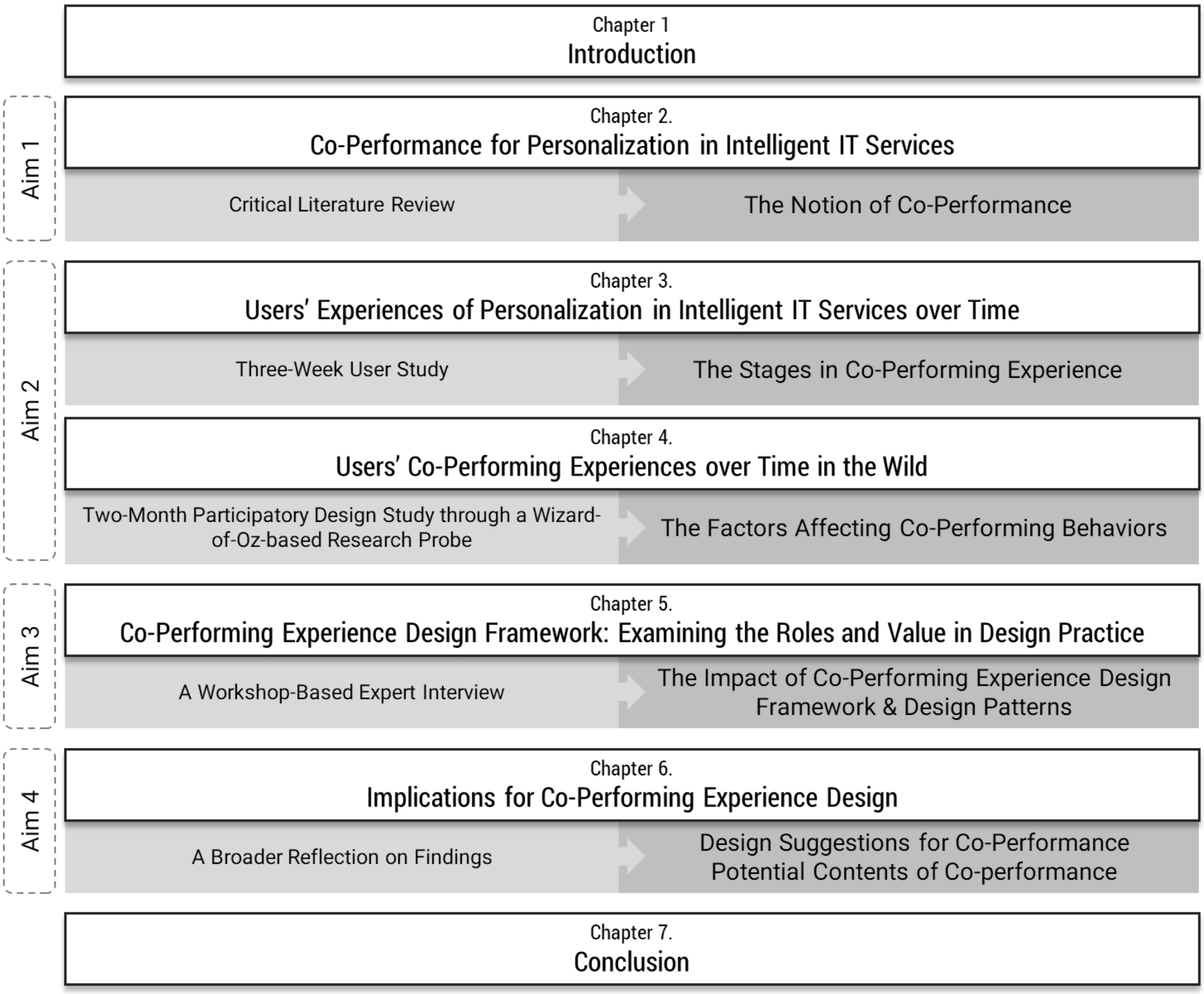

Figure 1-3. Dissertation Structure

CHAPTER 2.

Co-Performance for Personalization in Intelligent IT Services

Chapter 2.
Co-Performance for Personalization in Intelligent IT Services

This chapter reviews three major areas of research that this research builds upon: i) research on personalization in technology-based services and users' experiences issues in intelligent systems, ii) research on empowering users in the experience of intelligent IT services, and iii) research the notion of co-performance. By reflecting on the conceptual limitations in current approaches to cooperating with users, this chapter builds a theoretical background for the notion of co-performance as a theoretical lens toward empowering users in the experience of personalization in intelligent IT services.

2.1 User Experience of Personalization in Intelligent IT Services

To understand the importance of co-performance for personalization of intelligent IT services, it is necessary to understand how personalization is achieved in technology-based services. This section introduces the ongoing trends in personalization and the issues related to users' experiences of intelligent and autonomous systems.

2.1.1 Personalization in Technology-Based Services

Personalization, a broader term that includes user-adaptation, refers to *"the process of changing a system to increase its personal relevance to an individual"* (Blom 2000, p.1). Depending on who personalizes, technology-based services can be customized by users or automatically personalized by systems (Adomavicius and Tuzhilin, 2005; Fan and Poole, 2006), which is called as *user-driven personalization* and *system-driven personalization* respectively (Fan and Poole, 2006). In the user-driven personalization, systems explicitly require user inputs to clarify their preferences. In this sense, user-driven personalization is also referred as customization. In contrast, in the system-driven personalization, systems often covertly observe user behaviors and tailor the contents and appearance of the systems automatically. Although user-driven approach can be accurate, it demands the workload to users. While system-driven approach can be convenient, it can weaken the users' autonomy and controllability over the systems.

User-driven personalization has received much attention in late 1990s and early 2000s, especially after the introduction of interactive technologies, such as websites or customizable software (Sunikka and Bragge, 2012). However, with the emergence of intelligent technology that utilizes people's activity data collected from both online and offline environments, system-driven personalization is becoming increasingly prevalent in the emerging IT services.

Table 2-1. Current/Potential Input Data for Personalization in User-Adaptive Systems (Churchill, 2013)

Types	Examples
Person ("user") data	▪ demographic data ▪ knowledge-, expertise-, and experience-dependent personalization ▪ skills and capabilities ▪ interests and preferences ▪ intent, goals, and plans ▪ emotions ▪ physiological state
Behavioral and usage data	▪ movements (increasingly used for adaptive fitness applications) ▪ selective actions (information path analysis, link selection) ▪ ratings ▪ purchases and purchase-related actions ▪ broader task-related actions (bookmarking, printing, saving, sharing) ▪ temporal aspects of viewing behaviors (adaptation based on viewing time, analysis of micro-actions)
Usage regularities available from data	▪ usage frequency ▪ situation-action correlations, meeting requests, calendar entries ▪ action sequences, recommendations based on frequently used action sequences and those of others
Environmental data	▪ software environment, adaptation based on browser version, platform, device, configuration (e.g., location services on or off) ▪ hardware environment, adaptation based on device, bandwidth, processor or download speed, input devices, display devices ▪ locale (adaptation based on current geo location, social location, etc.) ▪ current conditions (hot, cold, ambient noise, light, dark)

Thus, most of intelligent IT services incorporate system-driven approach to personalization by following the process of **collecting**, **reasoning**, and **acting.** First, systems collect data about users through diverse channels. In the context of emerging technology-based services, diverse types of user-related data, including data about a user's characteristics, behavioral patterns, usage patterns, and surrounding environments (**Table 2-1**), are collected while people are using the services. Then, those data become the source of understanding those users (e.g., physical states, routines, preferences, interests, emotion, etc.). Based on the user profile developed through this process, systems provide personalized supports through diverse channels in people's everyday lives (e.g., smart phones, wearables, smart home appliances, and connected cars).

The notion of personalization has been pursued in diverse domains of research, including software agents, adaptive user interfaces, robots, and emerging IT products and services. For instance, the potential of automated personalization has been demonstrated through diverse prototypes of **intelligent agents** (Kay, 1984; Negroponte, 1975; Maes, 1994). Research on intelligent agents have extensively studied ways to support users with computer-based tasks, such as email management (Maes, 1994), meeting scheduling (Mitchell et al., 1994; Kozierok and Maes, 1993), news filtering assistant (Sheth and Maes, 1993), and entertainment contents selection assistant (e.g., a music recommendation assistant (Shardanand and Maes, 1995)). Also, a body of works in **adaptive user interfaces** (UI) has studied to develop an interface that automatically adjusts content, layout, or visual presentation based on individual users' use patterns in order to reduce the steps for UI navigation and selection (Billsus et al., 2002), as well as to optimize UI for people with accessibility issues (Gajos and Weld, 2005). In addition, researchers in the field of **socio robots** also emphasized a robot's memory and adaptation as important aspects of social robots to build a long-term relationship with the users (Dautenhahn, 2004; Ho et al., 2009; Lim et al., 2011). Some initial works attempted to build social robots that learn a user's name (Kanda et al., 2003, 2007) and an social robot that personalizes small talks when delivering the services based on the previous interaction history between users and the robot (Lee et al., 2012). The potential of automated personalization has been also appreciated in the new forms of products and services that have been emerged recently. For instances, **Internet of Things** (Cila et al., 2017) in home pursue to adapt domestic environments more proper to the family routines and lifestyles (e.g., Nest learning thermostat) and mobile phones become a central channel to deliver diverse personalized supports for users, such as 'nowcasting' in mobile phones (Sun et al., 2016).

2.1.2 User Experience Issues in Intelligent IT Services

As shown in the examples in the previous section, intelligent systems have great potential in supporting people in an unprecedented way. However, their adaptive, and sometimes proactive behaviors have been known to cause negative influences on users' experiences of the systems.

Issue of Transparency & Controllability

First, it is often difficult for users to understand how a system works (e.g., what it knows, how it knows the information, and what it is doing with the information), as intelligent systems are not often designed to be intelligible and transparent to users (Bellotti and Edwards, 2001). For example, context-aware systems have often confused people because those systems employ make decisions based on complex rules and learning models by deploying implicit inputs (Bellotti and Edwards, 2001; Lim, Dey and Avrahami, 2009; Hardian, Indulska and Henricksen, 2006). A study of more recent forms of conversational agents also highlighted that users experience difficulties in developing a proper mental model of system capability due to the lack of system feedback and transparency (Luger and Sellen, 2016).

Second, users can lose their sense of control over the systems, because intelligent systems often exhibit autonomously adaptive and proactive behaviors (Höök, 2000; Zimmerman et al., 2007; Weld et al., 2003; Montague, Hanson and Cobley, 2011). For instance, intelligent systems can create a "filter bubble" (Pariser, 2011), which limits users' exposure to diverse information by hindering users' opportunities to explore other types of information that they have not been interested before. The anecdotes in more recent works also highlighted these user experience issues as well. For instance, in the study of understanding the lived experience of Nest, a learning thermostat (Yang and Newman, 2013, 2012), the authors reported one participant who got annoyed by her Nest, as it automatically adjusted heating temperature of the home. It happened just after the participant turned the heating temperature down for her pregnant daughter, who was visiting and did not prefer a high temperature. Thus, the participant was unhappy with the changes made by Nest based on its own assumptions and that Nest did not provide the participant control over the changes.

Issues with Human-Centered Personalization of Intelligent IT Services

The aforementioned user experience issues become increasingly problematic in personalization of intelligent IT services, as the technologies are continuously advancing in inferring the traits and intents of users from the data about those users. For instances, a body of work in activity sensing technologies have suggested ways to infer diverse types of everyday activities of people from their physical activity data, including exercising (Morris et al., 2014), sleeping (Hao, Xing and Zhou, 2013), and transporting (Reddy et al., 2010). In addition, a body of work in interpersonal data collected from personal mobile phones (e.g., personal contact history) and social media have studied to model the types and strengths of social relationship among people (Min et al., 2013; Wiese et al., 2015). In the study of users' online traces (Kosinski, Stillwell and Graepel, 2013), researchers even reported that they were able to model latent traits of a user—a trait that is not known or disclosed at all—that are fairly private by using only his/her 'Facebook Likes' data, such as "sexual orientation, ethnicity, religious and political views, personality traits, intelligence, happiness, use of addictive substances, parental separation, age, and gender."

While all these advances in inferring technology can accelerate the trends for automated personalization in intelligent systems, it has rarely been discussed whether such level of inference and automated personalization are desired by users or not. These issues also raise the question of whether system-driven approach is an appropriate way to provide personalized support through intelligent IT services. Rather, this suggests that it is important to investigate the ways to provide personalized support that are perceptually acceptable and trustful by users, instead of delivering the services only focusing on its technical correctness. The following sections discuss how those kinds of user empowerments have been studied.

2.2 Empowering Users in the Experience of Intelligent Systems

As the issues of transparency and controllability become more problematic in the context of increasingly intelligent IT services, researchers have continuously emphasized the importance of empowering users in the experience of intelligent systems and personalized services (Lee et al., 2015; Churchill, 2013; Lustig et al., 2016). In this regard, researchers have made attempts to investigate the ways to increase the transparency of how intelligent systems works and to give users more control over the systems (Ball and Callaghan, 2011; Callaghan and Ball, 2012; Hardian, Indulska and Henricksen, 2006). Existing approach to empower users in the experience of intelligent and autonomously personalized systems are mainly three-fold: i) providing explanations, ii) giving users ways to control system behaviors, and iii) involving users in the process of systems' learning.

2.2.1 Providing Explanations

Providing explanations have been identified as an effective way to increase transparency of intelligent systems, such as recommender systems. In this regard, several types of explanations were proposed as a mechanism to solve the issue of transparency (Lim, Dey and Avrahami, 2009; Rader, Cotter and Cho, 2018; Kizilcec, 2016). *Why* explanations provide justifications for recommendation outcomes, but do not explain how the system works in detail. *How* explanations provide a description of how a system produce a recommendation to the users by detailing the function of the system. Recently, two additional types of explanations were also proposed in the recent study of algorithmic interfaces (Rader, Cotter and Cho, 2018): *What* explanation describes the existence of algorithmic decision making (e.g., algorithmic curation of Newsfeed on social media) in order to increase the algorithmic awareness (DeVito et al., 2018) of the users. *Objective* explanations describe how the system is developed (e.g., how the algorithms were designed and tested). The studies on the intelligibility research have investigated how those explanation mechanisms affect users' understanding and trust toward system behaviors and showed the positive influences of the explanations. For example, Cramer et al. (2008) revealed that providing an explanation of why certain contents are recommended can increase users' trust and acceptance of recommendations (Figure 2-1).

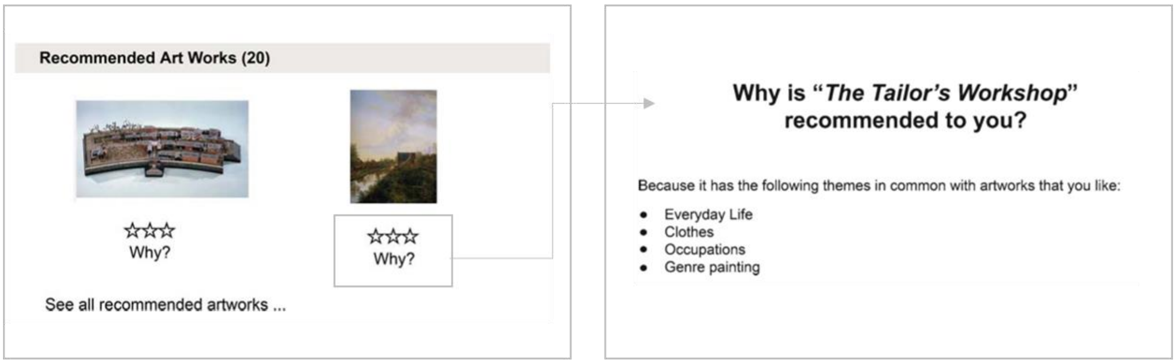

Figure 2-1. An Example of Why Explanations in Art Work Recommendation (Cramer et al., 2008)

2.2.2 Giving Users Control over the Systems

Providing a control interface for users to manipulate system behaviors is another popular way to challenge the controllability and transparency issue. For example, Kulesza et al. (2012) attempted to provide manual controls to the factors attributed to the recommendation results so that users can better understand the underlying mechanisms of recommendation systems (Figure 2-2). More recently, the controllability issue arose in the context of social media newsfeed algorithms as well. To give users more controllability over the system, Eslami et al. (2015a; b) developed a system called

FeedViz, which visualizes both filtered and unfiltered newsfeeds, so that users can compare the results and control the priority of contents in their newsfeeds. This line of works has repeatedly shown that giving people options increases their perceived control over the systems (Heckhausen and Schulz, 1995) as well as their actual ability to manipulate underlying mechanisms of recommender systems to make the personalization result better matched with their satisfactions, as they have opportunity to build a sound mental model toward how systems behave (Kulesza et al., 2012).

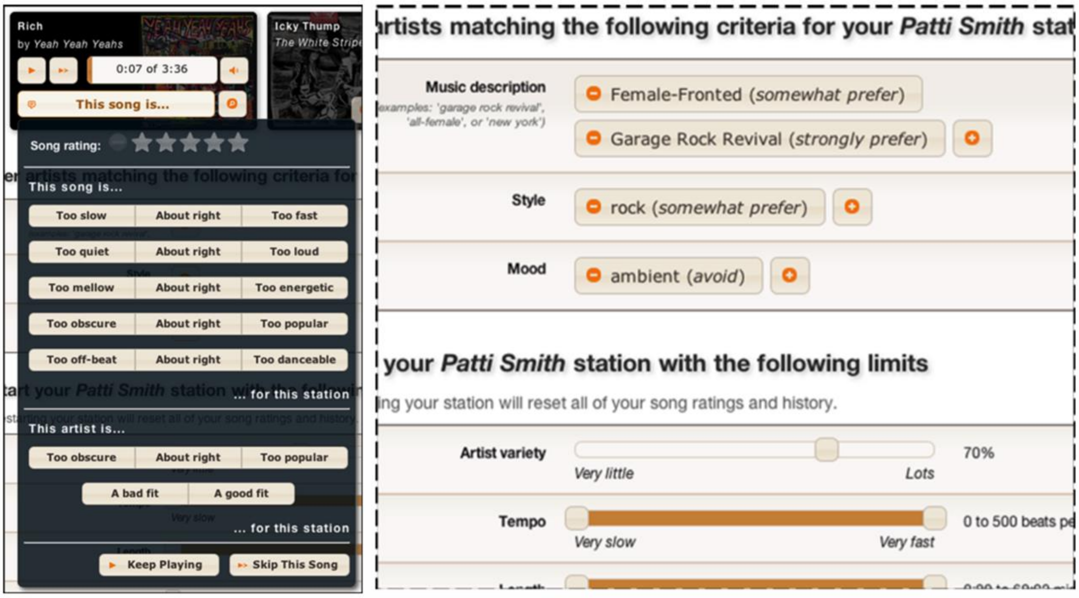

Figure 2-2. User-Debugging Interface for Music Recommendations (Kulesza et al., 2012)

These attempts suggest a way to increase the visibility of black-box processes of personalization in intelligent systems. However, increasing discourse (Lustig et al., 2016; Emanuel et al., 2016) calls for a new way of balancing the level of transparency, as it is becoming almost impossible for users to comprehensively understand the ever-increasing complexity of intelligent systems, and it violates the very purpose of intelligent systems in reducing users' cognitive overload (Höök, 2000).

2.2.3 Involving User Inputs in Systems' Learning Process

As a way to empower users in the experience of intelligent IT services, there also have been attempts to involve users in the process of systems' learning. For instance, the notion of *programming by demonstration* or *programming by examples* (Cypher, 1993; Lieberman, 2001) have been incorporated in designing interface agents, to make system learn the ways users perform a repetitive task 'over the shoulder'. Also, research on *active learning* have incorporated users in machine learning process by enabling them to label a set of data for machine learning (von Ahn and Dabbish, 2004). Users' inputs have been also incorporated in the field of crowdsourcing to improve systems' knowledge in a collective level (Cranshaw et al., 2017).

A body of work has demonstrated systems that explicitly interact with users to get inputs from those users. Aligning with this line work, Sheth & Maes (1993) demonstrated how a combination of technique of *artificial evolution* and technique of *learning from feedback* can be used to evolve a personalized system for automatic information filtering. Also, Dey et al. (2009) investigated how intelligent systems should ask users for input to improve system intelligence. In addition, Stumpf et al. (2012, 2009) explored how end users might interact with machine learning systems beyond the communication of simple right/wrong judgments and examined how those kinds of user feedback can be implemented into a system and how such user input actually increases the accuracy of machine learning results.

As user inputs were proven to contribute to improve systems' intelligence, previous research also investigated the ways to elicit more participation from the users. For example, a work on participatory sensing systems proposed giving information rewards to users only when users are participating in the system (Tomasic et al., 2014). Also, some of machine learning systems incorporated gamification approach to engage people in image labeling tasks (von Ahn and Dabbish, 2004). In addition, social comparison was also used to elicit users' intrinsic motivation to participating in improving systems' intelligence (Harper et al., 2007).

2.3 Co-Performance as a Theoretical Lens toward Designing for Personalization of Intelligent IT Services

One of the common characteristics of existing solutions to empower users in the experience of intelligent IT services is that those approaches involve *users' participation* to some extent. For example, explanation mechanisms invite users to have chances to explore and understand the ways how a system works, and control interfaces more explicitly involve users to manipulate the internal mechanisms or outcomes of the systems. Given that these mechanisms have been proven to increase transparency and a user's controllability over a system, users' participations in making system behaviors would still have potential to resolve these issues.

Meanwhile, while it was not clearly discussed in the previous research, this way of empowering users in the experience of intelligent IT services is theoretically conceptualized as *co-performance* (Kuijer and

Giaccardi, 2018). The authors proposed the notion of co-performance against the notion of smartness that are *"scripted at design time"* (Kuijer and Giaccardi, 2018, p.1). Instead, they argued that a technological artifact should be evolved over time by learning from the situated and sustained interplay with humans in the practice. In this regard, this conceptualization of co-performance provides a well-established theoretical lens to designing intelligent IT services that can be adjusted *together with users* (Lee et al., 2015; Huang et al., 2017; Eslami et al., 2015b), rather than making the systems decide what users would experience by themselves. In addition, the recent discourse on human-agent collaboration (Bellamy et al., 2017) and studies that developed intelligent systems to work with users (Huang et al., 2017) also confirm the importance of understanding user-agent interactions from the perspective of co-performance.

To pursue the notion of co-performance in this research as a theoretical lens toward designing for personalization in intelligent services, this section discusses why it is worthwhile to adopt the perspective of co-performance particularly in the context of designing for personalization in intelligent IT services by discussing the experiential quality that the notion of co-performance embrace in designing intelligent IT services: i) systems' openness to users, ii) reciprocal participation, and iii) interactions over time.

2.3.1 A System's Openness to Users

As shortly discussed earlier, the notion of co-performance appreciates a system that is not solely designed from the beginning, but rather have openness to be adjusted through use in a user's situated life contexts (Kuijer and Giaccardi, 2018). In their paper, the authors defined co-performance as follow:

"In contrast to 'smartness,' which focuses on a supposed autonomy of artifacts, co-performance considers artifacts as capable of learning and performing next to people. This shifts the locus of design from matters of distributions of agency at design time, to matters of embodied learning in everyday practice for both human and artificial performers. From this perspective, co- performance acknowledges the dynamic differences in capabilities between humans and artifacts, and highlights the fundamentally recursive relation between professional design and use." (Kuijer & Giaccardi 2018, p.1)

As this notion appreciates the process of shaping the role of artificial agency together with users, Kuijer and Giaccard (2018) noted the value of co-performance perspective as follow:

"a co-performance perspective could help the HCI community to formulate design methods apt to determine the desirable dimensions of openness of the technology and thus repair performances by the artifact that are deemed inappropriate under situated circumstances." (Kuijer & Giaccardi 2018, p.9)

Although they did not specify the notion of co-performance in terms of personalization perspective, overall conceptualization of their notion of co-performance are tightly aligned with what this research aims to pursue. Thus, this research will consider a system's openness to users as an important experiential quality to afford through user-system co-performance. By embracing the openness to users in relation to the issue of controllability and transparency, this research expects to investigate more human-centered ways of personalization and co-performance in intelligent IT services.

2.3.2 Reciprocal Participation

The notion of co-performance also embraces reciprocal participations of users and systems in personalization of intelligent IT services. In relation to this collaborative position of user-agent relationship, there have been attempts made to involve users in improving the system intelligence. For instance, the notion of *programming by demonstration* or *programming by examples* (Cypher, 1993; Lieberman, 2001) have been incorporated in designing interface agents, to make system learn the ways users perform a repetitive task 'over the shoulder'. Also, research on *active learning* have incorporated users in machine learning process by enabling them to label a set of data for machine learning (von Ahn and Dabbish, 2004). Users' inputs have been also incorporated in the field of crowdsourcing to improve systems' knowledge in a collective level (Cranshaw et al., 2017).

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While previous works contribute to demonstrate the feasibility and accuracy of involving users in intelligent learning systems, they tended to regard users as a 'worker' to improve machine intelligence. For instance, the goal of existing approach to involving users in systems' learning process has been oriented toward a system-centered perspective by questioning how the systems can get more information from more users. However, in the context of personal assistant services, users may also like to learn about systems to know how those systems can help the users. In this sense, it seemed also important to have a user-centered perspective by questioning how users' experience of the service should be supported over time to help them get to know about systems. Thus, highlighting reciprocal participations are deemed to be important to posit users and systems as an equivalent collaborator for personalized services.

In this regard, human-computer collaboration (Lucas et al., 2010; Bellamy et al., 2017) can be the most related concept to the notion of co-performance. Although the term 'collaboration' is aligned with co-performance as it also considers the practice of human and computer working together, it may not properly represent the notion of co-performance, because the term collaboration is often used in a context where *a specific task* exists to *achieve a shared goal*. Rather, the notion of co-performance has more emphasis on the practice of human and computer interacting *to understand* each other and *to express* themselves for the purpose of improving each other's understanding of the other, instead of carrying out certain tasks.

2.3.3 Interactions over Time

The notion of co-performance also considers temporality as an important experiential quality of intelligent IT services: *"Over the course of repeated performances and alongside changed body/minds, [...] the ideas of appropriate practice embodied in both human and artificial body/minds change."* (Kuijer and Giaccardi, 2018, p.4)

In fact, there has been a body of work that emphasized *temporality* as an important dimension of user experience in products and services in general. User experience research have investigated how users' perception of products and systems change over time. In the long-term design ethnographic studies, how the interactions between users and interactive artifact changes over time is described. For instance, Gaver et al. (2013) described ***a trajectory of technology adoption and appreciation***. When a new technology is first introduced, it may be initially embraced with excitement, as it is novel. After the initial excitement, people experience the frustration and disappointment, due to the technologies that potentially do not meet their expectations. Over time, people will enter into a state of understanding and the technology will be either abandoned or accepted. If accepted, peoples' experience with the technology may improve as they develop their ways of dealing with the difficulties in uses. Eventually, the technology can integrate into everyday life (Gaver et al., 2013). Odom et al. reported how this trajectory of appreciation unfolded with their Photobox prototypes, a domestic technology that prints four or five randomly selected photos from the owner's Flickr collection at random intervals each month (Odom et al., 2014). Karapanos et al. (2009) provided the description of the changes in user perception in a more systematic way. They proposed three phases in the adoption of the product, namely, *Orientation, Incorporation,* and *Identification*. They revealed that different product qualities affect the evaluative judgement of product. For example, stimulation and learnability are appreciated in orientation phase, whereas long-term usability and usefulness become more appreciated as people move into incorporation phase (Karapanos et al., 2009). User experience research have appreciated the value that can be achieved from long-term interactions between users and artifacts, such as product attachment, ownership, and emotional relationship (Bickmore and Picard, 2005; Peltu and Wilks, 2010; Turkle, Taggart and Kidd, 2006).

Despite of this importance of temporality, the existing approach to empower users have limitations as they mostly regard users' participations into the systems' learning as a task-oriented interaction that occur in a fragmented manner. However, since intelligent systems often learn and evolve over time, co-performance would take places over the course of using intelligent IT services. This temporal consideration raises more questions on how current systems support users' interactions with the systems over time. For instance, in the case of a system that provides explanations on why a certain recommendation is suggested, what if users cannot fully understand the explanation? Do the systems provide further options to those users in order to continue supporting them in understanding the systems' behaviors? If not, how should the systems be designed to react to those users in the following interactions?

However, considerations on temporal aspects of user experience in intelligent IT services have mostly focused on initial phase of interaction and do not much inform how to support users over time. For this reason, many researchers have reported that users' engagements with emerging smart products and services do not last over time. For instance, a survey of wearable activity trackers owners revealed that users abandoned the devices after a short period of actual use (Ledger and McCaffrey, 2014). Thus, the studies (Lazar et al., 2015; Epstein et al., 2016) have been emerged to investigate the reasons of the early abandonment of smart devices (e.g., smart band and activity tracking devices) and revealed that people abandon the devices because the ways those devices work were not often matched to their original conception of the devices (e.g., data collection) (Lazar et al., 2015).

To fill this gap, empirical studies in this dissertation are designed to observe users' perception and expectation of intelligent IT services *over time*. Also, the studies are designed to inquire users' perception and expectation of intelligent IT services and co-performing experiences repetitively over the course of use with intervals, instead of inquiring them though one-time interview. By doing so, this dissertation aims to inform the design of co-performing experience over time as well as the design of overall user experience over time in intelligent IT services.

2.4 Summary and Discussion

This chapter presented a critical literature review to build a theoretical background of co-performance by establishing a conceptual perspective of this research in investigating human-centered ways to empower users in the experience of intelligent IT services. Although users' participation has potential to empower users in the experience of personalization in intelligent IT services, the reviews of previous research highlighted that most of related works have been conducted from a technology-centered perspective. Thus, it revealed a lack in informing human-centered designs to support co-performance over time. With this gap in mind, this research aims to explore the notion of users' co-performing experience and investigate the ways to support users as an empowered co-creator of the personalized services over time. In doing so, the term co-performance is used to mainly refer to the participation of a user in a system's learning process to help the system acquire better knowledge of its user in providing personalized services. However, to highlight the mutual participation of a user and an agent in learning process, this research uses the term co-performance to refer to "a collaborative process of learning between a user and a system, in which a user expresses what s/he wants the system to learn about her/himself and the system expresses what it knows about the user."

One of the remained questions in pursing the notion of co-performance lies in its eventual outcomes: what does it mean to be intelligent from the perspective of human, which should be pursued in personalized intelligent services through co-performance?

Regarding this question, there has been a doubt about whether the ways system-driven inferences are used in current personalization approach are desirable or not in a human perspective. For example, while many social media curates the newsfeed based on the strength of social ties, studies have shown that users may not appreciate those smartness, because it often hides close friends from their newsfeed due to the algorithmic inferences (Eslami et al., 2015b). Also, several works, which investigated the role of proactive technology in home (Mäyrä et al., 2006; Koskinen et al., 2006; Lee et al., 2008; Taylor et al., 2006) have shown that people were happy to delegate ambient services and routine tasks to proactive technology, which automatically perform those tasks, but they wanted to keep control of more complicated and changeable tasks (Koskinen et al., 2006). These issues imply that products and services that are intelligent in technical terms (e.g., accuracy and performance) might not always be experienced as intelligent for users with own use context and personal value.

Emerging design research also show the importance of this question to be investigated in a design point of view (Dove et al., 2017; Valencia et al., 2014). For instance, Valencia et al.(2014) reported that designers of Smart Product-Service Systems face the challenges of defining value proposition in intelligent systems, which can dynamically change over time, *due to the lack of understanding on humans* and the lack of proper tools to be used in design practice (Valencia et al., 2014). Also, user experience designers, whose practices increasingly require the integration of intelligent technology into their products and services, experience difficulties in understanding how to utilize machine learning technology make their services *bear human value* (Dove et al., 2017).

Reflecting on these discussions, understanding human-centered meanings and values of personalized intelligent IT services would be important to pursue meaningful personalization through co-performance and to build on the challenging discourses around machine intelligence. With this question in mind, this research will investigate the human-centered meaning and roles of personalization in intelligent IT services throughout this research.

CHAPTER 3.

Users' Experiences of Personalization in Intelligent IT Services over Time

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Users’ Experiences of Personalization in Intelligent IT Services over Time

As the first step to investigate the human-centered ways to support co-performing experiences, this chapter presents an investigation of users’ experience of personalization in intelligent IT services (i.e. on-the-to personal assistant services) over time. Based on the findings, this chapter sets up the overall direction to support co-performing experiences, which will be further investigated in the rest of this research.

3.1 Study Aim

The aim of this study was to understand how users perceive on-the-go personal assistant services and what they expect from those services, because it was expected that such understanding provides implications on how to support co-performing experiences in a human-centered perspective. Since on-the-go personal assistants are not static in terms of data leverage, this study aimed to investigate users’ experiences of on-the-go personal assistant service throughout the overall cycle of use. Although recent studies have investigated the issues in using and adopting emerging personal assistant services, those works have more focus on moment-by-moment interactions, rather than users’ experience of the systems over time.

3.2 Study Method

3.2.1 Research Context

In this study, a health assistant service delivered through wearable activity tracking devices were selected as a basic instance of on-the-go personal assistant services. A wearable activity tracker was selected because it is one of the most accessible form of on-the-go personal assistant services that end-users could use and experience in their actual daily lives. In addition, wearable activity trackers provided a timely context to be studied among many other types of smart products and services, because they had been increasingly purchased by consumers, but often abandoned after a short period of actual use (Ledger and McCaffrey, 2014). Thus, this disappointing uptake of wearable activity trackers added the motivation of this study.

For the study, two commercial wearable activity tracking services, Fitbit Flex and JawboneUp 24, were selected as they had a dominant market share as of the study, July 2014. Both services collect users' daily activity data through the sensors embedded in the wearable devices and directly from users' logging (e.g., the traces of walking, exercising, and eating) and attempt to provide health-related assistance to help users manage their health behaviors (e.g., workout, sleep, and food intakes).

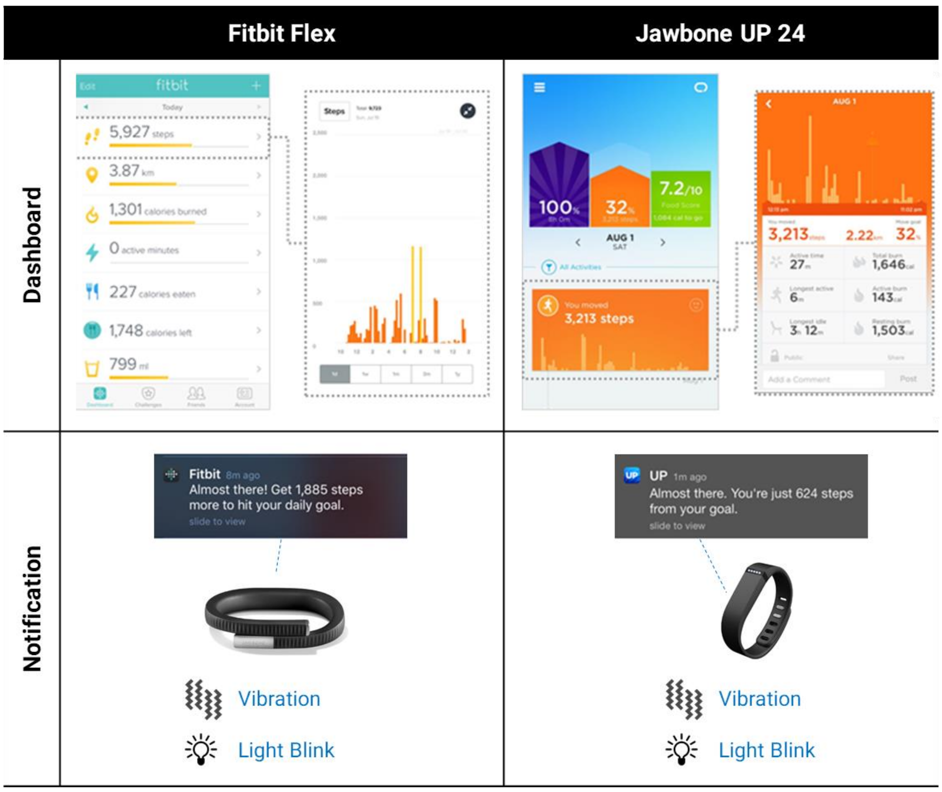

Figure 3-1. Personalized Advisory Information on Fitbit Flex and JawboneUp24 (July 2014)

While the ways that each system provides the personalized feedback to users are not identical, both services commonly provide two types of personalized advisory information based on users' physical activity tracking data (Figure 3-1): i) a *dashboard,* which summarizes a user's physical activities, food intakes, and sleep patterns in the quantified and visualized ways and ii) *notifications,* which remind a user's daily goals (e.g., daily goal of walking, water intakes, and workout) and recommend health-related activities to support users in achieving their daily goals. Although these services do not incorporate co-performance or provide advanced learning-based services, they were enough to understand how users would perceive and what they expect from the systems that explicitly collect their activity data and support them throughout a day.

3.2.2 Participants

To explore how young adults, i.e., the target user group of this dissertation, experience these on-the-go personal assistant services in their daily lives, participants who were in their 20s or 30s and have interests in managing their everyday health behaviors were recruited (Table 3-1).

Table 3-1. Detail Information of the Participants

Participant #	Age/Sex	Major Interests in Health
J1	27/F	**Food intake** (calorie-controlled diet)
J2	27/F	**Food intake** (nutritional supplements) **Sleep** (regular sleep)
J3	27/M	**Workout** (Balancing aerobic and anaerobic exercise) **Sleep** (regular and quality sleep)
J4	24/F	**Workout** (regular workout) **Food intake** (nutritional balance, water intake)
F1	20/M	**Workout** (regular workout) **Food intake** (nutritional balance) **Sleep** (regular sleep)
F2	19/M	**Workout** (regular workout) **Food intake** (nutritional balance, abstaining from alcohol)
F3	26/F	**Workout** (enhancing activity level) **Food intake** (nutritional balance) **Sleep** (quality sleep)
F4	31/M	**Workout** (cycling and swimming) **Food intake** (abstaining from caffeine at night)

These participants were recruited through an online screening survey, which included the questions about demographic information, personal health interests, and previous experiences of using wearable activity tracking services. Among 48 responders who applied to the study, eight participants (four females) who did not have previous experience with two activity tracking services were recruited to understand users' genuine thoughts, feelings, and behaviors with regard to the systems. Also, they were selected to include a varying degree of interests in health-related information supported by Jawbone and Fitbit (i.e., workout, food intake, and sleep). Each participant was randomly assigned to use either Fitbit or Jawbone and given the hardware for the study. In the rest of this dissertation, participants will be referred by the initial letter of the service they used in the study and their participant number (e.g., F1, J1).

3.2.3 Study Design

A three-week user study was designed to effectively observe interactions over time with wearable activity trackers. At first, each participant was invited to a lab and asked to setup the device and application by him/herself. During this process, participants were asked to speak out their thoughts, feelings, and expectations on the systems so as to capture their vivid initial experiences. After then, participants used their wearable activity trackers for three weeks in their daily lives, writing a diary of thoughts, feelings, and/or episodes related to the user of the activity trackers (Figure 3-2).

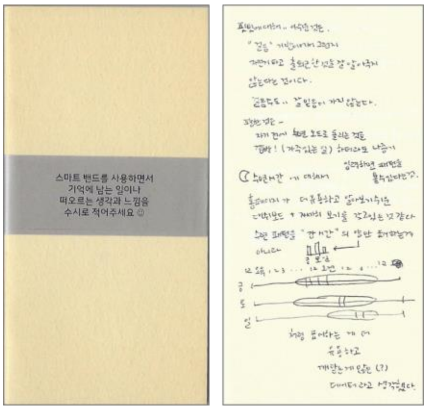

Figure 3-2. Diary: Participants were asked to write a diary of any thoughts, feelings, and episodes during the use of activity trackers (Example of F1)

Participants were not forced to mandatorily wear or use the tracker for the sake of the study in order to observe participants' natural engagement with the tracker systems. Finally, at the end of the third week, they visited the lab again and was asked to uninstall the tracker device. Participants were asked to think aloud their terminal impressions as well. By simulating the use experiences from installation to uninstallation, the three-week deployment was expected to allow participants a reasonable amount of time to explore and use the service.

Semi-structured interviews were conducted with each participant every week to understand their perceptions and expectations on the given tracker system. In each interview, the diverse aspects of experience with the tracker systems were inquired (e.g., use of the physical device, dashboard interaction, and use of third-party applications). Participants were asked to reflect on positive or negative experiences with the system by asking the features they used most/least meaningfully and the features they lost interests and no longer using. Detailed inquiries were followed to understand how such experience affected further interactions with the tracker system.

To further investigate participants' expectation on the tracker systems in a more explicit way, each participant went through redesign session after the three-week study. In the session, participants were asked to redesign the system in terms of functions, visualizations, and interactions. Based on the three-week experience of the activity tracker, participants marked that how they want certain features and interactions of the system to be redesigned either by drawing or by annotating on the screenshots of dashboard in their tracker application (Figure 3-3). After then, the reasons why they redesigned the features were inquired.

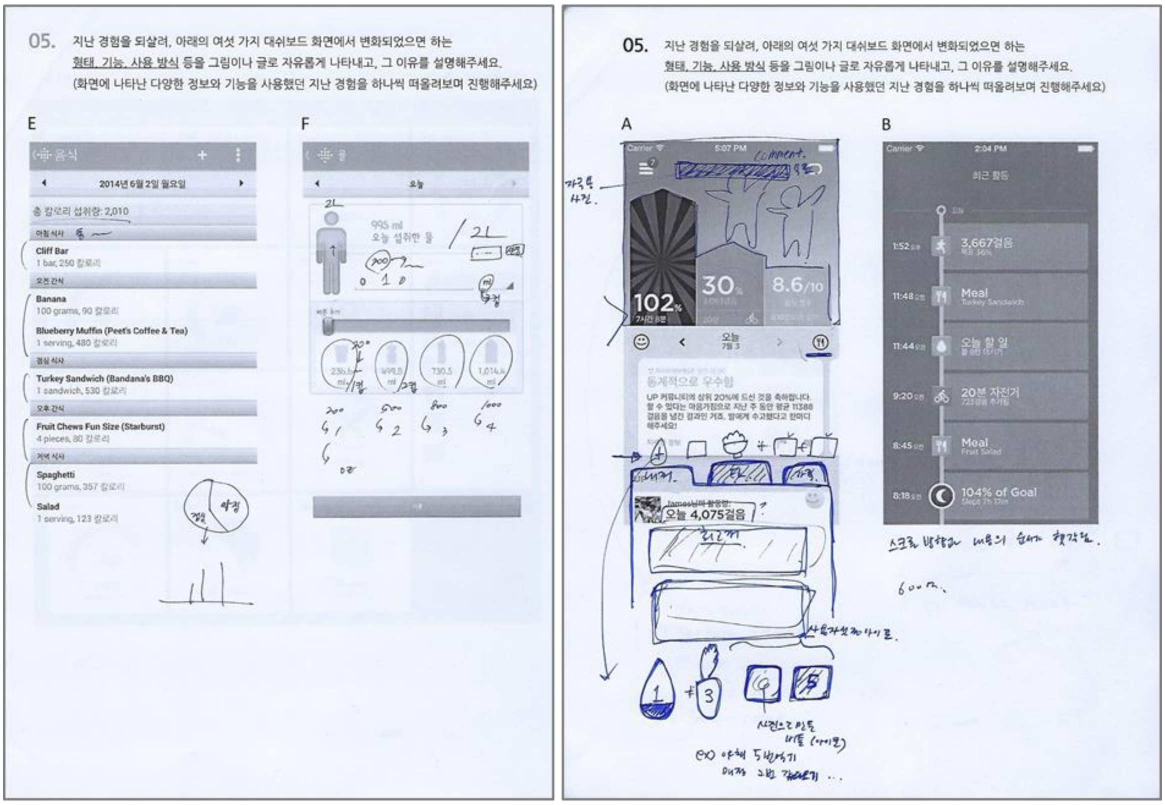

Figure 3-3. Materials for Re-design Session (left: for Fitbit users, right: for Jawbone users)

3.2.4 Data Analysis

For data analysis, all users' utterance from the interviews, diaries, and redesign sessions were transcribed and deconstructed by articulations of feelings, thoughts, and episodes with regard to the experience of wearable activity tracking service. Each articulation was specified by relevant features of the given tracker systems, and by day/week of the comments (e.g., day 1, week 1, week 2, and week 3). Similar articulations regarding the same feature from the same participant were grouped. This process resulted over 324 articulations of tracker users' experience with the systems.

Four researchers who conducted this study created aforementioned data set and went through thematic analysis. Four researchers developed initial codes with regard to user perception and expectation on wearable activity trackers, which underlie the feelings, thoughts, and episodes. The examples of initial codes include: expectation on complete data collection, expectation on learning, and expectation on becoming fit to personal routines, etc. Four researchers developed initial open codes by reviewing the data and iteratively analyzed the emergent patterns and themes across the data. By developing a thematic map of the codes, temporal patterns of user perception and expectation were identified, namely, Initiation & Experimentation stage, Intensifying & Integration stage, and Stagnation & Termination stage, which will be elaborated in the next section. Four coders individually coded all articulations by these stages. By cross-checking the results, all coders discussed whether other stages were necessary to describe the data and finally reached a consensus on the three stages.

3.3 Findings: Changing Perception and Expectation of On-the-Go Personal Assistant Services over Time

From the data analysis, it was found that participants tended to treat the wearable activity tracking services (i.e. on-the-go personal assistant services), as if they interact with human-like actors, and participants tended to evaluate their experience of the wearable activity tracking services by (unconsciously) applying the similar social rules they apply for human-human relationship. Such socio-psychological perception and expectation on the wearable activity tracking services changed over time, as users' perceived relationship the systems developed over time.

To better describe those changing perception and expectation of on-the-go personal assistant services, Knapp's interpersonal relationship development model was adopted (Knapp and Vangelisti, 2004), which describes the stages of interpersonal interactions in two directions of relationship development (Figure 3-4): the stages of coming together and coming apart. According to the Knapp's model the stages of coming together include *initiation, experimentation, intensifying, integration,* and *bonding* stage.

- **Initiating**: This stage refers to the very short moment of making the first impression. People try to exhibit behaviors that make them look pleasant, likable, and socially adept.
- **Experimenting**: This stage refers to the period where two encounters try to explore and experiment the common interests among them to get to know each other.
- **Intensifying**: In this stage, the relationship intensifies and become less formal. People may start to reveal personal information.
- **Integrating**: In this stage, people will start to make their relationship as much closer than before by calling them as boyfriend and girlfriend. As they share many aspects of their lives, their identity will be blended each other.
- **Bonding**: At this stage, people will make their relationship more durable by getting married or making a legal commitment to each other.

According to the Knapp's model, the stages of coming apart include *differentiation, circumscribing, stagnation, avoidance,* and *termination* stage.

- **Differentiating**: At this stage, people will start to behave individually rather with the partner.
- **Circumscribing**: In this stage, people will limit their conversations and will set the boundaries in their communication.
- **Stagnating**: In this stage, people will not pursue to maintain relationship.
- **Avoiding**: In this stage, people will intentionally avoid them each other.
- **Terminating**: As the final stage of coming apart, the relationship will end completely.

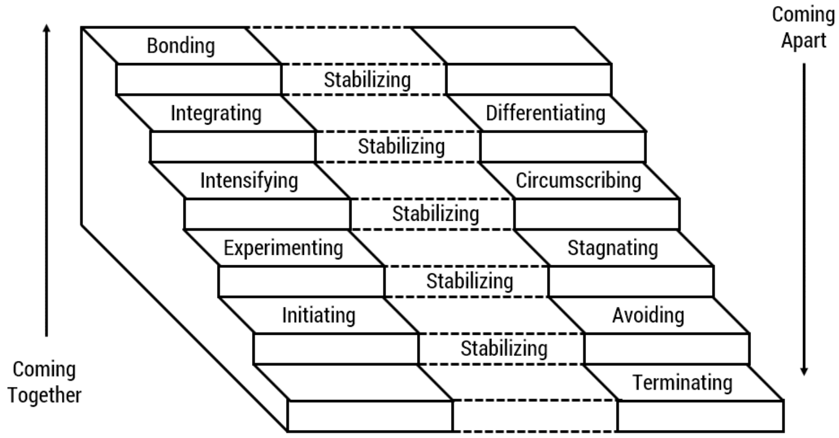

Figure 3-4. Knapp's Model of Interpersonal Relationship Development (Knapp and Vangelisti, 2004)

Knapp's model was built upon several communication theories such as social penetration theory (Altman and Taylor, 1973) and social exchange theory (Thibaut and Kelley, 1959). The theories suggest that human relationship develops through the process of self-disclosure and the exchanges of disclosing oneself to another should be reciprocal to develop and maintain relationship satisfaction. As Knapp's model comprehensively describes interaction patterns in each stage of interpersonal relationship, it was helpful to effectively highlight how the interactions with on-the-go personal assistant services changed over time, emphasizing the importance of transactions between users and the systems in each stage. Also, since Knapp's model clearly addresses the process of coming together and coming apart of two individuals who are initially unknown to each other, Knapp's model is more closely aligned with the context of this study, of which purpose was to unfold people's experience with newly introduced on-the-go personal assistant services.

For this reason, the changing perception and expectation was defined in three stages of user-system relationship adopting Knapp's model, namely, i) *initiation & experimentation*, ii) *intensifying & integration*, and iii) *stagnation & termination* stage. Although the terms proposed in Knapp's model were adopted in a much simpler manner in this research, human behaviors described in this model provide a clear lens to understand the characteristics of user-system interactions, highlighting the issues and design opportunities in each stage from a new perspective. Following describes what kinds of user experience issues emerged across three stages.

3.3.1 Initiation & Experimentation Stage

When participants first encountered the given wearable activity tracker, they explored and experimented various aspects of the tracker system. By doing so, they tried to understand what it is, how it works, and what value it would seemingly provide to them. This process was quite similar to the series of behaviors people display when they first meet another person (Knapp and Vangelisti, 2004): initiating a conversation with greeting, exchanging demographic information, and asking questions in order to seek the common interests or experiences.

UX Issue: A Gap between What People Imagine and What System Could Do

As it is important to make a good first impression for the further development of an interpersonal relationship, this first moment was also found to be important in the further use of wearable activity trackers. Nevertheless, it was especially challenging in the context of intelligent IT services like wearable activity trackers, because there was no salient way to probe how the future interaction might likely be. For example, the actual contents that would help users make the decision to adopt the product were often in a blank state. Participants could be able to understand the system only through use.

Thus, participants judged the system's ability by their knowledge and set their own expectation toward the systems. Many of the participants tended to have a high level of expectation for the *smartness* of the systems, as wearable activity trackers had been promoted for their advanced capabilities. They described that their activity trackers *"would record activities very conveniently"* (F1), even if they do not invest much effort, as the device *"seems to be carefully programmed"* (J3), and *"seems to be more accurate than other mobile applications for self-tracking"* (F4). This gap between what people imagined and what the systems could actually do at this stage often resulted in confusing and disappointing experiences. For instance, F3 had a high expectation toward automated data sharing among related apps, so he thought that his smart Fitbit would automatically recognize a third-party application, called MapMyFitness, and share his data on Fitbit, even if he did not manually connect them. Thus, he kept failing to use the third-party application until the end of the study. This finding also resonates with the findings from other studies of wearable activity tracker (Shih et al., 2015).

Meanwhile, making the first impression was also challenging when participants were well aware of technology. Since they distrusted the reliability of data collected through current technology, they tended to poorly judge the potential value of tracking certain data in a very early stage of use. Thus, this resulted early abandonment of certain features, like the example of F1:

"I will never use the meal logging. It is obvious that the tracker won't automatically recognize what I had for lunch and it would require manual logging. It is impractical and even unreliable."

Like these excerpts show, the first impression influenced further use of trackers.

3.3.2 Intensifying & Integrating Stage

After the initial experiences, the participants regularly engaged with the systems and expected the use of wearable activity trackers to be integrated into their personal routines (e.g., logging regular walking when commuting and reviewing daily activities before going to sleep). This expectation resembled to the one people have in intensifying and integrating stage, when they want to build closer relationship.

UX Issue: Imbalanced Returns of Accumulated Personal Data

As users were aware that the tracker had accumulated vast amount of their activity data over time, they started to expect much more sophistications in personalized activity reports and recommendations, which beyond mere numeric representations of their activity data. For instance, F2 and J1 wanted the systems to consider their own physical conditions, goals, and lifestyles when providing activity reports and recommendations (e.g., a comparison of their status with other people who had similar conditions). In addition, F2 hoped the system apply personally-meaningful units (e.g., a walk to home from office) rather than universal units (e.g., 150 m, 600 steps, 10 minutes, etc.) when recommending workout:

"Instead of just showing how much 'percent' I have to walk more today, how about saying, 'What about taking a walk to the cafeteria (near your office)?'"

Interestingly, it was noteworthy that the underlying reason for this expectation was that users thought that there is some kind of *social actor* behind the system, which have similar properties of human intelligence and sense, and this perception led users to have the expectation that the actor would follow similar social rules that are applied to interpersonal interactions. In particular, participants expected *reciprocity* in their interactions with wearable activity tracking services. Reciprocity is one of the social rules people apply when they exchange resources, such as information, emotion, goods, and services, with other people. According to social exchange theories, people try to repay what another person has provided for them. For example, if someone receives a birthday gift, s/he would be obligated to do the same on the gift-giver's birthday by the virtue of reciprocity. Thus, if someone violates this reciprocity norm by receiving others' favors without attempting to return, s/he would be disliked by others and their relationship may not be enhanced (Knapp and Vangelisti, 2004; Thibaut and Kelley, 1959).

Since participants had similar expectations on the reciprocity, some of the users tried their best to give their activity data properly. For instance, J2's explained why she were *enduring* the cumbersome manual logging by saying,

> *"I'm trying to keep logging the meal data as much detail as I can because logging more data about me would provide more accurate suggestions to me."*

For the similar reason, she also wanted to somehow let the system know the information that would help it to return the service more relevantly:

> *"If I can record the step counts during a specific route, for example, from my office to a near cafeteria, I would like to. And I hope the numeric data of my steps to be replaced with 'that unit' when Fitbit suggests something to me. How about saying, 'What about taking a walk to the cafeteria?' instead of just showing how much 'percent' I have to walk more today."*

However, the health assistant service constantly provided the activity reports and recommendation as it did from the beginning, participants showed social responses to the service as if a friend of them violate the virtue of reciprocity. For example, they felt their personal assistant service *"did not appreciate"* (F2) their efforts or *"discouraged"* (F1, J3) them from maintaining healthy behaviors, when they did not get proper feedback from the personal assistant service, such as acknowledgement of their efforts at maintaining and tracking healthy behaviors and emotional support for future behaviors. In addition, participants were disappointed when the current systems behaved without knowledge about the individual users. F1 said,

> *"It keeps sending me an alert to charge the device every midnight, the time when I am always in bed. […] It's quite disappointing that it doesn't know my 'activity timeline.'"*

Since she believed the systems could do so based on her sleep monitoring data, this discouraged her to keep using the systems. Also, J4 quit using the sleep monitoring function after Jawbone *"ruined"* (J4) his sleep log when he traveled to a different time zone.

3.3.3 Stagnation & Termination Stage

Participants fell into stagnation stage, when their experiences with activity trackers did not match with their expectation, due to the challenges discovered in early stages. J4, for instance, stopped using sleep monitoring function after two times of trial, because she could not fully understand how it worked. F2 also quit to use sleep monitoring, as he realized that *"the analysis is always similar,"* instead of showing the insights that are fit to personal lifestyle. When participants once entered into this stage regarding specific features, they did not try to explore the ways to better use the system anymore and rarely returned to resume using the features. The frequency of using the unsatisfactory features has faded out and naturally entered into termination stage. This was similar to how social relationships decay over time.

UX Issue: Limited Controllability to Personal Data

User experience issue arose during the uninstallation of the trackers. The participants tried to separate personal data from the device (i.e., the physical container of the data). However, the participants, and the interviewers as well, were surprised at the fact that there was no salient way to initialize or back up personal data from the device (at least at the point of our study; now user interface for backup data is added). Therefore, participants tried several workarounds that they *believed* were a way to initialize the device. Some of them deleted the mobile application, disconnected the Bluetooth connection with the tracker device, or logged out of the mobile application. For those who could not find such workarounds, interviewers helped them pair their device with our own account, which automatically terminated the connection with the participants' accounts. All of the participants, obviously, expressed strong concerns about the possibility of their data remaining in the device or the possibility of losing their accessibility to and controllability of the data they had accumulated. As a result, these series of experiences elicited users to have distrust toward the systems, even after all the positive experiences of using the services:

> *"It's like the system says, 'It's free to come join us, but you can't leave us when you want.' It doesn't make sense that I have to send an email to the customer center to delete my own data." –J2*

3.4 Design Implications: A Partnership Mindset Building Approach to Support Co-Performing Experience

The findings of this study show how users' perception and expectation on intelligent IT services changed over time, as their perceived relationship with the system developed over time. One of the noteworthy findings from the study was that users had the notion of social reciprocity in mind. While it was apparent in Intensifying and Integrating stage, where participants were trying to share their activity information as accurate as possible, anticipating more personally relevant analysis and interventions from the on-the-go personal assistant services, the virtue of reciprocity was also observed from the UX issues raised in the initial and terminal stages.

This notion of social reciprocity in users' mind implies that users would do have willingness to help the systems, as far as they can be sure the system would provide personalized services in return. Reflection this finding from a perspective of co-performing experience, helping users have *a partnership mindset* in using intelligent IT services would be an important starting point in supporting the co-performance over time. Indeed, this kind of partnership perspective have been envisioned as a way to understand human-computer relationship in the context of emerging intelligent technologies (Bellamy et al., 2017; Lampe et al., 2016). While previous research on co-performance have emphasized the importance of framing user-system interaction as a cooperative perspective, little works exist to inform *how* to support users building a partnership mindset in the first place. To fill this gap, this section discusses design implications for supporting co-performing experience through a partnership mindset building approach.

3.4.1 Design the First Conversation to Help Systems and Users Get to Know Each Other Better

First of all, the findings in initiation and experimentation stage highlighted how proper communication of the immaturity and a blank state of intelligent IT services would help reduce the possibility for misled expectations and early abandonment of the devices. The challenge of setting a proper initial expectation seems not only the case of activity trackers. Several recent works on other types of intelligent products and services also report how the misled initial expectation affected further uses. For instance, a study of Nest users (Yang and Newman, 2012, 2013) showed that some participants did not fully understand the way Nest worked and set a high expectation, resulting a disappointing experience. In addition, the authors of a study that investigated everyday use of

Conversational Agents (e.g., Google Now, Siri and Cortana) also revealed that users' expectation of Conversational Agents is far from the practical realities of use. These emerging studies imply that the initial experiences of intelligent systems are still important for the further use of the systems.

Current designs for this initial stage, however, are often oriented toward explaining the technical steps of connecting a device with a mobile application. Although such instructions can be useful, this hardly helps users understand what a system can and cannot do in the initial stage. Also, current intelligent IT services do not clearly communicate such learning and evolving ability to users and this black-box intelligence of system often make users being disappointed and abandon the system even before they get a full benefit of intelligent IT services.

A system could be designed to better inform users how the system's potential can be realized if it is properly used by the users. For instance, this initial stage could be designed with a series of conversations with the user by explaining why the system wants to know certain user information (e.g., initial 20 steps to calibrate and learn the way a user walks) and emphasizing how the answers from the user will help the system perform better over time. This first conversation would help users more explicitly perceive the system as a kind of social actor that has the capability to learn about its users through the interactions with them.

3.4.2 Develop a Partnership to Accumulate Relevant Knowledge about Users

The issue of meaningful returns of collected user data, which became apparent in the intensifying and integrating stage, has been also discussed in many related and emerging services (Andy Hickl, 2012). Especially, the reciprocity formed in users' mind in those stages suggests that the systems could be designed to explicitly involve their users to incrementally improve the knowledge of the systems so that the systems could become more meaningful and fit to individual users' contexts of use. For example, a user could help an intelligent IT service clarify the meaning of data when an unusual pattern is detected (e.g., unusually sleeping for a very short time on Sunday). If the user clarifies such data as a new routine (e.g., preparing for a class every Monday), the system would prepare to properly support the user within the given context of such a routine. By involving users and developing a partnership with them, the systems would be able to accumulate rich contextual knowledge about the users.

3.4.3 Support Maintenance of a Trustful and Sound Relationship that Empowers One Another

Finally, as the ways of terminating an interpersonal relationship also affect future interactions (Knapp and Vangelisti, 2004), terminal stage seems to be an important moment for product and service providers, in which moment they can provide a good last impression to their users. Nevertheless, terminating has been the most overlooked stage in existing intelligent IT services and thus, has much room to be improved. There could be many ways of supporting users to manage the ownership of their data at this stage. For instance, users may wish to discard all their data from the service or may prefer to leave certain data in the system to improve future service. If users want to leave some of their data in the system, how the data will be abstracted and transmitted should be carefully designed as well.

Meanwhile, designers should know that initializing the data from a tracker device does not always mean that the user wishes to quit maintaining healthy behaviors, as shown by the examples of people who were reinforced by their past experiences with activity trackers (Fritz et al., 2014). To explicitly address this future reinforcement, a system could be designed to provide final messages (Knapp and Vangelisti, 2004) to users as a form of virtual possession (Odom, Zimmerman and Forlizzi, 2010). It may represent the history of a user's health activities and give meaningful access to the full data. It can be used not only to encourage users to sustain their health behaviors, even without the device, but also to smooth the initiation stage with other self-tracking tools by utilizing the data that the user has already accumulated to warm up the cold-start with new devices.

3.5 Conclusion

This chapter investigated the changing user perception and expectation of intelligent IT services over time, as an effort to discover an overall direction for co-performing experience design. The results of this study suggest three stages of user-system relationship development, which should be carefully considered in designing co-performing experience in intelligent IT services. Based on the results, a partnership mindset building approach was proposed as a way to support co-performing experiences and an initial set of design implications for the partnership mindset building were suggested. Building on these initial implications, the notion of partnership mindset building and co-performing experience is further studied in the following chapters.

CHAPTER 4.

Users' Co-Performing Experiences over Time in the Wild

Chapter 4.
Users' Co-Performing Experiences over Time in the Wild

In the previous chapter, the notion of a partnership-mindset building approach was proposed as a way to support co-performing experiences inspired by the findings on users' socio-psychological perception and expectation of intelligent IT services. By simulating a partnership-mindset building approach based on the initial set of design implications discussed in Chapter 3, this chapter investigates users' actual co-performing experiences in the wild. The findings of this study will further develop the notion of partnership building for co-performance.

4.1 Study Aim

The aim of this study was to identify the factors to be considered in supporting co-performing experiences over time by enabling users to build a partnership mindset to co-performance. While previous works have investigated incorporating users' participation for systems' learning from a technology-centered perspective, little work has investigated how users would experience cooperating with the systems from their perspective. In addition, although previous research that utilized social and relational strategies in designing smart system discovered the benefits of embodying social skills in smart systems, such as increased user satisfaction and cooperation (Lee et al., 2012; Mennicken et al., 2016), social and relational strategies have rarely been addressed for empowering users as a cooperator of improving a system's intelligence and for improving the quality of personalized service experiences. To fill this gap, this study aims to investigate users' actual experiences as a partner and their expectation on co-performing experiences.

4.2 Study Method

To understand users' genuine co-performing experience over time, it was important to provide a setting, where study participants can naturally co-perform with the systems for the service that they have actual needs for personalization for their own context of lives. In this regard, users' co-performing experience and their expectation toward the service were difficult to be observed within the existing intelligent systems, which already have defined functions and ways of co-performing. For this reason, it was more proper to simulate the experience of co-performance through a research probe so as to prototype the co-performing experience for each participant's own service needs and to flexibly re-prototype the experience as participants' expectations might change over time.

4.2.1 Co-Performing Agent: A Wizard-of-Oz based Research Probe to Simulate a Partnership Building Approach to Co-Performing Experience

With this purpose, a Wizard-of-Oz based research probe, Co-Performing Agent, was devised first in order to simulate co-performing experience over time (Figure 4-1). In designing the probe, the initial set of design implications for partnership building was applied.

4.2.1.1 Ecosystem Overview

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 experience. For this purpose, the research context was specified as a user-created fictional service in a car environment. This was to provide study participants a likely setting of co-performing with an agent in their real lives for their actual service needs. To do so, a car environment was expected to have great potential as a research context, as it is one of the promising environments where people expect personalized services while moving between diverse physical spaces (e.g., home, office, and social places) that are tightly related to users' personal lives.

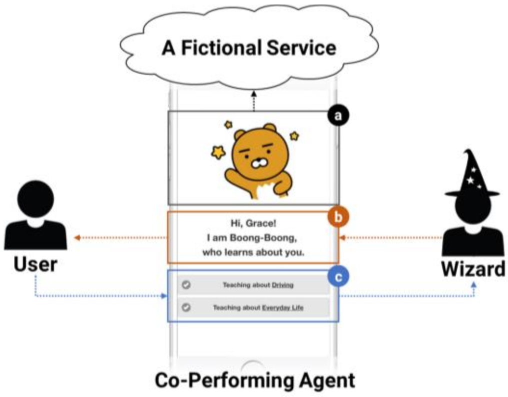

Figure 4-1. Co-Performing Agent Overview: (a) an agent profile, (b) an agent's learning message, (c) a teaching information panel

Co-Performing Agent probe was devised as a web-based mobile application to enable users to access it wherever they are. The probe consisted of three parts: an agent profile (Figure 4-1(a)), an agent's learning message (Figure 4-1(b)), and a teaching information panel (Figure 4-1(c)). To support users in having a partnership mindset for co-performance, Co-Performing Agent was designed 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 the study purpose, and the ways it was designed might not be the only ways to build a user–agent partnership, this probe was expected to provide a setting for initiating the investigations of users' co-performing experiences.

4.2.1.2 Partnership Enhancing Interaction

(1) First Encounter Interaction

As discussed in the chapter 3, 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 (Yang and Newman, 2012, 2013; Kim et al., 2016). Thus, Co-Performing Agent was designed to communicate its immature knowledge of a user during its first encounter with the user (Figure 4-2). The initial interaction was designed to be similar to the ways 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, Co-Performing Agent was designed 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).

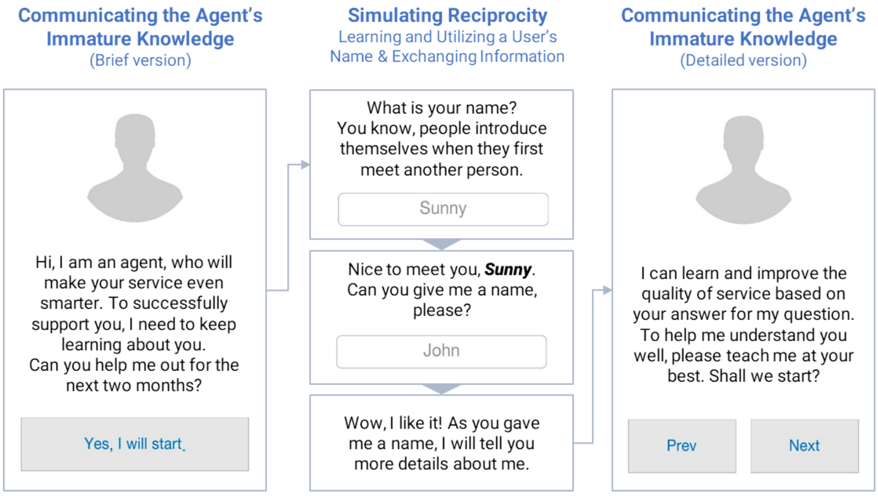

Figure 4-2. The Script for First Encounter Interaction

(2) A Teaching Channel for Users

To simulate the actual co-performing experience, Co-Performing Agent was also devised to provide users an explicit channel to teach their agent (Figure 4-3). 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).

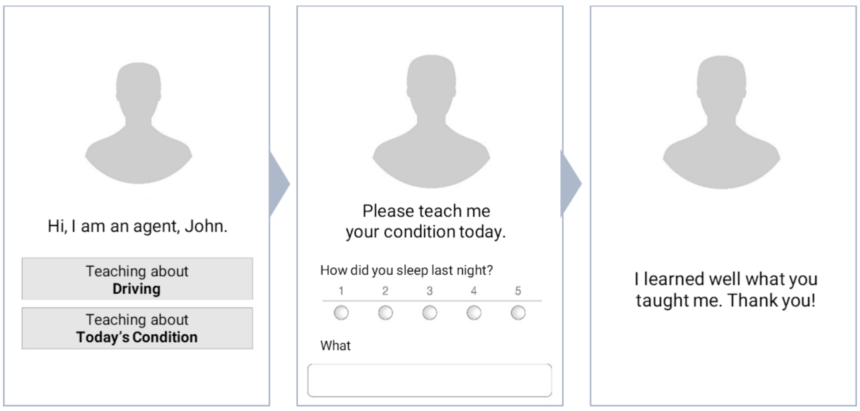

Figure 4-3. A Script for Learning Interaction

The contents of this teaching channel was intentionally designed to be empty at first and asked participants to decide what and how their agent will 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, Co-Performing Agent was designed to enable users to have control over the agent's learning.

(3) Agent's Learning Messages

To enable a user to know the growth of agent's ability over time, Co-Performing Agent was designed to provide an agent's learning messages. This was from the findings in the chapter 3, which showed that users often expect such reciprocal information transactions with the systems that leverage user's personal data. For example, participants in the study of Chapter 3 expected more personal nuance in the health-related recommendations, as they accumulated their activity data over time. Also, such users' expectations in data-leveraging services are quite aligned with the notion of social reciprocity, one of the social rules people apply when they exchange resources, (e.g., information, emotion, goods, and services) with other people. According to social exchange theories, reciprocal exchanges play important roles in maintaining relationships. Thus, for example, if people do not properly repay what another person has provided them, they will be disliked by others, and their relationships may not be enhanced (Knapp and Vangelisti, 2004; Thibaut and Kelley, 1959). In this sense, the reciprocity was regarded as an important notion to support users in building a partnership mindset over time.

From this motivation, as a feedback for a user's teaching, the agent's learning messages was developed in three levels 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 this setting was expected to enable users at least to think about how their co-performance works by showing them how the quality of the agent's knowledge of a user could be improved over time.

4.2.2 Participants

For this study, eight regular drivers (three females and five males) were recruited through an online screening survey, who were aware of agent-based interfaces, but did not have much experience of them. As they regularly drove their own car, they were expected to be able to easily think about their service needs for the context of this research and to have a motivation to start co-performing with the agent probe to improve the service. Participants were in their 20s or 30s (the average age=29.75, SD=2.87, min=26, max=35), 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 due to the potential to observe co-performing experiences for diverse personalization purposes. 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. These differences were expected to 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 IRB (Table 4-1).

Table 4-1. Participants Information of the Co-Performing Agent Study

Participant Number	Age/Sex	Regular Fellow Passengers	Driving Purpose
P1	29/Female	None	Commute
P2	29/Female	Colleague (weekdays) Boyfriend (weekend)	Commute & Travel
P3	32/Male	Colleague (weekdays) Wife (weekend)	Commute & Date
P4	31/Male	None (weekdays) Wife (weekend)	Commute & Date
P5	27/Male	Girlfriend	Commute & Date
P6	35/Female	Family with two kids	Drive kids to kindergarten & Grocery Shopping
P7	26/Male	None	Commute
P8	29/Male	Colleague (weekdays)	Commute & Business Trip

4.2.3 Study Design: Iterative Participatory Design Study

To investigate the human-centered ways of supporting co-performance over time, a two-month participatory design study was conducted by combining various designerly research methods, including a research probe, the Wizard-of-Oz method, and participatory design activities. 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 (Figure 4-4).

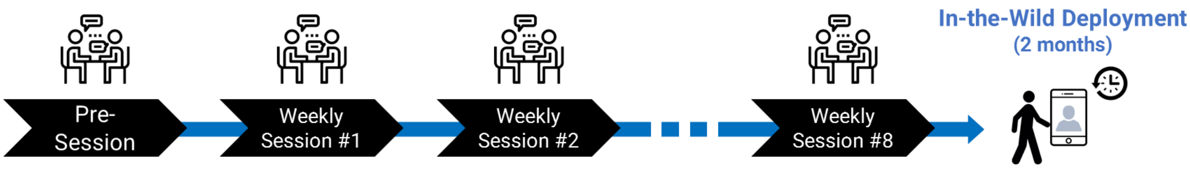

Figure 4-4. Overview of Study Procedure

4.2.3.1 Pre-Session

Participants visited the lab prior to the study and had an individual pre-session to create a fictional service that they need in their daily lives and to set up the Co-Performing Agent probe for that specific service needs.

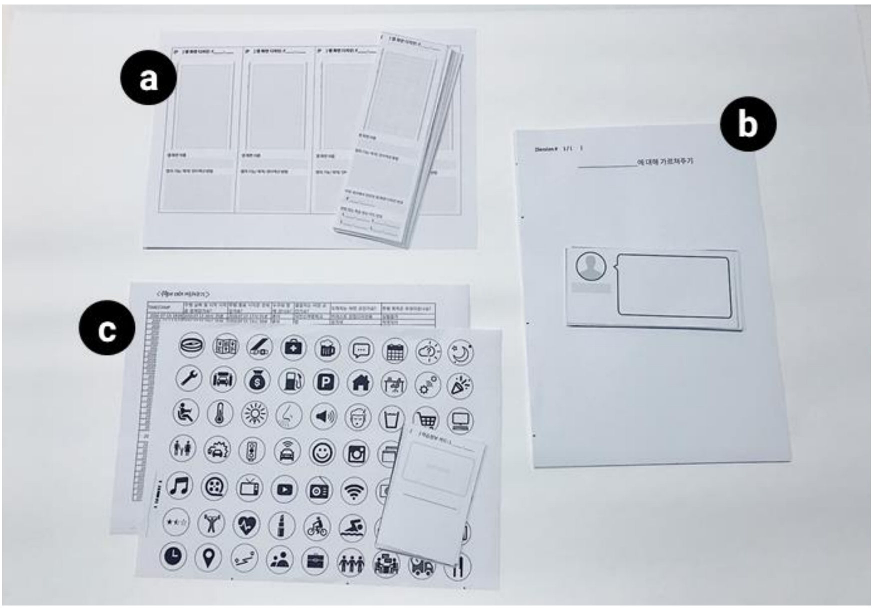

Figure 4-5. Materials for Participatory Design Activities

First, each participant was asked 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 4-2) and drew those features on a blank mobile screen template (Figure 4-5(a)), which was provided to participants to help them concretely imagine their fictional service.

Table 4-2. Major Features of a 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 P3 of 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 the user'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).

Then, each participant was given an individual access link for Co-Performing Agent to, 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). Participants was further asked to decide the agent's appearance and ways of speaking, if they wanted, as a way to inquire their initial perception toward the agent. As the last step to set up the Co-Performing Agent, each participant was asked to create a list of questions to teach the agent by filling out a blank question and answer template (Figure 4-5(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.). Participants were guided to list similar questions under a category and to specify the name of the category. This material was used 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, this study aimed to enable users to teach the agent more effectively.

Regarding all the features and contents created by participants, why each participant created such a fictional service and why he or she decided to teach such questions were inquired to understand participants' 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 (Figure 4-6), and all the materials created by participants were filed to use in their upcoming participatory design sessions.

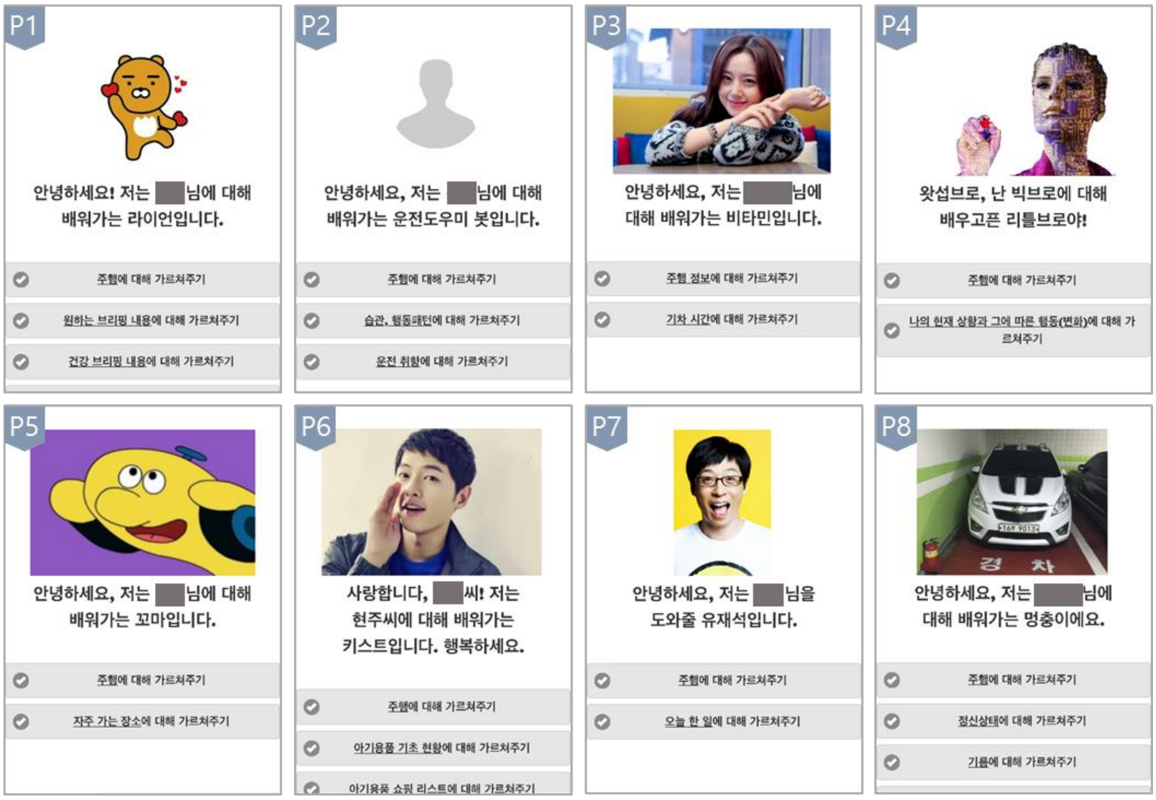

Figure 4-6. Each participant's customized co-performing agent probe

4.2.3.2 In-the-Wild Deployment of the Co-Performing Agent Probe

To simulate co-performing experiences, the customized Co-Performing Agent was deployed for two months (eight weeks) in the wild. Participants were guided to teach their agent 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 their natural engagement with the agent, however, participants were allowed to decide when and how frequently to teach as they liked.

During the two-month deployment, the agent's learning messages was provided by utilizing the collected user data (Table 4-3). In week 1, the learning message was not provided in order 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 mis-behaviors 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).

Table 4-3. 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-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?" (W7-recovery) "Sorry, I gave you the wrong recommendation. For your health condition, how about going to OO juice café for a drink?"
W7		
W8		

Co-Performing Agent was deployed 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 (Kanda et al., 2007; Sung, Christensen and Grinter, 2009). 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 provide the likelihood of actual learning during the study period.

4.2.3.3 Weekly Participatory Design Sessions

To inquire whether and how users' perceptions of and attitudes toward co-performance change over time, an in-depth inquiry session was conducted every week. During each session, a debriefing interview was firstly conducted to inquire participants' thoughts, feelings, and any challenges they had while interacting with Co-Performing Agent. Then, participants were asked to do three participatory design activities by reflecting on their experience: i) the *agent profile revising activity*, ii) the *service revising activity*, and iii) the *learning question revising activity*.

(1) Agent Profile Revising Activity: Inquiring the Changes of Perceived Relationship with the Agent

The agent profile revising activity was to inquire about users' changed perception of the relationship with the agent. Reflecting on their co-performing experience, participants were asked 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 as to provide the updated version of the Co-Performing Agent probe in the following week.

(2) Service Revising Activity: Inquiring the Changes of Perceived Ability of the Agent

The service revising activity was to inquire about users' perception of their agent's ability. For this purpose, participants were first asked to create *inferred information cards* (Figure 4-5(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 s/he had taught to their Co-Performing Agent up until the session. Then, participants were asked 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, participants' perceptions of their agent's ability were aimed to be investigated with more rationale.

<u>(3) Learning Question Revising Activity: Inquiring Users' Attitude toward Further Co-Performance</u>

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

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.

4.2.4 Data Collection & Analysis

Over the course of eight-week in-the-wild deployment of Co-Performing Agent, participants taught 1,837 different threads of information in total. More specifically, each participant taught his or her assistant about 230 times on average during the study, though there was a difference among the participants (the lowest frequency: 101 times, the highest frequency: 314 times). The types of user-taught information varied from basic driving history (e.g., time and place of departure and arrival, fellow passenger(s), and the purpose of driving) to information related to leisure experiences (e.g., daily exercise, preferences, interests, satisfaction, physical/mental conditions, etc.). All these data were used in the weekly participatory design sessions, where rich qualitative data about users' perception and expectation of co-performance was gathered in large quantities. Following summarizes the data collected from eight weekly participatory design sessions.

Participatory Design Session Outcomes

As a source to understand users' perceived relationship with the agent, the outcomes generated from the agent profile revising activity were collected (e.g., relationship analogy, appearance, the ways of speaking, etc.). The outcomes generated form the service revising activity were collected as a source to understand users' perceived ability of the agent. Those outcomes include 202 different types of inferred information cards and 141 times of modifications made to the initially-designed services (i.e. 17.6 times on average). As a source to understand users' attitude toward further co-performance, 255 times of modifications made to the initially-created learning questions were collected (i.e. 31.8 times on average).

Participatory Design Session Debriefing Interview Data

Along with these design outcomes, over 72 hours of interviews were audio-recorded and transcribed. This includes all the participants' utterance regarding their overall reflection on in-the-wild co-performing experience (e.g., the feelings and thoughts toward Co-Performing Agent) and the motivations regarding the three generative activities (e.g., the rationales of modifying the agent profile, service features, and learning questions, and the expected value of such modification to the participants).

Initial Coding for Participatory Design Session Outcomes & Debriefing Interview Data

After each weekly session, interview transcripts were re-organized with the related participatory design outcomes from the offline sessions. For each week, preliminary analysis was conducted by five researchers searching for emergent themes and patterns with regard to user–agent partnership and co-performing behaviors.

Analysis on the Patterns of Over-Time Changes in Co-Performing Behaviors and Factors Affecting the Changes in Co-Performing Behaviors

After finishing all the sessions, more holistic analysis was conducted regarding all the data gathered from the study in order to inquire whether and how users' perceptions of and attitudes toward co-performance change over time. This was conducted 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. Along with the changes, the underlying reasons and factors for the changes in users' co-performing behaviors and perception of their partnership were also analyzed. These analyses were initially conducted by five researchers by iteratively developing a thematic diagram of the initial codes. Then, similar process was iteratively conducted by the author over two years with intervals to increase the validity. During this process, the coding scheme was revised three times through multiple iterations of coding analysis. Also, the analysis results of participants' utterance were cross-checked with the analysis results of their outcomes from participatory design sessions.

4.2 Factors Affecting Co-Performing Behaviors and User-Agent Partnership

From the analysis, it was found that not all participants had built a resilient partnership with their agent. For example, only half of the participants (P1, P2, P4, and P7) satisfied with the ways they were interacting and showed continued willingness to help their agent for service evolution, whereas the other half (P3, P5, P6, and P8) did not show the clear willingness to help their agent for service evolution. Regarding this weak partnership, P3 said his agent was like “an intimate, but annoying friend,” because he was somewhat bored of helping his agent learn his routine repeatedly. To investigate the reasons of this difference, what enabled each group of participants to either strengthen or weaken their partnership with the agent was further analyzed. From the further analysis, three factors that affected user-agent partnership building were discovered: i) users’ initial mental model toward an agent’s capability, ii) iterative confirming experiences, and iii) changes in the styles of learning.

4.2.1 Users’ Initial Mental Model toward an Agent’s Capability

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 (Figure 4-7).

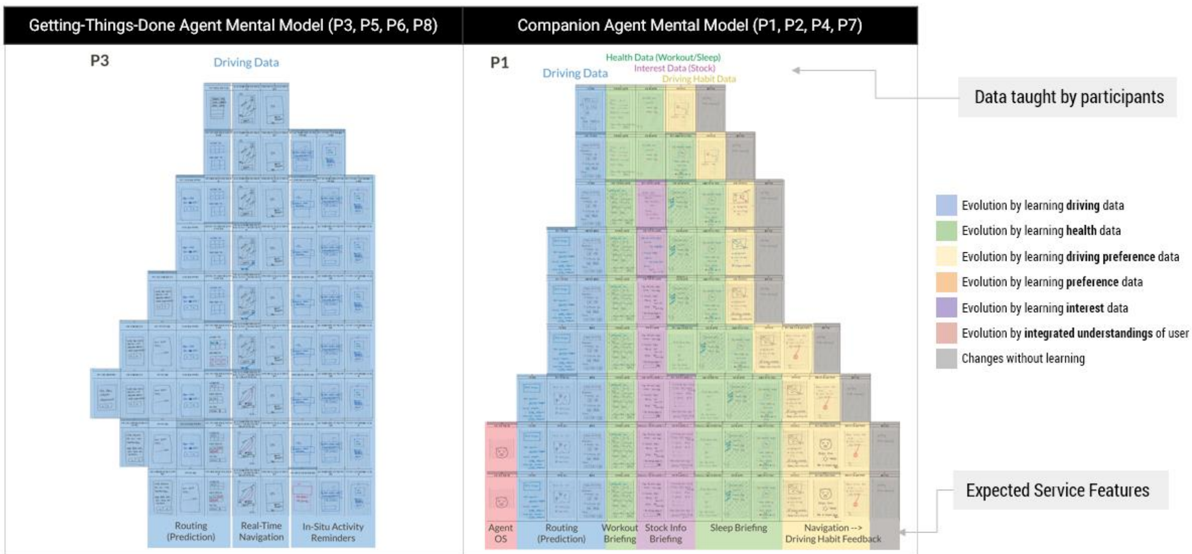

Figure 4-7. Differences in Co-Performing Patterns between Users with GTD Agent Mental Model (P3’s example) and User with Companion Agent Mental Model (P1’s example)

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 (Figure 4-7). 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 a level that it quantifies his travel history and suggest the most preferable places, but to a level that it could suggest new places where he might have not thought to visit but would be nice to try 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 (Figure 4-7). 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).

4.2.2 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. It was 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. Followings 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 the wizard researchers provided to each participant. When participants received a learning message that was reasonably improved based on what they had taught, they 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, there were also the 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 were 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 do not 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 that were 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 that 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.

4.2.3 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.

The analysis of the data gathered from the learning question revising activities revealed 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?" Although these proactive questions should be designed carefully, she thought that this kind of conversation could enhance their relationship.

4.3 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, this section discusses further implications for supporting constructive co-performance and a user-agent partnership development over time.

4.3.1 Support Co-Performance based on Users' Mental Model

Reflecting on the findings, supporting users' co-performance with an understanding of a user's mental model toward agent-based services would be important in enabling constructive co-performance over time. For example, in the case of Companion model users who have a higher innate motivation for co-performance, providing an advanced co-performing interface that guides them to teach their agent at their best would be helpful. In contrast, GTD model users may want to make their efforts as effective as possible, expecting their agent to automate some parts of data collection, like P6 in this study. However, since they may still want to have authority over the agents' behaviors, these conflicting and thus challenging user expectations should be carefully considered in designing co-performance for GTD mental model users.

4.3.2 Design a Learning Period as a Time for Building User Trust on Partnership

From the findings of this study, it was 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 support 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 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.

4.3.3 Rapport Building Interactions May Better Come Later

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 later interactions.

4.4 Discussion

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

4.4.1 Privacy and User 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 (Kosinski, Stillwell and Graepel, 2013). 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.

4.4.2 Temporal/Permanent Expiration of User Profile

During the two-month study, participants came to face the changes in their lives, such as changes in life patterns and concerns. Participants expected the ways their agents provided service to be reoriented in response to such changes in their lives. For instance, P4, who wanted to receive restaurant recommendations for dining with his wife, wanted to rule out uncooked seafood for a while from the recommendations, as the couple started to prepare for pregnancy. For this reason, 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 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 short breaks in a day, rather than the ones that require significant time and effort. She thought that it would be possible for her agent to reorient the service because it had accumulated enough data about her life patterns: *"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."*

While these kinds of temporal or permanent changes of a user's profile can happen, it is still unclear how to support users in helping their agents re-learn their profiles and how to support them in managing the expired profiles. Further research on this issue would extend the understandings on supporting user-centered co-performance over time.

4.5 Conclusion

This chapter presented a two-month user study that investigated human-centered ways to support co-performance over time by understanding users' interactions with Co-Performing Agent and investigating their perceptions through a set of participatory design activities. The findings of this study revealed three factors that affected co-performing behaviors over time; *users' initial mental models*, *confirming experiences*, and *changes in the styles of agents' learning*. Based on the findings, design implications for supporting constructive co-performance over time were discussed. Also, privacy and controllability issues around collecting and using personal data should be considered and studied further. As an initial work that investigated user–agent partnership approach, this research is expected to inspire future research into how technology can support co-performance over time.

CHAPTER 5.

Co-Performing Experience Design Framework: Examining the Roles and Value in Design Practice

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Based on the findings from the user studies, previous chapters discussed how users' perceived relationship with intelligent IT services changed over time (Chapter 3) and what affected users' co-performing behaviors over time and the resilience of user-agent partnership (Chapter 4). These empirical findings are expected to inform the practice of designing intelligent IT services, in which designers have challenges in addressing the human-centered experiences of the services (Dove et al., 2017). Integrating these findings into a design framework, this chapter investigates how these empirical findings inform the design of personalization and co-performance in intelligent IT services.

5.1 The Elements of Co-Performing Experience Design Framework

The co-performance design framework, which was developed based on the empirical findings of this research, consists of the three affecting factors of co-performance and the stages of user-agent relationship in on-the-go personal assistant services, which should be considered when designing for co-performance (Figure 5-1).

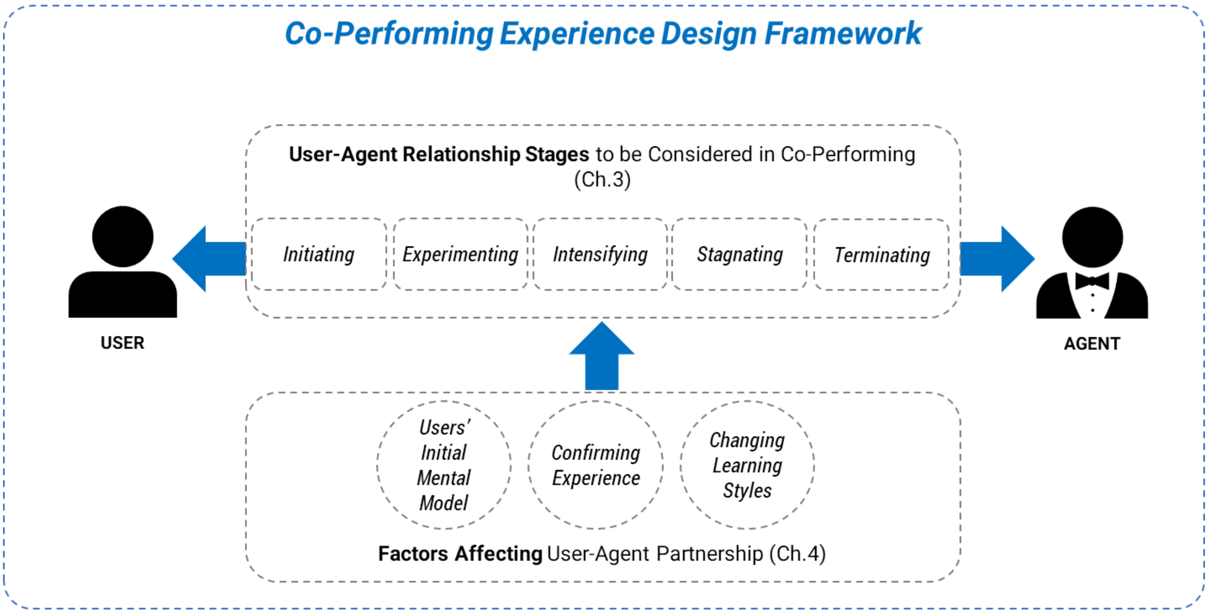

Figure 5-1. Co-Performing Experience Design Framework

5.1.1 User

User in this framework refers to the end-users of an intelligent IT service. As discussed in the chapter 4, users can be classified by their initial mental model toward agent-based service, namely, Getting-Things-Done mental model and Companion mental model. Users with a **GTD Agent mental model** tend to have a skeptical perspective on intelligent technology, and thus, consider optimization (e.g., optimization, automation, and streamlining) as a primary value to be achieved through co-performance. For this reason, these users tend to expect short-term and focused co-performance, expecting their agent to quickly develop simple service features through a short period of learning. In contrast, user with a **Companion Agent mental model** tend to have high expectation of the agent's ability. Thus, these users consider personalization as a primary value to be achieved through co-performance. For this reason, these users tend to expect long-term and multi-faceted co-performance, expecting their agent to serve highly personalized services over time with deeper understanding of users.

5.1.2 Agent

Agent in this framework refers to a perceived actor of collecting and reasoning users' behavioral data and personalizing the services. As found in the study in chapter 3, people would perceive intelligent IT services as a social actor, which have ability to learn and evolve, and users expect to interact with those systems in a reciprocal manner. Thus, making the social actor clearer in the eco system of intelligent IT service is important. However, the agent may not need to be embodied, having human-like representations, although Co-Performing presented in chapter 4 had a representation for the study purpose. Instead, communicating its ability and providing channels for users to control how it learns will be greatly impact users' co-performing experiences.

5.1.3 User-Agent Relationship Stages

This framework posits a user and an agent as the actors of co-performance and consider 1:1 relationship between a user and an agent. This framework defines five stages of user-agent relationship that should be carefully considered in designing co-performing experiences, namely, initiating, experimenting, intensifying, stagnating, and terminating stages. These stages were initially developed from the Chapter 3 in a more condensed form, initiation & experimentation stage, intensifying & integrating stage, and stagnation & termination. However, these stages were expanded to enable designers to think each stage more carefully. During this process, the intensifying & integrating stage was redefined to call as intensifying stage, because the study in Chapter 4 suggest user-agent relationship is continuously being enhanced through iterative co-performing and service evolution. Thus, enabling to think this stage as an integrated stage was considered to be more appropriate, instead of dividing those stages in two different ones. Through this reflection, user-agent relationship was determined in five stages and each stage was defined in terms of co-performing experiences. The finalized definitions for each stage are as follow.

In the **Initiating Stage**, users explore the systems to seek the potential value of sharing their data with systems and putting their efforts into co-performance. In the **Experimenting Stage**, users start to co-perform with agents, expecting the internal improvements of the system's knowledge of a user. In the **Intensifying Stage**, users expect the actual improvements in the agent's service offerings and re-orient the ways of co-performing with agents. In the **Stagnating Stage,** users neither try to co-perform nor expect improvements in the agent's service offerings. In the **Terminating Stage**, users try to explicitly stop co-performing with the system.

5.1.4 Factors Affecting Co-Performing Behaviors and User-Agent Partnership

This framework defines three partnership-affecting factors that should be considered in designing co-performance across five stages of user-agent relationship. The three factors are defined from the chapter 4, as i) users' initial mental model about agent's ability, ii) iterative confirming experiences and iii) changes in the styles of learning. Considering these factors are important to build a resilient user-agent partnership. First, considering **users' initial mental model** (i.e., Getting-Things-Done model and Companion model) is important because it affect users' overall attitude toward co-performance. Second, providing **iterative confirming experience**, through which users can realize the value of co-performing and the growth of the agent, plays role in motivating users' further co-performance. To do so, considering reciprocal transactions between what users taught and what agents provide is necessary. Lastly, **changing the styles of learning** is important because users would think the agent does not learn otherwise.

5.2 Study Method

The in-depth expert interviews were conducted, aiming to understand current challenges of designing for co-performance in design practice and to examine the roles and value of co-performance design framework in their given situations.

5.2.1 A Tutorial for Co-Performing Experience Design Framework

To examine the roles and value of the framework, a tutorial that elaborates the elements of the co-performance design framework were developed. While the purpose of this study was not to develop a complete toolkit for design practice, it was important to deliver the contents of design framework in a clear and understandable manner. To do so, a preliminary design workshop was conducted with three design students to get feedback on the usability and intelligibility of the initially developed tutorial as a reference material for design process. Through this process, the initial tutorial which was originally more prescriptive and integrated was revised in a way that can deliver each factor and stage in a more compact manner, giving readers more room to explore the potential solutions. The finalized tutorial consisted of co-performing eliciting cards and a co-performing user journey map (Figure 5-2).

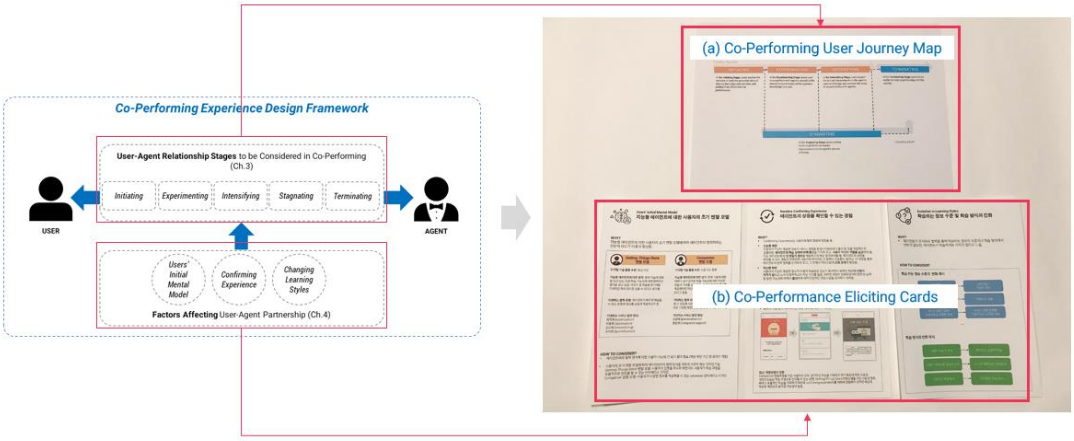

Figure 5-2. A Tutorial for Co-Performance Design Framework

Co-Performing User Journey Map

The co-performing user journey map (Figure 5-3) was designed to elaborate the stages in user-agent relationship development. Regarding each stage, description about the potential user perception and expectation of intelligent IT services are elaborated, as defined in the section 5.1. Also, the relationship among the stages were visualized so that designers can understand overall user journey.

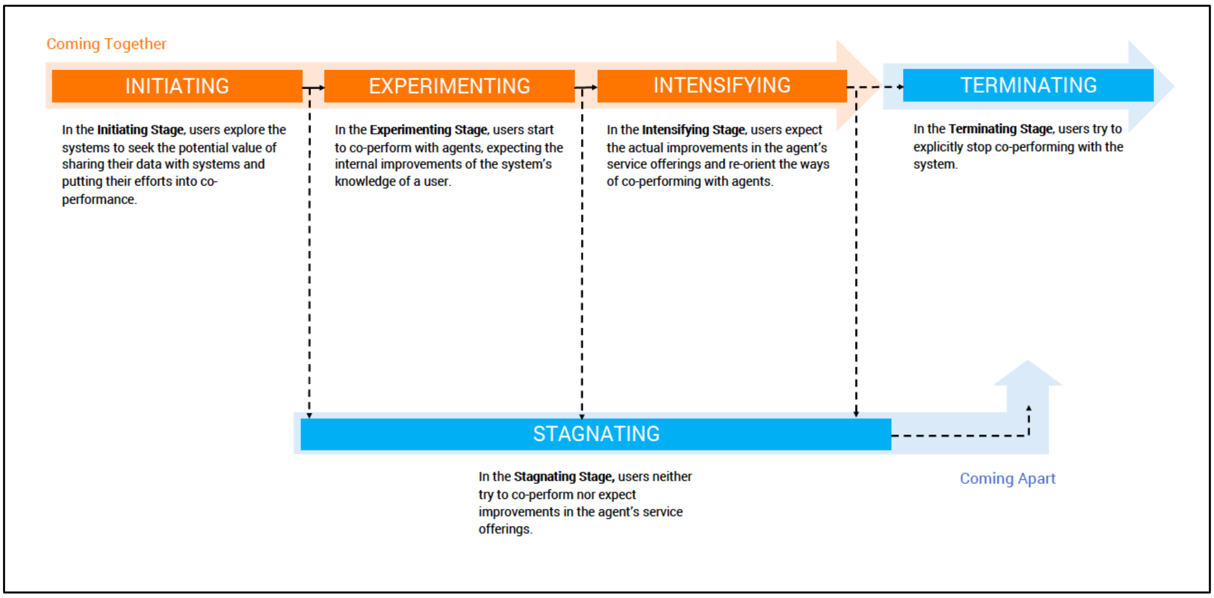

Figure 5-3. Co-Performing User Journey Map

Co-Performing Eliciting Cards

The co-performing eliciting cards (Figure 5-4) were designed to elaborate partnership-affecting factors. Each card describes how each factor affects users co-performing behaviors (based on the finding in the chapter 4) and how each factor can be considered in designing for co-performing experience. If any, related examples were included to effectively deliver the contents.

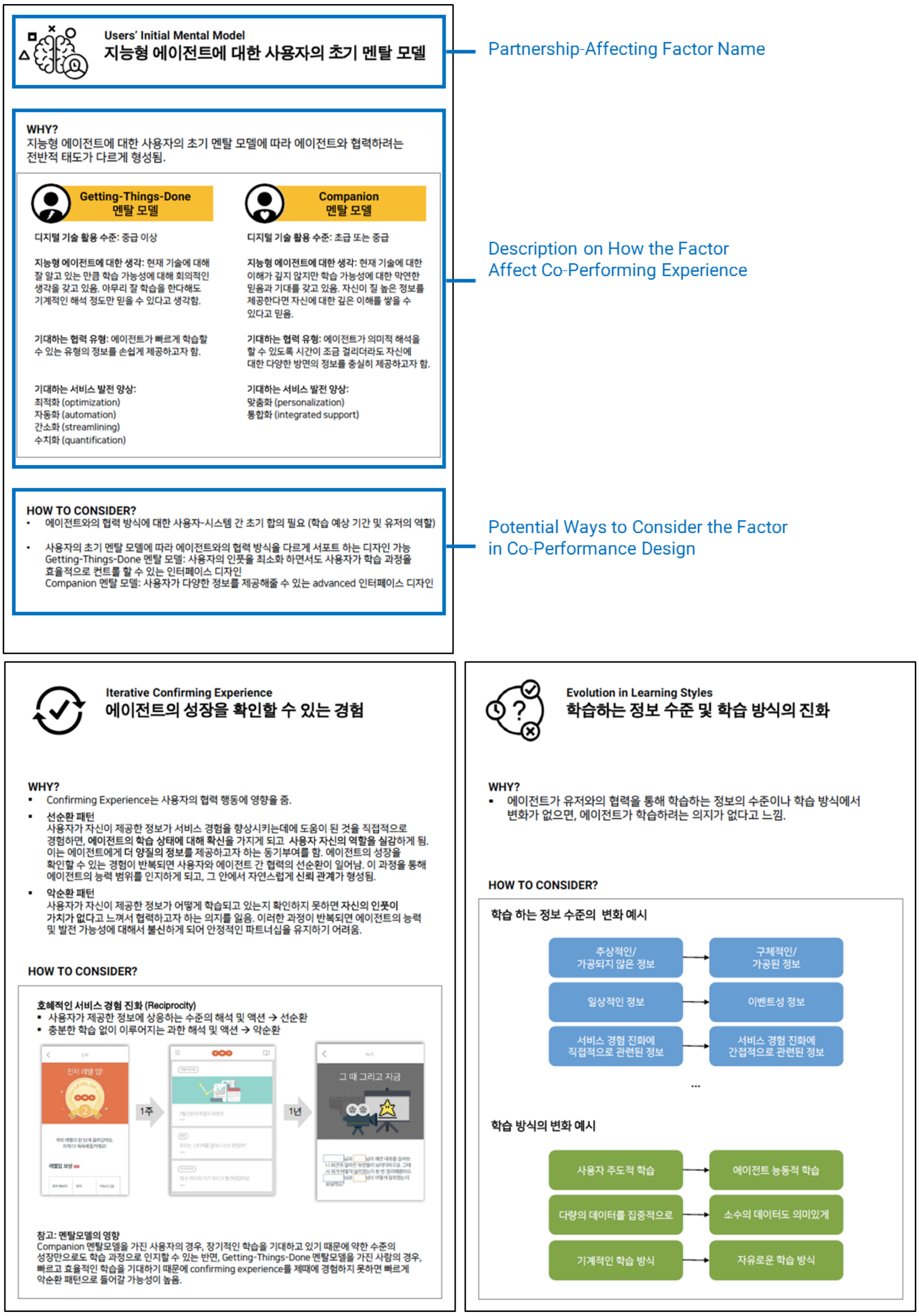

Figure 5-4. Co-Performing Eliciting Cards

5.2.2 Participants

To examine the genuine value and roles of the framework in design, professional designers' reflection and evaluation were critical, because only those of who have experiences in designing personalization for actual end-user services can discuss how the framework affect their design thinking and approach, reflecting on their current practices. For this purpose, eight professional designers (Table 5-1) (referred as D1-D8), who have experiences in designing user experience for data-driven personalization in their own service, were invited for an individual expert interview. This study aimed to recruit designers from diverse domains in order to examine how the framework would be interpreted and utilized to design co-performance for diverse personalization purposes. For this reason, the eight professional designers were selected from diverse IT-based service domains (e.g., music, shopping, news, leisure, health, and AI assistants).

Table 5-1. Participants Information for In-Depth Expert Interviews

Participant	Years of Work	Service Domain (Personalization Examples)	User Data
D1	10 years	**Shopping** (preference-based shopping items recommendation)	In-app User Behavior Logs
D2	5 years 5 months	**News** (interest-based news recommendation) **Leisure** (context-based place recommendation)	In-app User Behavior Logs
D3	6 years	**Music** (preference-based music recommendation) **In-Car Assistant** (location-based navigation recommendation)	In-app User Behavior Logs
D4	3 years	**Mobile AI Assistant** (context-based app shortcut suggestion)	On-Device User Behavior Logs
D5	1 years 4 months	**Mobile AI Assistant** (context-based dashboard personalization)	On-Device User Behavior Logs
D6	3 years 8 months	**Photos** (location/tag-based personal album curation)	Offline User Behavior Logs
D7	6 years 11 months	**Leisure** (credit card usage pattern-based place recommendation) **Mobile AI Assistant** (context-based personalized reminder)	Offline User Behavior Logs
D8	3 years	**Health** (dietary pattern-based advice/recommendation)	Offline User Behavior Logs

5.2.3 Procedure

The in-depth interviews were designed to compare participants' design approach before and after utilizing the co-performance design framework so as to examine how the concept and elements of co-performance design framework affected designers' current design approach. Thus, the major interview questions inquired (i) their current practices on co-performance based on co-performance design framework and (ii) how the concept and elements of co-performance design framework affected the ways they design user-agent co-performance and overall user experience design for personalized service. The interview started with the brief introduction to co-performance for personalized experience of intelligent services. To effectively investigate these questions, the expert interview consisted of four sessions (Figure 5-5): *Sharing* session, *Reflection* session, *Design* session, and *Debriefing* session. The expert interview was conducted with designer participants individually and each interview took about two hours.

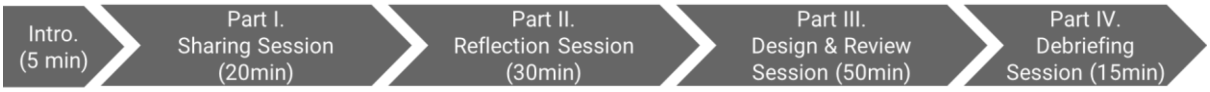

Figure 5-5. Overall Procedure of the Expert Interview

Part I. Sharing Session

The purpose of sharing session was to build a shared ground for the discussion by understanding designers' overall approach to co-performance in their current design practice. To initiate the discussion, the experts were asked to share their experience of designing user experience for personalized services (e.g., service type, motivation, incorporated user data, expected personalization outcomes) and whether they incorporate users to improve user profiling for personalization. If any, then, designers were asked to further explain how they were designing the co-performing experience, including examples of the service features and interactions. If they do not consider co-performance in their design, the underlying reasons for such design decision making were inquired.

Part II. Reflection Session

The purpose of reflection session was to further inquire each designer's current practice focusing on the specific elements of the co-performance design framework. To do so, the constructs of the co-performance design framework were explained to designers by utilizing the tutorial (Figure 5-2). Designers were asked to explain whether and how they considered each element for designing co-performing experience, what their design considerations in a user's perspective, and what the biggest challenges in the design process were. If they do not consider co-performance in their design, the underlying reasons for such design decision making were inquired.

Part III. Design & Review Session

In the third session, designer participants were asked to redesign co-performing experiences in their current service by applying the co-performing design framework they reflected upon in the previous session. They were guided to express their ideas either in a basic ideation worksheet or in a stage-based ideation worksheet (Figure 5-6) by drawing or elaborating features, interactions, and scenarios related to supporting user-agent co-performance. The purpose of this session was not to improve the quality of service per se, but to enable professional designers to deeply reflect on co-performance design framework. During this session, designer participants were allowed to revisit the tutorial as they wanted. After they finished redesigning, participants were asked to explain their redesign ideas and the design rationales in relation to the co-performance design framework.

Figure 5-6. Worksheets for Ideation

Part IV. Debriefing Session

In the final session, debriefing interviews were conducted to understand the impact of co-performance design framework. The debriefing interview questions included followings:

- How did the framework change the ways you design co-performing experience, comparing to your current practice?
- What were the most helpful/challenging elements of the framework in designing co-performing experience? Why?
- What do you think of the value of the framework as well as the design outcomes?
- How do you think this framework would help you in the future practice?
- Were there any parts that need to be improved?

5.2.4 Data Collection and Analysis

During the design sessions, 45 design ideas about co-performing experience were collected and transcribed. Along with the design outcomes, 16 hours of interviews were audio-recorded and transcribed. Regarding the transcribed data, thematic analysis was conducted. First, initial open-coding analysis was conducted by reviewing the data in terms of three research questions of this study: (i) current practice for supporting co-performance (CP), (ii) characteristics of the ideas generated with an understanding of co-performance design framework (ID), and (iii) the value of co-performance design framework in design (VL). Through an iterative coding analysis, the emergent patterns and themes across the data were explored. Also, a thematic map of the codes was developed to understand the roles and values of the elements of the framework (FW) (Figure 5-7). To obtain the objectivity of the analysis, the coding scheme was revised three times by iteratively conducing sub-level coding analysis.

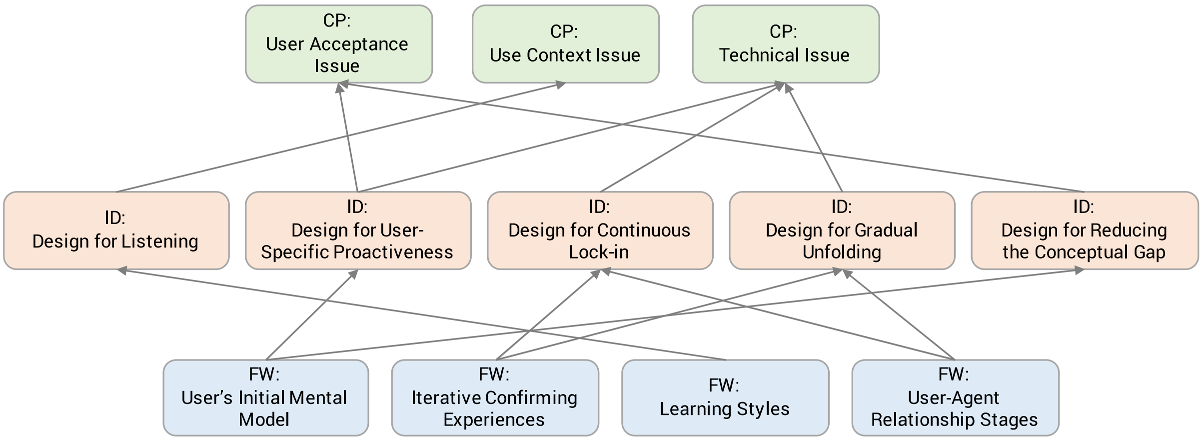

Figure 5-7. A Thematic Map of Codes

5.3 Findings

5.3.1 Current Practices and Challenges for Co-Performance Design

Although the designers in this interview study were aware of potential benefits of co-performance in improving the quality of service, the analysis of their current practices revealed that they had a tendency to minimize the co-performance between users and systems. The services of the designers in this study, were highly relying on big data analysis and thus, personalization in those services was mostly achieved through personalization algorithms with very limited level of co-performance. For instance, asking a user agreement to personal data collection was the simplest level of co-performance, although several designers said it was still challenging to get such permission from users (P7, P8). Another example of co-performance that the designers currently incorporated in their service was asking for one-time labeling for service personalization, such as registration of the location of a user's home and office for personalizing in-car navigation support (P2).

The reasons for such limited uptake of co-performance were associated with three major issues designers have to challenge in practice to accommodate co-performance in the actual systems: *user acceptance* issue, *use context* issue, and *technical limitation* issue.

User Acceptance Issue: A Premise that Users are Not Tolerate Enough to Participate

The first reason that designers do not incorporate co-performance in their service design was due to their *premise* that users are generally not tolerate enough to take time and efforts to participate in making service improvement, i.e. user acceptance issue. Since users are generally uncomfortable with such *"demanding"* (D1, D2) systems, which ask users for help, designers tended not to try accommodating co-performance in their service. For example, D3 was very skeptical about involving users in personalization due to the user acceptance issue:

> *"I think such systems, which ask users rate their preference, for instance, do not survive at the end, because users do not put much efforts for rating. It seems to elicit negative reactions from users, if systems ask users to answer questions regarding this and that. So, I think systems should get feedback implicitly by observing what users do without letting them know necessarily." (D3)*

Also, drawing her previous experiences of designing a mobile personal assistant in 2017, D7 explained that how the notion of co-performance was rejected during the service visioning process, because users are not "ready" to adopt the notion, and how the cover personalization driven by systems was advocated more:

> *"We rather thought the other way around. We aimed to personalize the assistance by covertly collecting user data for a while, because we thought such co-performance is too radical to be adopted by general users with their current level of understanding with this technology." (D7)*

As these shows, designing systems, which support users *by the systems themselves*, seemed to be regarded as the virtue of *smart* services among professional designers. For this reason, designers tended to focus on *implicit signals* from user behaviors, through which they can infer users' needs and preferences (e.g., users' skipping behaviors to infer their music preference and to lower down the priority for recommendation (D2)). In fact, those implicit learnings from user behaviors are still making certain level of personalization possible in diverse recommendation services in these days. However, they barely support users to understand how the system works (i.e. transparency) and to have control over systems' behaviors (i.e. users' controllability).

Use Context Issue: Trade-Offs between Quality of Personalization and User Experience

Another reason for the limited uptake of co-performance was that co-performance can interrupt users interacting with the service for their own purpose at a given time (i.e. use context issue). This was tightly related to the use contexts determined by the primary purpose of services. D2, for instance, had a concern on incorporating explicit interactions required for co-performance in the context of using an in-car navigation service, because he thought that providing *instrumental supports* (i.e. navigating) is more important than personalization in such a context:

> *"I tried to avoid getting explicit feedback from users. Since in-car assistance service should always be ready to support users at any time, I feel reluctant to cut off the on-going interactions to get additional information from users." (D3)*

Adding to this concern, D6 also explained why his design team decided to sacrifice the quality of personalization for more fluent and convenient user experience,

> *"In fact, in the photo app, personalization is often somewhat supplementary service compared to the very primary purpose of the service, storing personal photos. Thus, our design principle for recommendation feature is not to cause inconvenience at least while using the service. […] Thus, we feel reluctant to ask user for creating personalized tags for system-curated albums, it may improve the further service though." (D6)*

As these excerpts show, designers tended to think that asking for co-performance is often inappropriate or not reasonably necessary in their service, even though the quality of personalized services they offer might not be as good as it could be. Due to the trade-off between service personalization and user experience, co-performance was not readily adopted in the services.

Technical Issues: Limitations in Implementation due to Complexity of Translating Designs into Algorithms

The last, but not least reason was related to technical limitations in developing systems that incorporate user inputs for further service personalization or evolution. Although the notion of machine learning and artificial intelligence have become commonplace in IT products and service, such intelligent technology is still in the progress of development in industry. Thus, designers were skeptical about co-performance, because there are clear technical limitations to provide quality services, even if they incorporate co-performance in their service. Regarding this issue, D6 explained how designers' visionary scenarios are easily flatten while implementation:

> *"We could propose more intelligent service scenarios than current service. However, even if we do have better ideas, we are asked to simplify the logics so that engineers can develop algorithms with clear input and output." (D6)*

D2 also added that iteratively learning and evolving services are particularly challenging to be designed, because such iterative scenarios should be concretely determined in advance so as to be implemented:

> *"Changing the contents and ways of learning might be very challenging for engineers and designers, because it may take time and resources to know what to learn further and it would be hard to determine how to learn even before implementing." (D2)*

For this reason, many of the designers were considering personalization as a simple if-then mechanism, which does not attempt to extend the knowledge of users a step further.

Reflection: The Absence of Human-Centered Design Guidelines Amplifies the Challenges

This section highlighted the designers' limited attempts to incorporate user inputs in a system's learning process, even though most of them see the value of user inputs for further personalization of the service. While designers mentioned three issues that show the reason for the limited uptake of co-performance, the biggest problem found from the interview was that designers do not have user-centered guidelines that can help them make informed design decisions on whether and how to support users' co-performing experiences. For instance, even in the cases of simple co-performance (e.g., agreeing to location tracking or one-time tagging), designers had not tried to consider enabling users as a partner, with whom they potentially interact over time and improve the service in a reciprocal manner. Rather, designers relied on providing monetary reward to users in order to initiate their co-performing behaviors, instead of challenging the issues in a designerly way. These issues add the urgency of some guiding information even for a limited extent of co-performance.

5.3.2 How the Framework Informed the Practice of Co-Performing Experience Design: Five Design Patterns

From the analysis of how the framework affected designers in terms of their design thinking and design outcomes, the patterns that describe the impacts of co-performance were identified. As the framework enabled particular patterns of design to support co-performing experiences, the roles of co-performance design framework are defined in a form of five design patterns: i) design for listening, ii) design for user-specific proactiveness, iii) design for continuous lock-in, iv) design for gradual unfolding, and v) design for reducing the conceptual gap.

Pattern 1. Design for Listening

The Role of Framework: Enabling to Think Intelligent Services More Open to User Inputs

As discussed earlier, most designers, in their practice, had not specifically considered the explicit means to receive user inputs or feedback, because they had thought that it is the back-end systems (e.g., big data analysis and algorithms) that should be enhanced to provide improved personalization, thinking users as the one who receive the finalized services. However, the overall notion of partnership that co-performance design framework suggests enabled designers to realize the necessity to design intelligent systems more open to users so that even the small inputs from users can be the source of personalization and service improvements. As result, the framework motivated designers to explore the opportunity to learn from users more actively than before, aiming to improve their service even further.

Resulted Design Examples

This shift in thinking the necessity of co-performance inspired designers to develop ideas about diverse input channels through which user can put their feedback or relevant personal information on the service. To listen user inputs without harming users' current flow of interaction, two types of input channels were designed for this design pattern (i.e. *design for listening*). On the one hand, several designers created **in-situ learning interfaces (**Figure 5-8**)**, aiming to unobtrusively invite users to co-perform with systems, while users are using the service**.** For instance, in the context of news recommendation, D1, added a floating button aside from a news article so as to get user feedback on whether and how the recommended article was helpful or not. Also, D3 redesigned the shopping recommendation service, which was originally designed to just list up recommendation items, by adding a new button, through which users can let the system know they are "not interested" in the recommended items.

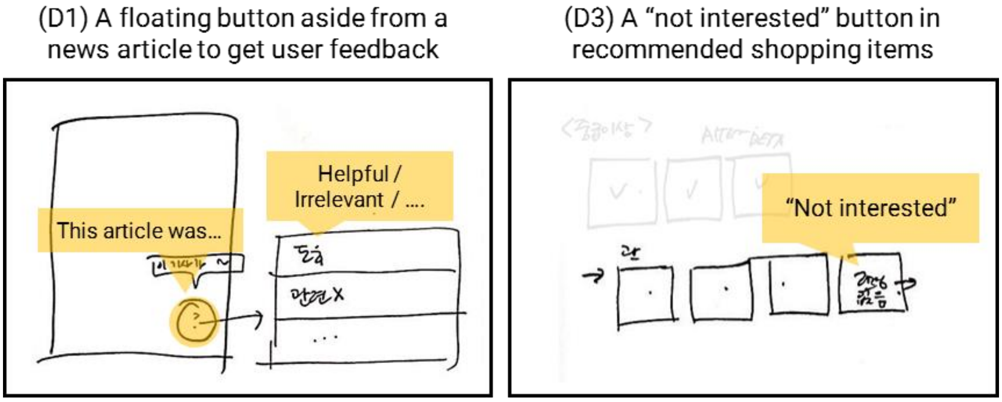

Figure 5-8. Examples of Design for Listening Pattern (Left: D1, Right: D3)

On the other hand, some of the designers (D2, D5) created the scenarios for **serendipitous conversation for learning** user information, which can be taken place not necessarily during the service use, but in-between the service encounters. For instance, D5 created a scenario for his mobile AI assistant service that occasionally initiates conversation to learn about users, while users are idling (e.g., asking user information that are not directly related to an immediate service improvement, but has potential to be utilized for personalization after all, such as user's birthday or feelings). D2 also created a scenario of the in-car AI assistant that asks learning questions to users *after* they finish using the service (e.g., requesting to label the frequently visited place after driving).

Expected UX Value: From a Service Receiver to a Co-Creator

Designers expected that these features would change the overall images of their service from a service deliver to a listener, which shows the *"curiosity" (D6)* and *"interests" (D2)* toward users, rather than just delivering the service without any communication with users. Also, they expected that this way of learning would improve the current personalization more personally relevant to users. As they described, these kinds of designs for user inputs would be an important starting point to support users' co-performing experiences and service personalization.

Pattern 2. Design for User-Specific Proactiveness

The Role of Framework: Enabling to Think User Types in Terms of Co-Performing Attitudes

Considering users as a non-active participant of co-performance had been a prevalent pre-conception of most designers, as discussed in the previous section. Thus, most designers in this study mentioned that they never had considered users with Companion mental model in designing personalization in their services. However, reflecting on the two types of users' initial mental models proposed in the framework (i.e., GTD agent mental model and Companion mental model), they were able to remind *active users* in their services, who are highly-engaged in giving their inputs and feedback on the services. For this reason, designers became able to try segmenting their current users in terms of potential co-performing attitudes (e.g., users' potential acceptance toward agents' requests), instead of regarding all their users might not have willingness to co-perform with systems.

Resulted Design Examples

This shift in thinking users resulted the second design pattern, namely, design for user-specific proactiveness in co-performing. Designers developed different co-performing strategies for different user types. First, several designers designed co-performing interactions by **differing the frequency of agent-initiated learning**. For example, D6 redesigned his photo album curation service in a way that it sends requests for user tagging more regularly to users with Companion mental model so as to support those users in curating their photo album more meaningful to them. The second approach to accommodate users' mental model was to co-perform with users by **providing different input interfaces** that are more suitable for users with each type of mental model. Connecting the aforementioned idea of D6, he thought of a more advanced tagging interface for users with Companion mental model, which learns user-created tags and suggests potentially-relevant tags in the following tagging interactions. In this way, he aimed to enable Companion mental model-type users to more concretely tag the system-curated albums and to more conveniently co-perform with the system over time. The last approach was to **differ the proactiveness in recommendations** depending on users' mental model (Figure 5-9). D7, for instance, designed the place recommendation service to provide recommendation alerts more frequently and in an assertive tone to users with Companion mental model, while providing those alerts less frequently to users with GTD mental model, because such proactiveness can cause negative feelings from GTD mental model-type users.

(D7) Differing Recommendation by User Types

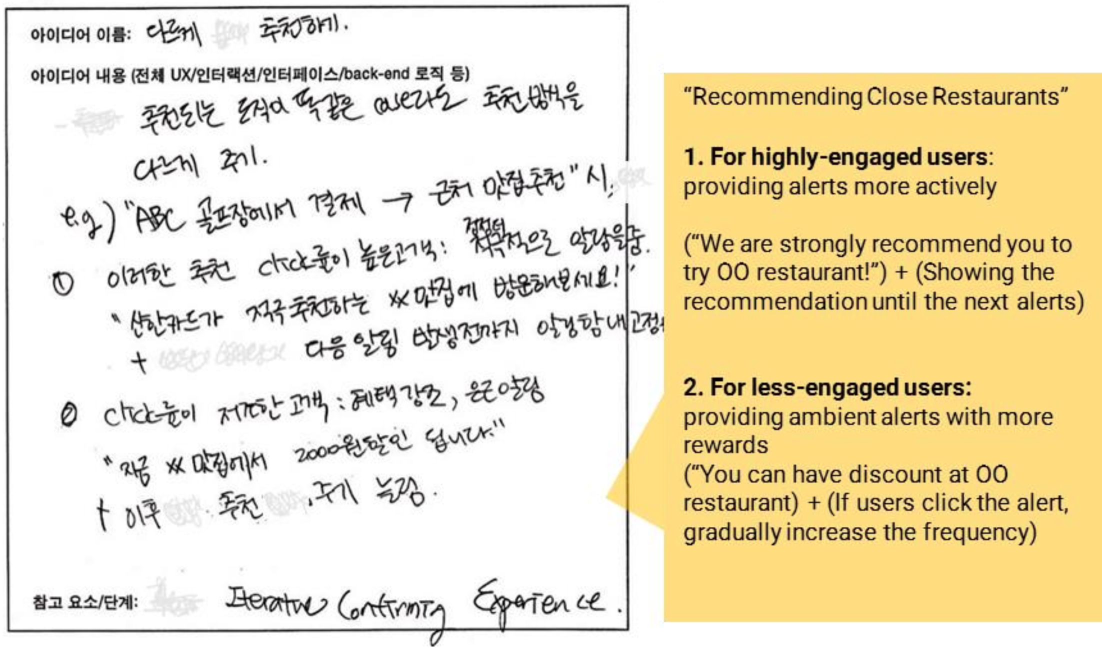

Figure 5-9. An Examples of Design for User-Specific Proactiveness Pattern (D7)

Expected UX Value: Toward More Acceptable and Pleasant Proactiveness

Regarding these design examples, D7 said this way of designing proactiveness would increase the opportunity to engage less-interested users with the service, instead of "giving up those users." (D7) Also, by considering serving those Companion model users, designers mentioned that they were able to specify their co-performing strategies even further for the users who have relatively low expectation of service evolution and willingness to cooperate with the systems. Comparing to current "demanding" (D2) systems, designers expected to design a system proactiveness in a more acceptable and pleasant ways.

Pattern 3: Design for Continuous Lock-In

The Role of Framework: Enabling to Think User Satisfaction from an Extended Timeframe

In any services, providing a positive and satisfying experience to users are important to build an exclusive relationship with the users. Designers in the study often referred this as customer 'lock-in' from a service provider's perspective and explained the concept as the one that they want to achieve through their service offerings eventually. Meanwhile, designers mentioned that they had considered a user's lock-in as *discrete* states (e.g., like yes or no questions). However, reflecting on the stages of user-agent relationship and iterative confirming experience proposed in the framework enabled designers to consider the notion of user lock-in as a *continuous* process of accumulating the positive experiences of the service. In this sense, designers were inspired to think of for the ways to provide satisfying service experiences over a more extended timeframe of user journey.

<u>Resulted Design Examples</u>

In this line of thought, designers were inspired to develop ideas to continuously provide satisfying user experiences even after they soundly serve the primary service. First, designers tried to **enhance personal nuance on their service offering** by advancing recommendation contents and recommendation labels (Figure 5-10). For instance, D4 thought of the ways to provide highly-personalized recommendations with labels that are distinctively personalized to a specific user. Also, D6 explored ways to provide additional types of album curations over time based on the user-created tags on the uploaded photos on his album curation service (e.g., identifying a user's personally-significant places from the user's tagging data and diversifying album curations for those places, instead of continue suggesting those photos equally with the photos taken from other places). In addition, designers specified **relationship recovery scenarios** for the situations where users are in stagnating relationship with the service. Their approach varied from recovering ideas through *follow-up interactions* that actively inquire the reason for stagnation (D5) to *distancing interaction* that intentionally reduce intrusive interactions as much as possible and maintain the status-quo-relationship until their users until they show their interests again (D4).

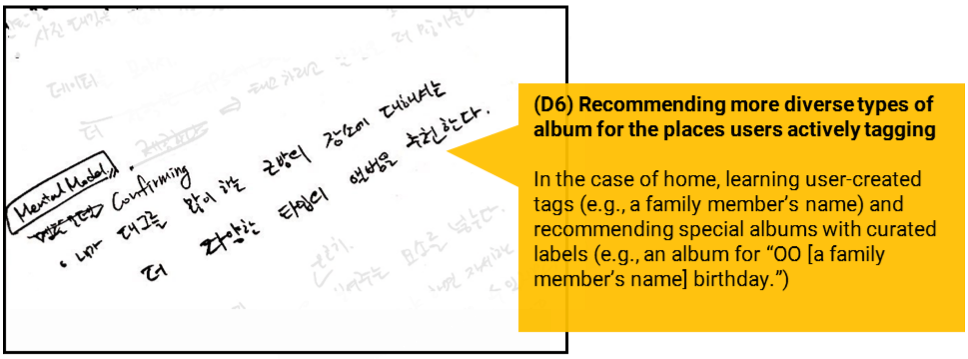

Figure 5-10. An Example of Design for Continuous Lock-In (D6)

Expected UX Value: Avoiding the Abandonment in Advance

In this way, designers were able to think of user satisfactions "in the continuous flow of user-system interactions," (D5) rather than thinking user satisfaction as a static and discrete one that can be maintained over time once it is achieved:

> *"'Locking-in' users in the service is one of the important measures of user satisfaction. One of the refreshing ideas of this framework for me was about circulous model of user experience. We usually think lock-in as much like on/off thing. However, this circular model enabled me to think of how we can CONTINUE the virtuous cycle of interactions and change the flow of interactions if users enter into the vicious cycle of interaction." (D5)*

Pattern 4: Design for Gradual Unfolding

The Role of Framework: Enabling to Think the Situations Where the Learning is Incomplete

Since designers tended to think users as the one who receive the finalized services, designers mentioned that they had designed personalization in their service mostly focusing on the final moment of service delivery. However, reflecting on the user-agent relationship stages proposed in the framework, designers tried to think more consciously about user-system interactions in the situations where the system's knowledge of a user is incomplete to provide fully personalized services (i.e. the experimenting stage).

Resulted Design Examples

The considerations on the experimentation stage resulted the fourth design pattern, called design for gradual unfolding. Designers tried to **gradually unfold their personalization scenarios** before providing highly-personalized services. For instance, D4 designed gradually unfolding scenarios of context-based personalized services as follow:

> *"It would be better to show the personalization one-by-one starting from the ones that users can easily infer why the personalization happened and how their previous input is connected to the results. For example, in the case of context-based personalization, which is originally designed to personalize the service by considering time, place, and occasion integratedly, time-based personalization can be provided first before providing such highly-sophisticated suggestions." (D4)*

Also, as a way to the gradual unfolding, designers developed several **fail-soft design** ideas for the experimentation stage (Figure 5-11). The original meaning of fail-soft refers a system's behavior that terminates nonessential components when an error occurred on the system, while running only the essential components. In the context of recommender systems, fail-soft designs often provide more than one options to users so as to recover the potential inference errors while still moving users closer to their goal (Lieberman et al., 2004). In this study, designers tried to fail soft in the experimentation stage, by *making personalization only when it is highly accurate*, aligning with D4's design intention in the aforementioned design example. As a way to fail soft in similar regard, D6 even utilized visualizations to ambiently provide confirming experiences in the experimentation stage (e.g., marking the collection of photos taken from a user's potentially-significant places only with colors, instead of instantly naming the albums with systems' assumptions).

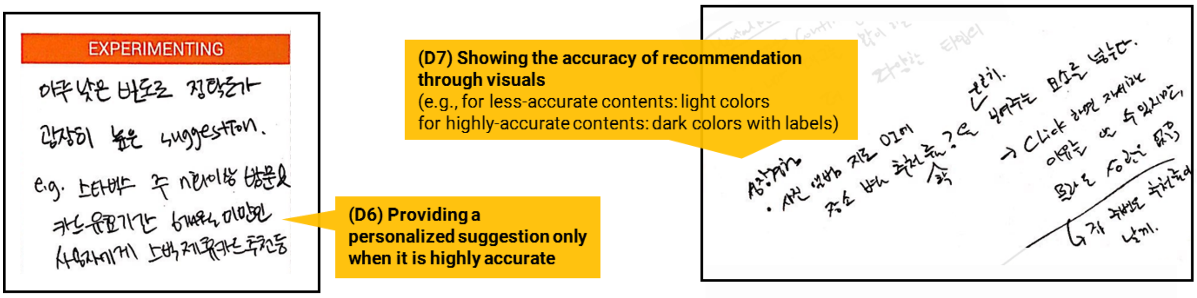

Figure 5-11. Examples of Fail-Soft Designs (Left: D6, Right: D7)

<u>Expected UX Value: Building a Trustful Relationship before Providing Proactive Services</u>

By considering user-system interactions during the experimentation stage, designers expected to build a trustful relationship with users, because they can avoid providing unreasonably proactive supports without enough knowledge of users. Also, designers expected that these features would make systems more transparent to users, as systems are designed to provide only the personalization that are intelligible to users. Such transparent personalization would provide proper level of confirming experience in the experimentation and would successfully lead users into the intensifying stage for more diverse and proactive supports by the systems.

Pattern 5: Design for Reducing the Conceptual Gap

The Role of Framework: Enabling to Think the Gap between What Designers Intend and What Users Would Expect

One of the notable patterns discovered from the redesign session was that designers tried to think of the ways to reduce the conceptual gap between a users' expectation of the agent ability and the agent's actual ability determined by the designers. Reflecting on users' initial mental models suggested in the framework, designers realized that the agent that they intend to design in their service might not necessarily be aligned with users' expectation of the service in terms of potential intelligence and the ways of co-performance. In this sense, designers became to revisit the overall design concept of their agent and explored the diverse ways to communicate the intended capability of the agent to their users.

Resulted Design Examples

To reduce the conceptual gap, designers made two types of attempts (Figure 5-12). First, designers detailed **introducing messages** in the initiation stage as a way to reduce the conceptual gap. For instance, D4 and D5 detailed the script of introducing messages for mobile assistants' reminder services as "I will remind your schedule, if you let me know the 'time' and 'name' of the schedule." rather than just saying, "Please let me know your schedule for reminder." The reason that they detailed the script in a more concrete form was that their agent did not have ability to extract the time and the name of a schedule from natural human languages. Thus, by specifying the ways users should co-perform with the systems, D4 and D5 wanted to prevent users from having disappointing experiences in the early stages. Second, some designers tried to **specify the overall concept of agent** they would pursue in their service by questioning the level of intelligence they aim to serve with their current technology. In this sense, D2 specified the character of agent as "smart but sloppy" agent to effectively communicate its currently immature recommendation capabilities.

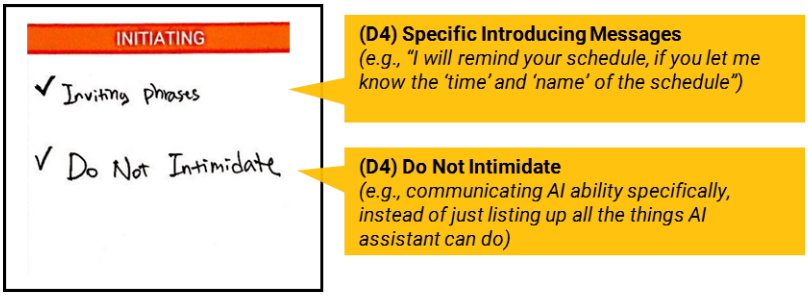

Figure 5-12. Examples of Design for Reducing the Conceptual Gap Patterns (D4)

Expected UX Value: Enabling Users to Build Coherent and Transparent Anticipation

Designers expected that these features would enable their users to build a more consistent mental model about their agent. Designers mentioned that this holistic envisioning of an agent's ability had been achieved in current practice to a limited extent, because each designer often takes a responsibility for only partial features of overall services. Thus, these efforts on reducing the conceptual gap would enable users to have more coherent anticipation toward the service and to have clearer understandings on how to co-perform with the system over time.

5.4 Discussion

5.4.1 The Potential Roles of Co-Performing Experience Design Framework in Overcoming the Current Challenges in Design Practice

The results of in-depth expert interview showed five different patterns that co-performance design framework can help designers make informed decisions for building user-agent partnership and supporting user-agent co-performance. Reflecting on this finding, this section discusses how the framework would help designers in overcoming the current challenges they have discussed earlier with regard to deploying co-performing features in their service.

Helping Designers More Readily Address the User Acceptance Issues as a Design Problem

As discussed in the section 5.3.1, designers tended to avoid incorporating user inputs in the learning and personalization, due to their assumptive premise that their users are unfavorable of intelligent systems that ask users' help. However, through the redesign session with co-performance design framework, they were able to remind *active* users who are highly-engaged with giving their inputs and feedback on the service. By considering serving those companion-model type users, they were able to specify their co-performing strategies even further for the users who have relatively low expectation of service evolution and willingness to cooperate with the systems (related to the pattern #2, design for user-specific proactiveness). Also, they put more efforts into communicating the agent's ability and how users' inputs to be utilized for further services (related to the pattern #5, design for reducing the conceptual gap).

Regarding user acceptance issue, D7 made a notable comment that are worthwhile to reflect on:

> *"Perhaps we may have underestimated users' interests toward personalized services, just because we cared their task-oriented experience too much. But I have heard that younger*

generations are more relating them with these kinds of intelligent assistant services, similar to Companion mental model users described here. Maybe some of our users have such a mindset." (D7)

This comment implies that user acceptance issues should be addressed more explicitly by designers, as this particular point of time is somehow a transitioning phase, in which end-users are just getting to know the intelligent technology, which probably take significant time for current systems to be perfect enough to totally understand users' contexts. In this sense, co-performance design framework takes an initiative to sensitize designers with this user acceptance issue as a design problem to be addressed in their service.

Helping Designers Take a Step Forward for Personalization beyond the Use Context Issues

Co-performance design framework also enabled designers to tackle use context issues (related to the design pattern 1, design for listening). During the redesign activities in the expert interview, designers realized that getting user inputs and feedback can be happened without disturbing users' current use of the service and found ways to *invite* users to teach the agent wherever users are not occupied by a more primary task (e.g., in-situ learning interfaces without sacrificing user experience). Also, some of the designers were able to find learning opportunities that are not necessarily happening in the context of using the service, before or after using the service (e.g., serendipitous conversation for learning).

While these interfaces are very basic design elements for co-performance, designers mentioned that they did not have chances to consciously think of such opportunities to *listen* users' voices due to the issues they were facing in current practice, missing potential opportunities to personalize the services even further:

"We were aware that our recommendation algorithms are not accurate enough yet, but I realized that we haven't even tried to understand the reasons why users did not satisfy with the suggested recommendation from THEIR point of view. We might be able to implement some kind of questioning interfaces that ask why users are not engaged with the service, for example, if users keep skipping our recommendation." (D6)

As his comment implies, challenging the use context issues through an active exploration for the unobtrusive co-performing opportunities would enhance the potential to support users in a more personally-relevant way.

Helping Designers Challenge the Technical Issues Together with Engineers by Enabling them to Build a Shared Understanding on Design Decisions

Finally, co-performance design framework, as a whole, enabled designers to tackle technical issues as well. From the analysis of design outcomes, it became salient that the limited design approach that designers previously related to the limitation of current technology was not necessarily a difficulty of implementation. Rather, this was a problem of communication, because designers did not have proper reference to persuade other collaborators regarding why particular co-performance scenarios are necessary for both user experience and system performance. From the debriefing interview, it was observable that designers became more *"confident"* in their design decisions for personalized service experience. In the case of D6, he said,

> *"I realized the potential value of this idea [a more advanced tagging interface for photo album curation (related to the design pattern 2)] and it does not seem to require much technical advance actually. I may take initiatives to implement this feature even if the development requires much efforts." (D6)*

This comment implies the potential role of the framework as a design principle, through which designers and their collaborator (e.g., engineers and marketers) can make informed decisions on their design of co-performance in intelligent IT services. By doing so, the framework would play a communicative role among such multidisciplinary teams, supporting them to build a shared understanding on their design decision.

5.4.2 Implications for Utilizing the Framework in Different Design Contexts

While the framework helped all participants as described above, there were notable differences in the ways the framework was utilized by the participants depending on the types of service they applied the framework and by the design phase they were in. This provides implications for utilizing the framework in different design contexts as follow.

What Type of Intelligent IT Services are More Suitable?

One of the reasons for conducing this expert interview not just with the designers who were working on on-the-go personal assistant services, but also with those who were working on other types of intelligent IT services was to investigate how this framework would be a guide for broader ranges of intelligent IT services, which still share some characteristics of on-the-go personal assistant services. Reflecting on the ways the framework was used by designers in different design contexts, this framework is expected to provide the most comprehensive guide to the service context, which is an agent-based service and has the characteristics of continuously collecting information about users.

First, this framework is expected to provide the most comprehensive guide to **agent-based services**. In the case of D4 and D5, who applied the framework for the agent-based mobile AI assistant services, they explored the design opportunities through overall stages in the co-performing user journey map by considering the implications of partnership-affecting factors from the initiation stage to the termination stage while. In contrast, participants who applied the framework for non-agent recommendation systems (e.g., D1: news curation on a search portal platform, D3: shopping recommendation services on a search portal platform) tended to focus on designing interactions for learning at a specific stage rather than considering an overall experience. This implies that the relationship development stages make more sense in the agent-based services, where the metaphor of human-human relationship development is readily applicable in the user journey.

On the other hand, it was found that the presence of agents is not the only the factor that determines the types of services that this framework can readily inform. Instead, the framework also usefully informed the designs of co-performing experiences for the services, which **continuously** collect a user's activities that can be used to build a deep understanding of the users (e.g., D7: continuous tracking of a user's consumption history, D8: continuous logging of a user's meal). For instance, designers of those services tended to consider a user-system relationship more carefully, as those services are expected to be perceived more closely by the users. Thus, they tended to design co-performing experience for continuously build the trust and gradually unfold the services (i.e., design pattern #3 & #4). Although AI speaker (D2) is an agent-based service, in contrast, designers less focused on developing the deeper user-agent relationship, as it currently tends to gather a user's information in a fragmented manner and rarely provides personalized services. Rather they tended to focus on other qualities of co-performing experience, such as reducing the conceptual gap (i.e., Design Pattern #5).

At Which Design Phase, is this Framework Effective?

From the study, it was found that the elements of co-performing experience design framework guides designers to rethink the relationship between users and systems, which often require them to reframe the ways they design user-system interactions in their services. Due to this reason, it was found that the elements of co-performing experience design framework were more readily and flexibly used by the participants, when they carried out the redesign activities for the services, of which personalization algorithms are not stereotyped yet. For instance, in the case of participants who were working on the services that had been successfully run for years and had secured pool of users (e.g., D1 & D3: preference-based recommendation service), they tended to utilize the framework only in a limited extent, as they felt a bit of difficulties in breaking the out of box from the established notion of personalization in their services. However, in the case of participants whose practice were still at the stage of planning and developing the intelligent services, they tended to use the framework in a more flexible and interpretive manner (e.g., D4 & D5: mobile AI assistant, D7: personalized services in finance domain, D8: personalized services in health domain). This implies that what this framework pursue in design is more like a newly framing of user-system relationships. Therefore, this framework will be useful in the design phase of planning a new intelligent personalized service or reorganizing an existing service into a new concept, which would require a breakthrough, rather than changing a part of the existing formalized services.

5.5 Conclusion

In this chapter, the roles and value of co-performance design framework were examined through expert interview, which incorporated redesign activities for in-depth reflections of professional designers on their current practices on designing user experience and user-agent co-performance. The result of expert interviews showed that co-performance design framework enabled designers to challenge the issues they currently face with regard to user acceptance, use context, and technical limitations. Although there remain many challenges to be studied through future research, the constructs of co-performance design framework would enable designers to make more informed design decisions to build a user-agent partnership in their service context and to take an initiative role as a designer in multidisciplinary collaboration.

CHAPTER 6.

Implications for Co-Performing Experience Design

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Implications for Co-Performing Experience Design

As a way to empower users in the experience of intelligent IT services that are increasingly decide what users would experience automatically, this research investigated the ways to support co-performance between users and systems by considering users' experience in participating as an active co-creator of the service. As an answer to the primary research question of this dissertation, "*How intelligent IT services should be designed to support users' co-performing experiences?*", this chapter provides implications for co-performing experience design by reflecting on the findings from the previous chapters. Then, the discussion on how the notion of partnership building approach can enhance users' co-performing experiences is followed.

6.1 The Framework Revisited: Implications for the Relationships among the Elements of Co-Performing Experience Design Framework

Regarding users' perception and expectation of co-performing with intelligent IT services over time, this dissertation investigated two research questions, including *"How do users experience personalization and co-performance in intelligent IT services over time?"* and *"What do users expect from intelligent IT services by co-performing with the systems over time?"*. While the framework proposed in Chapter 5 provides overall understanding on users' perception and expectations toward co-performing with intelligent IT services, more clarifications on the relationships among the elements of the framework would guide designers more readily in their practice. Reflecting on the findings from user studies (Chapter 3 and Chapter 4) and the perspective of designers (Chapter 5), this section revisits the elements of co-performing experience design framework and discusses the ways to enhance its comprehensiveness.

6.1.1 Reflection on the Stages of User-Agent Relationship Development

One of the contributions of this dissertation is in articulating the stages of how user-agent relationship in intelligent IT services would develop over time. While there have been a body of work that considered the relational aspects of human-computer interaction (Bickmore and Picard, 2005; Bickmore and Cassell, 2001; Nass, Steuer and Tauber, 1994), none of the work provided a concrete taxonomy for designers to understand the dynamics in their interactions over time. In addition, while previous research investigated how users experience interactive artifacts over time, little work adopted a relational perspective in articulating user-system interactions over time. For example, Karapanos et al. (2009) provided a framework that describes the phases of users' experience over time as *Orientation*, *Incorporation*, and *Identification*, their articulation of the phases were described focusing only the changes of users' behaviors, as they considered the behaviors of interactive artifacts as static as they were in the first state.

Meanwhile, the findings from Chapter 4 and Chapter 5 showed that the stages described in this research can be regarded as the potential user journey for co-performing experiences in intelligent IT services. In this regard, some of the designers (D4, D7) in the expert interview study (Chapter 5) questioned whether there would be any stages after the intensifying stage, as they thought that there will be a stage where users' expectation on personalized services do not expand anymore and users would like to maintain the status-quo relationship. While this was questioned by only two designers, including the bonding stage in the co-performing experience design framework is considered to be worthwhile, because it enhances the comprehensiveness of the framework.

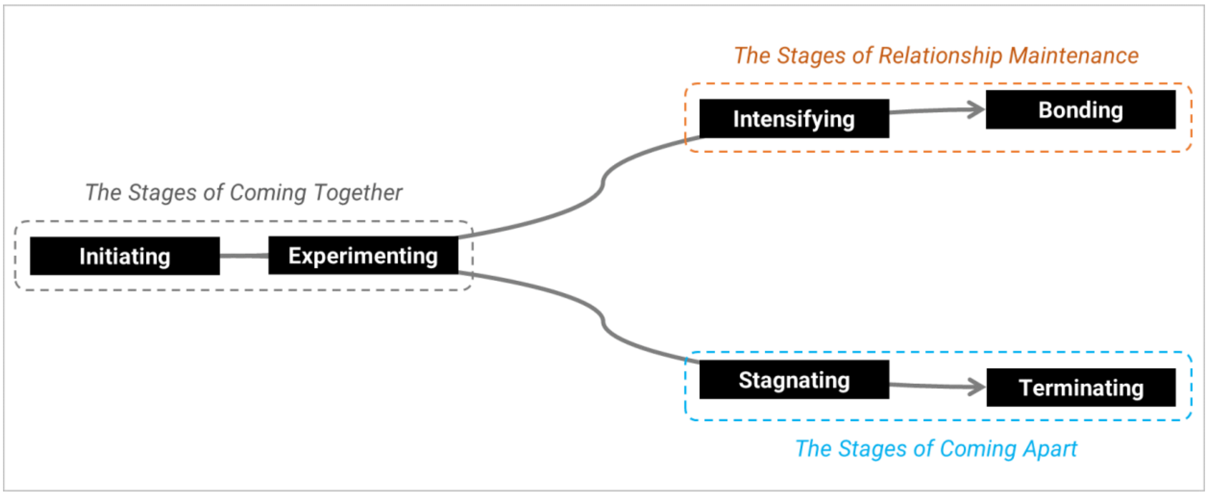

Figure 6-1. User-Agent Relationship over Time: user-agent relationship would develop over time starting from the stages of coming together (grey) and then move either toward the stages of relationship maintenance (orange) or toward the stage of coming apart (blue)

To summarize, the stages of user-agent relationship in intelligent IT services would start from **the stage of coming together** (i.e. initiating and experimenting stage). Then, their relationship moves either toward **the stages of relationship maintenance** (i.e. intensifying and bonding stage) or toward **the stages of coming apart** (i.e. stagnating and terminating stage). In this regard, the quality of user experience in initiating and experimenting stage would decide the quality of user-agent partnership in the later phases of interactions (Figure 6-1). The movements through the stages of user-agent relationship is quite aligned with the movements through the stages of human-human relationship described in the Knapp's model (Knapp and Vangelisti, 2004), as both have move forward and move backward process.

6.1.2 Relationships between User-Agent Relationship Stages and Factors Affecting Co-Performing Behaviors

The factors affecting co-performing behaviors (discussed in Chapter 4) would have influences in the soundness of transitions between the stages in user-agent relationship in intelligent IT services. The resilience of user-agent partnership that participants had built with their Co-Performing Agent provide implications for which factors would contribute most for which stages of transitions in the framework (Figure 6-2).

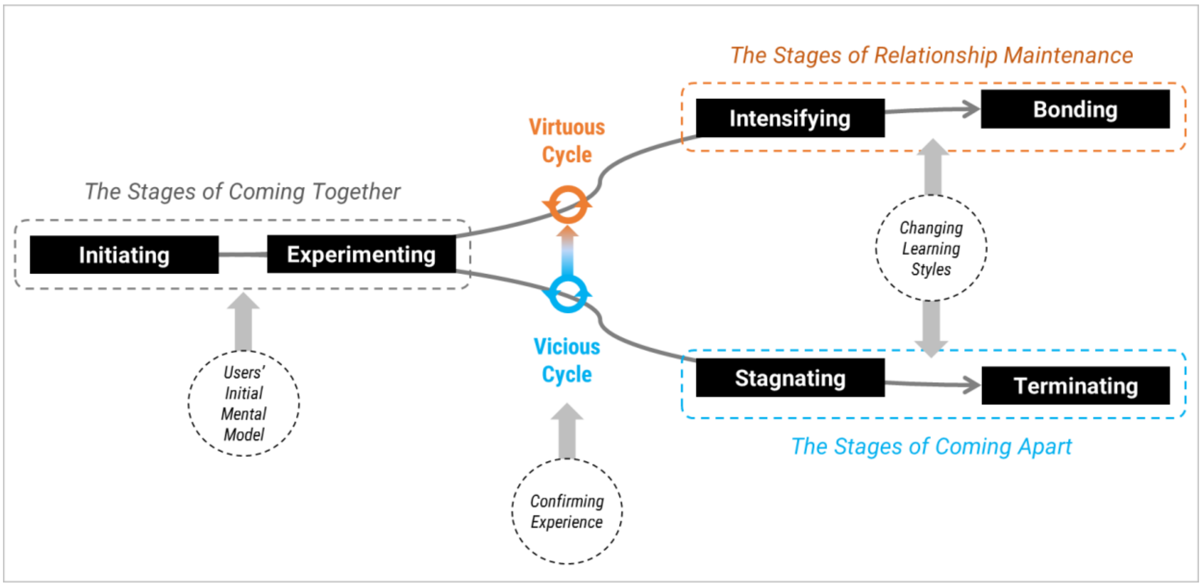

Figure 6-2. Relationships among the Elements of Co-Performing Experience Design Framework

Users' Initial Mental Model for a Sound Transition from Initiating to Experimenting Stage

First, understanding a user's initial mental model would be important for an agent to adjust the ways to co-perform with the user considering their underlying expectations of service evolution and preferred styles of co-performance (i.e., a short-term co-performance to teach simple aspects of a user's life to increase the efficiency-related values of the service vs. a longer-term co-performance to teach more subjective and multi-faceted aspects of a user's life to increase the personal relevance and to get more integrated service).

This process of probing a user's initial mental model toward agent-based services would be effective, if it is done before the co-performing interaction actually start. Even if an agent is able to automatically detect each user's mental model and provide tailored co-performing interactions, allowing users to choose the preferred styles of co-performing would enhance user's controllability and reduce the potential risks that can be caused by the agent's assumption on a user's mental model. In doing so, the two types of initial mental model we found from this study (i.e., GTD Agent and Companion Agent) would be used as a metaphor to communicate with the user regarding the styles of co-performance and the core value that each type of agent pursues in service evolution (e.g., efficiency vs. personalization).

Depending on the mental model that a user has, the agent could be designed to engage the users in co-performance with different strategies. For instance, in the case of Companion model users who have a higher innate motivation for co-performance, providing an advanced co-performing interface that guide them to teach their agent at their best would be helpful. However, GTD model users may want to put their efforts as effective as possible, expecting their agent to automate some parts of data collection, like the example of P6 and P8 in our study. However, since they may still want to have authority over the agent's behaviors, this conflicting and thus challenging user expectations should be carefully considered in designing co-performance for GTD mental model users.

Iterative Confirming Experiences for a Sound Transition from Experimenting to Intensifying Stage

Providing iterative confirming experience would contribute to support a sound transition from experimenting stage to intensifying stage, because it was found that building a user's trust and partnership toward the agent takes time and is necessary to proceed to intensifying stage, where users and agents would co-perform for a more advanced level of personalization. Providing iterative confirming experience through which users can experience reciprocal service evolution would enable users to enter into **the virtuous cycle of user-agent partnership**. However, most of current learning and adaptive services do not explicitly consider the time-taking nature of building a user's trust and partnership toward the agent. Rather, those systems pursue to provide proactive supports as quickly as possible without concerning whether and how their users would trust the intelligence of systems. This collapsed interaction phase for co-performing and confirming experience might cause users entering into **the vicious cycle of user-agent partnership**, where they would not want to disclose their information and avoid the co-performance with the systems. For this reason, providing iterative confirming experiences by explicitly designing for learning period in between the experimenting and intensifying stages would support more effective and constructive co-performance over time.

Changing Learning Styles either for Stabilizing or Recovering User-Agent Relationship

The third factor, i.e. the agent's learning style, is deemed to be important either for stabilizing user-agent relationship in the intensifying stage or recovering user-agent relationship that fade from stagnation stage to termination stage. Successful co-performance in the experimentation stage will enable systems to serve the primary service personalization in a more reliable way. While it is obviously important to maintain the quality of primarily personalized services, co-performance between users and systems might be continuously necessary to reorient the service for changing user interests and states and to provide potentially more advanced personalization, as discussed in the chapter 4. Thus, after entering into the intensifying stage, supporting effective, but meaning-laden co-performance would be important to reduce user burden as well as to explore further personalization opportunities.

In addition, changing learning styles would be also important if users might have entered into the stagnation stage, because in this stage, users may neither try to find better ways to co-perform with systems nor anticipate improvements in agents' service offerings. As found in the chapter 3, the continued interactions in the stagnation stage can lead to a permanent abandonment of the service. Thus, if users fall into this stage, changing the contents and ways of agent's learning to the reason for stagnation would play an important role in recovering user-agent relationship avoiding them to fall in to the termination stage.

6.2 Design Principles for Co-Performing Experience in the Stages of User-Agent Relationship

Synthesizing and reflecting on the findings of previous chapters, this section provides design principles on how to consider the partnership affecting factors (i.e., the results of Chapter 4) across user-system relationship stages in partnership building (i.e., the results of Chapter 3) (Figure 6-3).

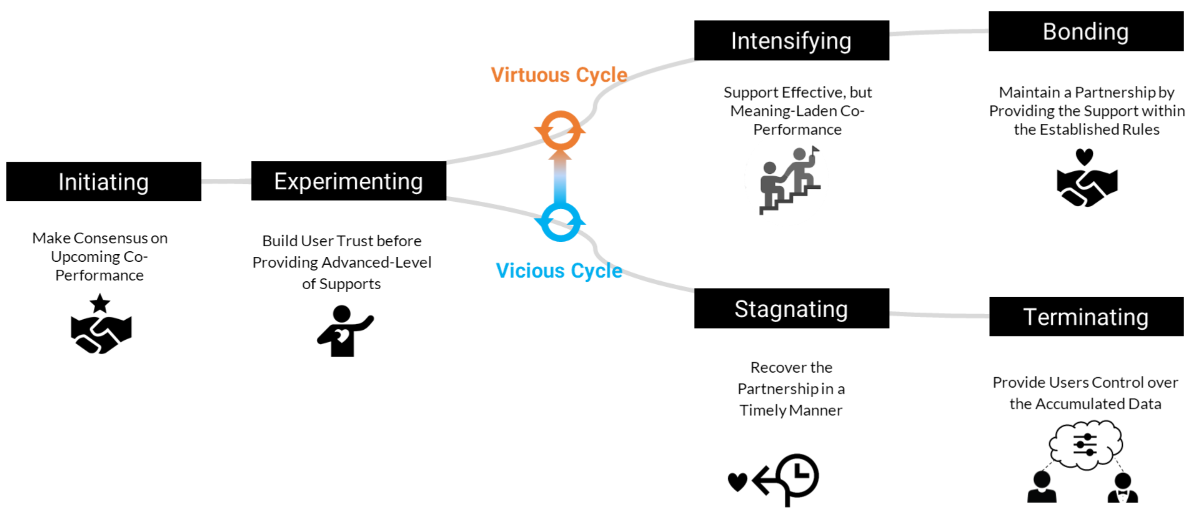

Figure 6-3. Design Principles for Co-Performing Experience

6.2.1 Initiation Stage: Make Consensus on Upcoming Co-Performance

The chapter 4 showed that a user's initial mental model (i.e. as described as Getting-Things-Done mental model and Companion mental model in this study) toward agent-based services greatly affect shaping users' overall attitude toward co-performance. This suggest supporting users' co-performance with an understanding of a user's mental model toward agent-based services would be important in enabling constructive co-performance over time. Meanwhile, the in-depth expert interviews of designers (chapter 5) revealed that designers also would have an intended way of co-performance in their service, which may not necessarily be correspond to users' expectation on co-performance. Thus, these findings imply that the initial stage of co-performance should be designed to reduce the gap between designers' intention and users' expectation on co-performance.

To make such consensus on upcoming co-performance, **communicating a system's current and potential capabilities** (e.g., what a system can or cannot offer with its initial knowledge of a user and how its knowledge and service would be improved through users' co-performance) would be helpful, as applied in designing Co-Performing Agent in the chapter 4. This can be more concrete for users to set their partnership mind, if systems can **clarify the expected time and the level co-performance** expected from users even before starting co-performance. In addition, in the case where systems can be adaptive to users' mental model, **orienting the ways of co-performance to users' mental model** would be possible either by inquiring a user mental model or by negotiating the form of upcoming co-performance. For example, in the case of Companion model users who have a higher innate motivation for co-performance, providing an advanced co-performing interface that guides them to teach their agent at their best would be helpful. In contrast, GTD model users may want to make their efforts as effective as possible, expecting their agent to automate some parts of data collection, like P6 in our study. However, since they may still want to have authority over the agents' behaviors, these conflicting and thus challenging user expectations should be carefully considered in designing co-performance for GTD mental model users.

6.2.2 Experimentation Stage: Build User Trust before Providing Advanced Level of Support

From the findings of this study in chapter 4, it was 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 support 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. To resolve these problems, designs of the experimenting stage will be very important, as this stage provides a kind of 'a grace period,' in which time users radically develop their partnership with systems. In this sense, building user trust through iterative confirming experiences will be most important in this stage.

To build such trust and partnership, providing confirming experience through **a transparent personalization** of the service will be helpful, even if the level of personalization is not much advanced in this stage. For instance, directly showing or communicating how user feedback is reflected on the following personalization can be an example of such transparent personalization. In addition, personalizing services in a **fail-soft** manner could be also helpful, which would help systems avoid over-assertive tones in delivering personalized services. By allowing users to have time to understand how co-performing works and the value of co-performance in this way, systems would also be able to learn about users better and build a more trustful partnership with users before providing advanced-level of personalization in the next stage (i.e., intensifying stage).

6.2.3 Intensifying Stage: Enhance the Partnership through Opportunistic Agent-Initiated Learnings for Advanced Service Personalization and Advanced User Controls

Successful co-performance in the experimentation stage will enable systems to serve the primary service personalization in a more reliable way. While it is obviously important to maintain the quality of primarily personalized services, co-performance between users and systems might be continuously necessary to reorient the service for changing user interests and states and to provide potentially more advanced personalization, as discussed in the chapter 4. Thus, after entering into this stage, supporting effective, but meaning-laden co-performance would be important to reduce user burden as well as to explore further personalization opportunities.

In this sense, supporting co-performance through **opportunistic agent-initiated learnings** would be effective in this stage. Reflecting on the findings regarding the changing styles of learning, the level of information for agent-initiated learning can include i) information about newly emerged patterns, ii) information about the changes occurred in an original behavior pattern, and iii) information that are indirectly related to the service itself but have potential to further improve the service. As found in the study of Co-Performing Agent, this way of co-performance will effectively communicate a system's willingness to improve the service and will enable systems to service continuously satisfying service experience. However, the timing and frequency of those opportunistic learnings should be carefully designed so as not to harm their partnership, by considering users' life patterns and mental models. At the same time, **providing advanced controls for users** to manage what systems know will become more important in this stage, as their potential concerns on privacy may increase over time.

6.2.4 Stagnation Stage: Recover the Partnership in a Timely Manner through Follow-Up Interactions or Intentionally Distancing Strategies

If systems fail to deliver satisfying services or to build a sound partnership with users in any of the aforementioned 'coming together' phases, users may fall into the stagnation stage. In this stage, users may neither try to find better ways to co-perform with systems nor anticipate improvements in agents' service offerings. As found in the chapter 3, the continued interactions in the stagnation stage can lead to a permanent abandonment of the service. Thus, if users fall into this stage, it will be critical to recover the user-system partnership in a timely manner so that their co-performance can be continued over time.

To recover the partnership, incorporating **follow-up interactions** to understand the reasons why users became entered into the stagnation stage would be the starting point. For instance, if users' response rate to systems' requests for co-performance decreases, systems may ask questions to inquire the reason for the decreased participation by providing a simple survey through which users can easily give feedback on the system. However, in some cases, those follow-up interactions would even deteriorate user-system relationship, because users might feel such interactions as intrusive, if they already have loosened their willingness to cooperate with systems. If that is the case, **intentionally distancing** user-system relationship for a while would be a possible strategy. For instance, as discussed by the designers in the in-depth interview (chapter 5), systems can reduce agent-initiated co-performing, while providing the service focusing on what users most satisfied, even if the service is somewhat limited in terms of hyper-personalization. Although it may take time to recover the partnership, this way of partnership recovery would provide users some control over systems by maintaining status-quo-relationship in an unobtrusive manner and would potentially lead users to resume co-performing gradually over time.

6.2.5 Termination Stage: Appreciate the Partnership by Giving Control over Accumulated Data and Supporting Future Co-Performance

Although terminating would not be a desirable situation to be happened from a service provider's perspective, users might want to terminate their service use. As discussed in the chapter 3, this termination stage has been the most neglected phase of interaction in intelligent IT service design. However, given that users might have shared huge amount of personal information with systems through co-performance, it would be important to appreciate the partnership users have shown as well as the data accumulated through their co-performance.

In this sense, **providing users the control over the accumulated data** would be extremely important. For instance, in the termination phase of interaction, systems can give some options for users to decide how the accumulated data will be treated after the termination. The immediate options for users can be i) deleting all data from the service, or ii) partially deleting data to leaving data that can contribute to building public database (e.g., database for local places), while deleting or abstracting sensitive personal information from the service. However, reflecting on the comments given by wearable activity trackers and the discussions made during the in-depth expert interview, additional control options can be designed to **support future co-performance** as well. For instance, temporal data storing can be an option for users who may have potentially return to the service. Data export can be another option to support future co-performance so that users can easily start co-performance with other related services with already developed personal database.

6.3 Potential Contents of Co-Performance: Reflection on User Expectation toward Co-Performing Agent's Knowledge of Users

Besides revealing the factors affecting the resilient partnership in co-performance, the study in chapter 4 also revealed four categories of higher-level personal information that participants expected their agent to learn from their activity data: i) personal life modes, ii) personal values and concerns, iii) personal skills and knowledge, and iv) changes in life. Although those expectations were not salient at the beginning of co-performance, it became apparent from the overall analysis of the inferred information cards and service revisions created by participants over eight weeks. As these types of information cannot be easily learned by systems, these empirical evidences reconfirm the importance of co-performance. At the same time, this higher-level personal information provides empirically-driven clues on how to design the contents of co-performance. For this purpose, this section elaborates user expectation pattern related to each categories of higher-level personal information and provides implications for design.

6.3.1 Personal Life Modes rather than Time, Place, People

The first user expectation for service evolution was that participants expected the service of their agent to be specialized for individual users' contexts of use. For instance, daily commuters (P3, P4, and P7) expected their agent's ordinary navigation service, which did not consider the contexts of use, to be branched specific to their commuting context and lunch time context respectively (e.g., providing commuting-related information when driving around 9:00 am on weekdays and providing restaurant recommendation when driving at noon). Also, P8, who frequently drives from one place to another, expected the agent's music recommendation service to differ depending on his own driving situations (e.g., recommending cheerful music when driving back home, English news when driving to his second language class, and recommending podcasts when driving for long distances).

The underlying reason for this expectation was that *users have their own rules when using a service*, and thus, they expected these rules to be considered by their agent as well. Some of these rules were mundane and can be applied to a large population of users (e.g., "reminding to-do-list when commuting" and "showing restaurant recommendation lists first at lunch time" for ordinary commuters), but some of the other rules were specific and meaningful only to the specific users (e.g., P8's example of music recommendation; playing "cheerful music when commuting," "English news when going to English class," or "nothing when driving short distances"). Like P8's example, it was noteworthy that participants had their own ways of defining the contexts that should be supported by their agents. In this sense, two married men (P3, P4) expected their agent to support them by developing two different modes of restaurant recommendation service: one for weekdays and the other for weekends. P4 wanted restaurant recommendations only on weekends, because he usually spent the weekends with his wife, exploring good places around town. P3 had a similar expectation, as he could spend time with his wife only on the weekends, due to living in an area two hours away from his wife. *"I think Vitamin* [his agent name] *can recommend separate lists of hot places to go depending on whether I am driving with my wife or not. When I am driving alone, it doesn't make sense to me that Vitamin recommends places near my wife's place." (P3-W2)*

This finding suggests implications for designing context-based supports for intelligent agents. Currently, we often design immediate adaptations of a service to the apparent context, such as time, place, and people. However, this finding shows that even if a given context of different users can be the same at a surface-level interpretation, they may give different meanings to a given context and even have different needs for the same context. For example, “the weekend” would mean “family time” for P3, who is in a long-distance relationship, but it would mean different for P7, who is single and sometimes works even on the weekend as well. Similarly, while daily commuters would need commuting support around 9:00 am, such support would not make sense to P6, a housewife with two kids who were not commuting. In addition, if an agent understands the meaning layer of the context, the agent not only would be able to provide more proper supports, but it would also be able to extend its services. For instance, P4’s expectation showed such possibility. As his agent learned the meaning he gave to a context (e.g., “the weekend” is “family time”), he thought that it could extend its restaurant recommendation service to other types of supports that might be necessary to the given context (e.g., leisure time activity recommendation service for the weekend). To make this evolution possible, there needs to be more investigation in effective ways of learning each user’s meaningful contexts and ways to integrate these into design of context-based support of intelligent agents.

6.3.2 Personal Values and Concerns rather than Preference and Interests

Another user expectation was that participants expected their agent to become more sophisticated in terms of inferring user preferences from their behavioral data (e.g., restaurant visiting history) to provide more personalized recommendations. Initially, participants liked their agent’s recommendations even though it only provided a list of items they liked before. However, over time, they wanted their agents to provide preference/interest-related recommendations not only based on the apparent preference/interest that can be inferred from the frequency of choices (i.e., how many time users visited a specific places), but also based on a more higher-level understanding of what they *value* and *care*. For instance, P4 wanted his agent to suggest restaurant recommendations by considering that he gives more priority to the location or atmosphere of a restaurant than the price of dishes when he goes out with his wife, instead of recommending restaurants just based on the frequency of his visits to individual restaurants. Also, P2 expected her agent to know that she goes on a diet and to consider her dietary concern when recommending the menu for meals, instead of keep recommending high-calorie foods just because she enjoyed them before.

The underlying reasons behind this expectation would be that users have their own criteria for decision makings. Thus, P4 even added questions to let his agent know why a certain restaurant recommendation was and would be particularly inappropriate for a particular situation, where he care one criteria more than another (e.g., he cares the distance to home more than the quality of food on Friday night, because he and his wife enjoying spending time around home on Friday night).

Like these examples, participants had expectations that their agents could improve their understanding of users' preference and interests up to the abstract level of values and concerns. Thus, users may think that their agents do not learn if this level of interpretation does not appear on their recommendations. This finding may have implications on how we deploy preference-based recommendations into intelligent systems. In addition, just inferring value/concern-level preferences should not end with simply confirming a fact that users already know. Rather, designers should think more about how to translate such understanding to a real service, through which users can be supported by the systems in a value/concern level. Thus, there needs more consideration on how to learn about these kinds of personal values and concerns and what to support users through these understandings.

6.3.3 Personal Skills and Knowledge rather than Service Needs

As agents build knowledge of users over time, participants expected that their agents would become more critical when delivering the services. For instance, P6 wanted her agent to recommend workout routines that she had not tried before (e.g., home-training routines), instead of suggesting the workout that she already tried and used to do (e.g., treadmill workout). Regarding this, P6 said that recommending what she already knows was not helpful for her in changing health behaviors.

The underlying reason for this expectation would be that users have their own knowledge and skills. For this reason, P2 especially appreciated when her agent probe provided a message saying, "Why don't you drive to the station without my support this time?" She appreciated this message because she was not even aware of that she had not try learning the ways to navigate to her frequent destinations, and the suggestion motivated her to cultivate her geographic knowledge for future driving. In this case, if the agent kept supporting navigation based on the user' request, then it would be remained as a passive commander, rather than an active supporter of the user.

These findings imply that considering users expertise or know-how would make the service even more supportive and personally relevant over time. To do so, systems may need to learn the reasons why users' service needs are continued over time, while they were not much engaged in the service use. By reflecting on the meanings, systems would be able to try other ways to support users so that such offerings could be more persuasive and helpful.

6.3.4 Changes in Life

As discussed in the section 4.5.2, participants expected the ways their agents provided service to be reoriented in response to such changes in their lives. The underlying reason for this expectation may seem obvious, as the changes in a user's life require changes in an agent's support as well. For instance, if P4's agent did not change the food recommendation criteria in response to his wife's pregnancy, it might be behaving tactlessly by providing assistance that was no longer related to them. However, reflecting on P1's comments, we could realize that this expectation could come from the deeper needs of users wanting to continue pursuing their desired selves, even if the situations in life changed over time. P1 said, "Even if I am getting busier, I still have needs for exercise. I feel like something is missing today, if I did not exercise at all." In this sense, if P1's agent did not change the workout recommendations in response to her changed life pattern, then it would have discouraged her from continuing to exercise at all and would make her feel herself incomplete. This finding suggests a new possibility of intelligent IT services as an enabler, which not only helps users but also helps users to be their desired selves.

This way of evolution would be a critical dimension in designing intelligent agents, as intelligent IT services have great potential in supporting users for a long period of time. Nevertheless, there can be a trade-off in identifying the exact meaning of the changes, as it may require users to label the meaning of the changes. If an agent tries to help a user before its user builds a comfortable relationship with the agent, then a user might feel uncomfortable and may not appreciate the support.

However, P1 showed that supporting life changes even without understanding exact meaning of the changes still have value for users. For example, in the case of P1, she got a message from the agent saying, *"You may feel tired these days, as you've been through a hectic life. I would like to recommend you have a glass of warm milk before going to bed. Good Night!"* Regarding this, P1 explained how she moved from the message of her agent, which did not know the exact meaning and context of her life pattern changes, but tried to take care of her life just based on the facts that it knows. She compared this with encouragement from friends: *"It's difficult to talk to other people about the tedious things of my life such as whether I slept well yesterday or not. Thus, just encouraging me by saying 'good luck!' would be the best cheer that they could do for me. But Ryan was different. It noticed how I might feel these days, even though Ryan doesn't know anything about the thesis proposal and even the fact that I am preparing one. What I did was just give the score of my sleep (i.e., self-evaluated sleep quality) to Ryan every day, and then Ryan noticed that my life has been changed and I do not feel very well these days. When it gave me the message that takes care of all* *the things happening around me, it moved me a lot and I even captured the screen because I didn't want to lose the message. Since we (she and her agent) have our own way of talking, it was so touching and helpful."*

In this sense, an agent may not have to identify the exact meaning of the changes in a user's life, unless a user explicitly requests the support (like P4's pregnancy example). Instead, supporting users' life changes within agents' knowledge would be a safe approach to this evolution. Like this, designers should consider the trade-off when supporting users' life changes.

CHAPTER 7.

Conclusion

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Conclusion

This concluding chapter summarizes the major findings of this research and highlights the contributions of the research. Lastly, this chapter also discusses the limitation of this research and suggest future research on co-performing experience design.

7.1 Major Findings and Contribution of the Research

As an effort to answer the primary research question, "*How intelligent IT services should be designed to support users' co-performing experiences?*", this dissertation investigated design requirements for supporting co-performing experiences through two major in-the-wild user studies, each of them required three-week and two-month investigations respectively. The design requirements and implications discovered from those studies were developed as a co-performance design framework. The impact of the framework was examined through in-depth expert interviews, which incorporated redesign activities with a reflection on current design practice for co-performance. The summary of major research findings of this dissertation is as follows:

- **The stages in user perception and expectation in the over-time experience of intelligent IT service:** The three-week field study of wearable activity tracker revealed how users' perception and expectation of intelligent IT services change over time. This further revealed these user perception and expectation is socio-psychological. Highlighting those socio-psychological perception, the three stages of user-system relationship were defined: i) initiation &

experimentation stage, ii) intensifying and integrating stage, iii) stagnation & termination stage (chapter 3).

- **Factors that affect users' co-performing behaviors and user-agent partnership building:** The two-month field study of Co-Performing Agent investigated users' actual co-performing experiences. This study revealed three factors that affect users' co-performing behaviors as well as the resilience of user-agent partnership over time. The three factors are: i) users' initial mental model toward agent-based services, ii) iterative confirming experience, and iii) changes in the learning styles.

- **Co-performance design framework as a principle:** Synthesizing the aforementioned findings, a co-performance design framework is proposed. The framework defines a user and an agent as two actors of co-performance. Also, the framework defines the stages in user-agent relationship that should be considered in supporting co-performance and the three partnership affecting factors that should be considered across the stages.

- **The impact of design framework in designing for co-performance**: The in-depth expert interview study highlighted the limited uptake of co-performance design in practice due to the three issues designers have to deal with: i) user acceptance issue, ii) use context issue, and technical issue. This study specified the role of co-performance design framework in a form of five design patterns, as the framework enabled particular patterns of design to support co-performing experiences: i) design for listening, ii) design for user-specific proactiveness, iii) design for continuous lock-in, iv) design for gradual unfolding, and v) design for reducing the conceptual. These patterns enabled designers to challenge the aforementioned issues in practice by enabling them to i) communicate more with users about systems' ability, ii) differentiate co-performing strategies, iii) explore opportunities to learn from users, and v) make more informed decision to convince other collaborators in multidisciplinary teams.

- **Design suggestions for supporting co-performing experiences :** The broader reflection on the overall findings suggested design suggestions for co-performing experiences in each stage of user-agent relationship: i) in the initiation stage, make consensus on upcoming co-performance, ii) in the experimentation stage, build user trust through transparent personalization and a fail-soft approach, iii) in the intensifying stage, enhance the partnership through opportunistic agent-initiated learnings for advanced service personalization and advanced user controls, iv) in the stagnation stage: recover the partnership in a timely manner through follow-up interactions or intentionally distancing strategies, v) in the termination stage: appreciate the partnership by giving control over accumulated data and supporting future co-performance.

- **Potential contents of co-performance:** Further reflection on users' expectations toward Co-Performing Agent's knowledge of users suggested four potential contents for co-performance that should be pursued in human-centered personalization of intelligent IT services: i) personal life modes, ii) personal values and concerns, iii) personal skills and knowledge, and iv) changes in life.

This research makes empirical, theoretical, and methodological contributions (Wobbrock and Kientz, 2016) with regard to the research question "*How intelligent IT services should be designed to support users' co-performing experiences in a human-centered way?*" and in the field of Design and Human-Computer Interaction.

First, the three-week deployment study of wearable activity trackers makes empirical contributions by articulating three stages in how people's perception and expectation on on-the-go personal assistant service change over time. At the same time, this study makes theoretical contributions by connecting those stages with Knapp's model of interactional relationship development in communication theory and thereby extending a body of work related to Computers as Social Actors (CASA) in the context of newly emerging technologies.

Second, the two-month study of a wizard-of-Oz-based research probe, Co-Performing Agent, makes empirical contributions by reporting users' co-performing behaviors in the wild contexts. Based on the results, this research introduces the elements that affect users' co-performing behaviors, which have rarely been studied and conceptualized in the previous research on user-agent interactions and human-computer collaboration.

Third, the in-depth expert interview study provides an integrated and validated thought framework, through which designers can explore potential *design spaces* (Findlater and Gajos, 2009; MacLean, Bellotti and Shum, 1993) for co-performance in designing user experience of personalized services. By doing so, this research makes contributions in empowering designers by making research outcomes more accessible to design practice.

Finally, this dissertation makes theoretical contributions by proposing the notion of co-performance between users and their perceived agents in intelligent IT services. This relational perspective might contribute to resolve two known issues of user experience in intelligent IT services (i.e. transparency and controllability) by making users' interaction with their perceived actor more explicit. This can be seen as trivial changes for designers, as they already provide their services in a human-like manner. However, in a user's perspective, the actor of personalization is still unclear, unless they are explicitly communicated in the system. Indeed, recent research have shown that even the functionally-identical system can be perceived differently depending on how it is conceptualized (Clark, Newman and Dutta, 2017). For instance, they showed that device-oriented conceptualization of smart home elicited less capability scenarios than data-oriented, and agent-oriented conceptualization of smart home. Like this, high-level abstraction of on-the-go personal assistant services by explicitly conceptualizing the social actor may affect lower-level design decision making for co-performance. Thus, co-performing between users and the conceptualized agents might provide one way to dissolve problems in building a sound user mental model in emerging intelligent IT services due to the dissonance between how the systems are designed by the designers and how the systems are actually perceived and experienced by users as well.

7.2 Limitation and Future Research

While this research provides initial contributions for co-performing experience design, there are several limitations inherent in this research. The limitations of this research can be summarized as follow: i) the investigation of co-performing experience was conducted through a research probe, ii) the research investigated co-performance focusing on a 1:1 user-agent relationship, and iii) the research investigated co-performing experience through simple question and answer form. Although these were not the primary scope of this research, complementing these limitations with further investigations would enhance the understanding on designing for co–performing experiences. Reflecting on each limitation, three directions for future research is suggested as follows.

7.2.1 Investigating Co-Performing Experiences for a Longer-Term Period

First, in this study, the investigation of co-performing experience was conducted through a research probe, which might have limitations in fully simulating realistic experiences. Thus, it might have limitations in fully understanding the situations where co-performance is taken place in a real time. Although it was not the primary purpose in this research to develop an actual working system that supports co-performing experiences, further investigation of users' co-performing experience in a more realistic settings and systems would enhance the validity of this work. Also, in that case, agent-initiated learning could be more actively implemented and tested by end-users. By doing so, the ways to identify transitions between the stages could potentially be found.

7.2.2 Investigating the Potential Roles of Co-Performing Agent in Service Ecology

Second, this research investigated co-performance focusing on a situation where a single user, a single agent, and a single service are connected to each other. However, there can be more than one users, agents, and services that participate in co-performance in an overall service ecology (Polaine, Løvlie and Reason, 2013; Forlizzi, 2008). In this respect, how a user's co-performing agent would play a role in a service ecology would be worthwhile to study further. In fact, from this research, it was observed that Co-Performing Agent becomes a rich knowledge base of a user for personalization. This implies the potential role of co-performing agent as a central medium for personalization in intelligent IT services. In similar way, the further investigations on a co-performing agent's roles in the broader service ecology (e.g., where a user is connected to many other services through the agent or in the situation where the user is connected to other multiple co-performing agents) would bring new insights on supporting co-performing experiences.

7.2.3 Investigating Co-Performing User Interfaces that are Significant and Engaging

In this research, co-performing experience was simulated and investigated through simple question and answer form. While this type of user interface was sufficient to develop initial understanding on co-performing experiences, investigating diverse types of user interfaces for co-performance would enhance users' co-performing experience that are more engaging in specific service domains (e.g., co-performing user interfaces for music service). At the same time, the validity of user inputs created through co-performing interfaces also should be demonstrated and examined so that users can create user inputs not just engaging in experience-wise, but also significant in systems' learning perspectives.

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무엇보다도, 길었던 대학원 생활동안 늘 함께 고민해주시고 제가 성장할 수 있도록 기다려주셨던 임윤경 교수님, 감사드립니다. 교수님께 배운 생각과 마음가짐은 연구 뿐만이 아니라 앞으로의 제 삶에 늘 길잡이가 될 것입니다. 그리고 바쁘신 와중에 학위논문의 심사위원으로서 긴 논문을 검토해주시고 건설적인 조언을 아끼지 않으셨던 산업디자인학과 남기영 교수님과 Andrea Bianchi 교수님, 그리고 전산학과 김주호 교수님과 오혜연 교수님께 깊이 감사드립니다. 심사위원 교수님들의 조언 덕분에 이 논문을 잘 마무리 할 수 있었습니다. 또한, 수업이나 콜로키움을 통해 디자인 연구에 대한 배움을 주셨던 모든 산업디자인학과 교수님들, 그리고 보다 다양한 분야의 사람들과 소통하고 연구를 함께 발전시켜나갈 수 있도록 교류의 기회를 만들어주신 HCI@KAIST 교수님들께도 감사드립니다.

가까운 곳에서 힘이 되어주었던 많은 선후배들과 친구들에게도 감사드립니다. 대학원 생활 시작부터 끝까지 연구와 삶에 대한 고민을 함께 나누고, 늘 곁에서 더 성장할 수 있게 도와주었던 여름 언니, 고맙습니다. 그리고 그 시간을 묵묵히 함께 해 준 영욱 오빠에게도 감사합니다. 학위논문 마무리 시점까지 함께 마음 써 준 CIxD 연구실 식구들, 김한경, 고동윤, 남호연, 박선정, 신인건, 이유미, 황유진, 언제 어디서나 늘 힘이 되어준 졸업생, 김민경, 김대성, 노세영, 석진민, 설유림, 손보경, 우종범, 윤재식, 이원준, 이순주, 조영걸, 조재성, 그리고 잠깐의 방문 이후에도 많은 도움을 주었던 Jasmine Jones 에게도 감사합니다. 또한, 연구에 대한 갈증을 함께 나누었던 스터디 멤버들과 ID KAIST 친구들, 그리고 HCI@KAIST 친구들에게도 감사합니다.

대학원 생활 내내 늘 저를 믿고 함께 기다려주신 부모님과 모든 가족들께도 이 기회를 빌어 감사의 말씀을 전하고 싶습니다. 항상 저의 결정을 존중해주셨기에 어려운 순간들이 있었을 때에도 다시 힘을 내서 이 과정을 끝까지 마무리 할 수 있었습니다. 그리고, 이제는 저의 가장 가까운 가족이 되어 긴 시간 함께 견뎌준 재을에게도 고마운 마음을 전합니다. 디자이너로서, 그리고 한 사람으로서 우리가 같이 머리 맞대고 질문하면서 함께 답을 찾아갈 앞으로가 더 기대됩니다.

마지막으로 이 학위 연구가 마무리 될 수 있도록 귀한 시간을 내어주신 모든 실험 참가자분들, 짧은 시간이었지만 MSRA 인턴 기간동안 기업에서 연구자의 역할에 대한 본보기를 보여주셨던 멘토 Darren Edge 와 여성 연구자로서의 커리어를 늘 지지해주셨던 Hong Tan 박사님께도 감사드립니다.

지난 10 여년간 디자인 연구를 공부하면서 사람들을 이해하고 돕는 것의 기쁨을 알게 되었습니다. 이 곳에서의 배움을 잊지 않고 사람들을 위하는 일을 하며 살 수 있도록 노력하겠습니다. 긴 여정을 함께 해주신 모든 분들께 다시 한 번 감사드립니다.

Curriculum Vitae

EDUCATION

Ph.D. in Industrial Design 2019
Creative Interaction Design Lab (Advisor: Youn-kyung Lim, Ph.D.)
Korea Advanced Institute of Science and Technology (KAIST), Korea

M.S. in Industrial Design 2012
Creative Interaction Design Lab (Advisor: Youn-kyung Lim, Ph.D.)
Korea Advanced Institute of Science and Technology (KAIST), Korea

B.S. in Industrial Design 2010
Korea Advanced Institute of Science and Technology (KAIST), Korea

RESEARCH EXPERIENCE

Research Intern

- **Human-Computer Interaction Group, Microsoft Research Asia** (Mentor: Darren Edge) — Beijing, China, SEPT. – DEC. 2013

Research Assistant
Creative Interaction Design Lab, KAIST (Advisor: Youn-kyung Lim, Ph.D.)

- **Development of Intelligent Interaction Technology Based on Context Awareness and Human Intention Understanding** (Institute for Information & Communications Technology Promotion) — 2016 – 2018
- **Developing User-Centered Design Guidelines for Personalized Intelligent Services in the Connected Cars** (Naver Labs.) — 2016
- **Developing UX Scenarios for User Lifestyle-Personalized Health Promotion based on Physical Activity Data** (KAIST) — 2014
- **Value Construction with Digital Things** (Vodafone) — 2011 – 2012
  Collaboration among Carnegie Mellon University (US), University of Granada (Spain), KAIST (Korea), and Vodafone (Germany)
- **Development of a Theory and a System for a New Interaction Design Paradigm** (National Research Foundation of Korea) — 2010 –2011
- **Development of a New Prototyping System for Creative Interaction Design** (KAIST: High Risk High Return Project) — 2009 – 2011
- **Supporting Experience-Centered Interaction Design through Interaction Quality-Centered Approaches** (National Research Foundation of Korea) — 2009 – 2011

PUBLICATIONS

International Conferences

- **Design Opportunities in Three Stages of Relationship Development between Users and Self-Tracking Devices. Da-jung Kim**, Yeoreum Lee, Saeyoung Rho, and Youn-kyung Lim. In *Proceedings of the Annual ACM Conference on Human Factors in Computing Systems (CHI 2016)*, May 2016, San Jose, USA.

- **Friends in Activity Trackers: Design Opportunities and Mediator Issues in Health Products and Services.** Yeoreum Lee, Min Gyung Kim, Saeyoung Rho, **Da-jung Kim**, and Youn-kyung Lim. In *Proceedings of International Association of Societies of Design Research (IASDR 2015),* November 2015, Brisbane, Australia. **Best Paper Award**
- **Dwelling Places in KakaoTalk: Understanding the Roles and Meanings of Chatrooms in Mobile Instant Messengers. Da-jung Kim** and Youn-kyung Lim. In *Proceedings of Computer-Supported Collaborative Work and Social Computing (CSCW 2015)*, February 2015, Vancouver, Canada.
- **Bridging Research and Practice in Design: Reflections of the Project on Value Construction with Virtual Possessions.** Moon-Hwan Lee, Tek-Jin Nam,Yeoreum Lee,Yea-kyung Row,Youn-kyung Lim, **Da-jung Kim**, Jinmin Seok, William Odom, John Zimmerman, Jodi Forlizzi, Ana L´opez Higuera, Mauro Marchitto, Jos´e Ca˜nas, and Heather A. Moore. In *Proceedings of International Association of Societies of Design Research (IASDR 2013)*, August 2013, Tokyo, Japan.
- **Understanding the Curation Activities of Creating Personal and Social Meanings for Virtual Possessions.** Jin-min Seok, **Da-jung Kim**, Youn-kyung Lim, Tek-jin Nam, Moon-hwan Lee, Yeoreum Lee, Yeakyung Row, Bokyung Sohn, John Zimmerman, Jodi Forlizzi, William Odom, Ana L´opez Higuera, Mauro Marchitto, Jos´e Ca˜nas, and Heather A. Moore. In *Proceedings of International Association of Societies of Design Research (IASDR 2013),* August 2013, Tokyo, Japan.
- **Fragmentation and Transition: Understanding Perceptions of Virtual Possessions among Young Adults in Spain, South Korea and the United States.** William Odom, John Zimmerman, Jodi Forlizzi, Ana L´opez Higuera, Mauro Marchitto, Jos´e Ca˜nas, Youn-kyung Lim, Tek-Jin Nam, Moon-Hwan Lee, Yeoreum Lee, **Da-jung Kim**, Yea-kyung Row, Jinmin Seok, Bokyung Sohn, and Heather Moore. In *Proceedings of the Annual ACM Conference on Human Factors in Computing Systems (CHI 2013)*, April 2013, Paris, France.
- **iSpace: Interactivity Expression for Self-Expression in an Online Communication Environment. Da-jung Kim** and Youn-kyung Lim. In *Proceedings of the Annual ACM Conference on Designing Interactive Systems (DIS 2012)*, June 2012, Newcastle, United Kingdom. **Honorable Mention**
- **Handscope: Enabling Blind People to Experience Statistical Graphics on Websites through Haptics. Da-jung Kim** and Youn-kyung Lim, In *Proceedings of the Annual ACM Conference on Human Factors in Computing Systems (CHI 2011)*, May 2011, Vancouver, Canada.

International Journal

- **Interactivity Attributes for Expression-Oriented Interaction Design.** Youn-kyung Lim, Sang-su Lee, and **Da-jung Kim**. *International Journal of Design 5(3)*: 113-128. (2011)

Posters & Doctoral Consortium

- **Design for User Autonomy in the System-Driven Personalization of Social Media.** **Da-jung Kim.** In *Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work and Social Computing Companion (CSCW 2016 Companion, Doctoral Consortium)*, February 2016, San Fransisco, USA.
- **My Own-Style Interaction: Exploring Individuals' Preferences to Interactivity.** **Da-jung Kim**, Youn-kyung Lim, and Hyeon-Jeong Suk. In *Proceedings of Extended Abstracts on Human Factors in Computing Systems (CHI EA 2011, Work-in-Progress),* May 2011, Vancouver, Canada.
- **Interactivity Sketcher: Crafting and Experiencing Interactivity Qualities.** Jong-bum Woo, **Da-jung Kim**, Suin Kim, Jaesung Jo, and Young-kyung Lim. In *Proceedings of Extended Abstracts on Human Factors in Computing Systems (CHI EA 2011, Work-in-Progress),* May 2011, Vancouver, Canada.

HONORS, AWARDS, AND GRANTS

Best Paper Award at IASDR'15	2015
Microsoft Research Asia Fellowship Finalist	2012
Honorable Mention at DIS'12	2012
Dean's List (Department of Industrial Design, KAIST)	2007 – 2009
Government Fellowship (Korea Ministry of Science and Technology)	2006 – 2009

TEACHING AND MENTORING

Teaching Assistant

User-Centered Service Design for IT Convergence (KAIST ITC201)	Spring 2015
Design Methodology (KAIST ID303)	Fall 2014
Product Design Program (KAIST ID340)	Fall 2010
Undergraduate Individual Research (KAIST ID495)	Fall 2011, 2014
Undergraduate Graduation Project (KAIST ID490)	Spring 2012
Undergraduate Research Project (KAIST URP Program)	Fall 2011

KNOWLEDGE AND SKILLS

Relevant Coursework

Interface Design, Interaction Design, Media Interaction Design, Design Methodology, User-Centered Design Methodology, Research Methodology, Design Research Issues, Introduction to Programming, Social Computing.

Skills

- **Design Research Methods**: Ethnography, Focus Group, Contextual Inquiry, Interviews, Cultural Probes, Participatory Design, Survey Design & Statistical Analysis, Experience Prototyping, Affinity Diagramming, Coding Analysis, Scenario Development, User Journey Mapping, Service Blueprint, etc.
- **Programming**: Arduino, Basic circuit and sensor knowledge, HTML, CSS.
- **Prototyping & Visualization Tools**: InVision, Sketch, Illustrator, Photoshop, Flash, After Effects, Premiere, Rhino, SolidWorks, 3Dmax.
- **Language**: English, Korean