INVESTIGATING SEARCH PROCESSES IN COLLABORATIVE EXPLORATORY WEB SEARCH

by

Zhen Yue

B.S., Nanjing University, 2005

M.S., Peking University, 2007

Submitted to the Graduate Faculty of

School of Information Sciences in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

University of Pittsburgh

2014

UNIVERSITY OF PITTSBURGH

SCHOOL OF INFORMATION SCIENCES

This dissertation was presented

by

Zhen Yue

It was defended on

April 1, 2014

and approved by

Bernard J. Jansen, Ph.D., Associate Professor, College of Information Sciences and Technology, Pennsylvania State University

Peter Brusilovsky, Ph.D., Professor, School of Information Sciences, University of Pittsburgh

Ellen Detlefsen, D.L.S., Associate Professor, School of Information Sciences, University of Pittsburgh

Jung Sun Oh, Ph.D., Asistant Professor, School of Information Sciences, University of Pittsburgh

Dissertation Advisor: Daqing He, Ph.D., Associate Professor, School of Information Sciences, University of Pittsburgh

INVESTIGATING SEARCH PROCESSES IN

COLLABORATIVE EXPLORATORY WEB SEARCH

Zhen Yue, PhD

University of Pittsburgh, 2014

People are often engaged in collaboration in workplaces or daily life due to the complexity of tasks. In the information seeking and retrieval environment, the task can be as simple as fact-finding or a known-item search, or as complex as exploratory search. Given the complex nature of the information needs, exploratory searches may require the collaboration among multiple people who share the same search goal. For instance, students may work together to search for information in a collaborative course project; friends may search together while planning a vacation.

There are demands for collaborative search systems that could support this new format of search (Morris, 2013). Despite the recognized importance of understanding search process for designing successful search system (Bates, 1990; Hearst, 2009), it is particularly difficult to study collaborative search process because of the complex interactions involved.

In this dissertation, I propose and demonstrate a framework of investigating search processes in the collaborative exploratory search. I designed a laboratory-based user study to collect the data, compared two search conditions: individual search and collaborative search as well as two task types through the study. I first applied a novel Hidden Markov Model approach to analyze the search states in the collaborative search process, the results of which provide a holistic picture of the collaborative search process. I then investigated two important components in the collaborative search process – query behaviors and communications. The findings reveal

the characteristics of query and communication patterns in the collaborative search. It also suggests that although the collaboration between two people on search did not achieve a higher performance than two individuals, the collaboration indeed make people feel more satisfied with their performance and less stressed. The results of this study not only provide implications for designing effective collaborative search systems, but also show valuable research directions and methodologies for other researchers.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1.0 INTRODUCTION

Information seeking was traditionally studied as an individual activity. However, users may collaborate with others when the information need is complex and exploratory, a scenario that is similar to that they collaborate on other complex tasks in workplaces and daily life. Previous research (Morris & Horvitz, 2007) showed that collaboration in a simple search task may not bring many benefits. However, when the search task is exploratory, it may be in the searchers' best interests to collaboratively explore the information space and participate in shared learning (White & Roth, 2009). For instance, students may work together to search for information in a collaborative course project; friends may search together while planning a vacation; healthcare providers might collaboratively search for information to diagnose a patient's illness (Reddy & Spence, 2008); or family members might collaboratively search the web to buy a car (Morris, 2008). Therefore, although information seeking has been studied traditionally as an individual activity, collaborative information seeking has attracted a significant amount of attention (Hansen & Järvelin, 2005).

1.1 PROBLEM STATEMENT

A recent survey reported that the percentage of respondents engaged in collaborative web search on a daily basis had increased from 0.9% in 2006 to 11% in 2012 (Morris, 2013) . As the needs of collaborative search continue to gain more and more attentions, researchers have developed many new systems and interfaces to support collaborative information seeking and retrieval (Amershi & Morris, 2008; Diriye, Golovchinsky, Dunnigan, & Alto, 2012.; Golovchinsky & Adcock, 2008; Morris & Horvitz, 2007; Shah & Marchionini, 2010a). The design of a well-functional system for collaborative search is still a challenging task and way more complex than designing a system for individual search. The previous studies found that the understanding of users' information search process can facilitate the development of search systems. For example, Bates (1989) incorporated a "berry-picking" information search process model into a real search interface designing, and Hearst (2009) emphasized the necessity to understand human information search processes in designing successful search systems. However, those studies of information search processes mainly focused on the individual search. Previous researches (Hyldegard, 2006; Shah & González-ibáñez, 2010) further found that it was inappropriate to directly apply individual search process models to the collaborative search. Both of the studies found that the social dimensions of collaborative search were not covered in the individual search process models.

I assert that the design of collaborative search systems can benefit from studies of collaborative search processes. Due to the fact that there are much fewer studies focusing on investigating collaborative search process in comparison to the studies of individual search process (Shah & González-ibáñez, 2010), a comprehensive investigation on collaborative search processes can fill the gap in this research field. Search and communication are two major components in the collaborative search process, which are also my focuses in this dissertation study.

Specifying information needs as search queries and refining those queries during search sessions are two key steps in an exploratory search process (Belkin et al., 2001). Researchers have devoted massive efforts to understand users' query behavior during web search processes, such as query tactics (Bates, 1979), patterns of query reformulation (Jansen, Booth, & Spink, 2009) and the effects of contextual factors on users' query behaviors (Ingrid Hsieh-Yee, 1993). Researchers have also developed successful techniques to support query formulation and refinement towards more effective and efficient searches, such as query expansion (White & Marchionini, 2006) and query suggestions (Kelly, 2011). However, as a much more complex form of exploratory search, collaborative exploratory searches have seldom been the focus of query behavior studies. It is unclear how users' query behaviors would be different in a collaborative setting, making it difficult for researchers to design query support in a collaborative search system. Previous research pointed out that the successful assistance to queries and subsequent refinement must be designed based on the understanding of users' query behaviors (Jansen et al., 2009). Therefore, it is important to study the query behaviors involved in the collaborative search process. If we can learn when and how team users generate queries and reformulate queries during the collaborative search process and the associated collaborative context of their searches, it is possible for the collaborative search system to provide targeted query supports that are efficient and effective for team users.

Compared to individual search process, a unique component of collaborative search process is the communications among multiple users. Many collaborative search studies have showed the important role of communications in the collaborative search process (Reddy, Jansen, & Krishnappa, 2009). Users may communicate with other users in a collaborative search to seek for help or brainstorm for search strategies (Twidale, 1997), or to share knowledge and maintain awareness among multiple users (Foley & Smeaton, 2010). Most existing collaborative search systems have implemented features for supporting communications among multiple users, such as instant message (Morris & Horvitz, 2007; Shah, 2010). However, few studies have considered the cost and benefits of communications in the collaborative search process (González-Ibáñez, Haseki, & Shah, 2013). On the one hand, communications could be effective in establishing common ground among multiple users (Hertzum, 2008). On the other hand, communication could also introduce extra workload or distract users from their search tasks (Carroll, Rosson, Convertino, & Ganoe, 2006). Therefore, it is imperative to conduct an investigation on communications in the collaborative search process, and to examine the relationships between communication patterns and search outcomes. All of these will help researchers to understand the benefits and costs of communication, and to design systems for supporting effective communications in the collaborative search process.

The ultimate goal of investigating search processes is to understand users' information seeking behavior so that the design of search systems can be user-centric and based on the understanding of users' needs. With regards to exploratory search, researchers had developed many features to support the information exploration process, such as querying support, offering facets and visualization, and supporting histories and workspaces (White & Roth, 2009). Adding collaboration factor to the exploratory search imposes more challenges on the search system design. The studies on the collaborative search processes can shed light on the improvement of system design for collaborative search.

How to investigate and support search processes in collaborative exploratory search is an open question requiring systematic studies. The previous research methods and findings in individual exploratory search can provide some guidance for the study of collaborative exploratory search. However, we must explore the new methods because the interactions involved in collaborative search are much more complex than individual search. The interactions exist not only between the user and the system, but also among the multiple collaborative users. How to model these interactions and support them are worth studying.

1.2 CURRENT RESEARCH STATUS

In the individual search, researchers have employed two major approaches to investigate the information search process. One approach focuses on qualitative constructs, such as stages and context in the search process. Kuhlthau’s model (1991) and Marchionini’s (1995) model adopted such an approach. The other approach tried to derive search patterns through the analysis of logged user behaviors. These studies were based on the units of search behaviors, such as actions (Chen & Cooper, 2002; Holscher & Strube, 2000), search tactics (Xie & Joo, 2010), and search strategies (Belkin, 1995), which are labeled either by human raters (Xie & Joo, 2010) or automatic methods (Chen & Cooper, 2001, 2002). The manually labeling method is more controllable but requires extensive human efforts and is difficult for scaling to large datasets. By contrast, the automatic methods need fewer human interventions. However, such methods missed a global view of the entire search process as the search states are arbitrary chucked sequential actions.

To investigate the collaborative search process, Hyldegard (2006) and Shah et al.(2010) attempted to map the individual information search model into a collaborative web search. Both papers found this approach inappropriate. Although not specifically targeting a collaborative web search, Evans and Chi’s social search model (2008) contributed to the study of the collaborative search process. The model was built upon survey data rather than logged user data. Considering the complexity of interactions involved in the collaborative search, studying collaborative search processes through logged user behaviors remains a problem.

A few studies have been specifically designed to compare information search in individual and collaborative conditions. Lazonder (2005) compared pairs of students with individual students in web search tasks and found that pairs produce better search outcome than individuals. Joho et. al (2008) compared two conditions of synchronous search with independent search. In one of the synchronous condition team members only share search history while in the other synchronous condition they can communicate with each other. The major findings from this study are that collaboration was helpful to diversify search vocabulary and reduce redundancy in finding relevant documents. However, the search performance was not improved in collaborative conditions than two artificially combine independent users. Shah and González-Ibáñez (2011) compared team users and single user in five different conditions. One of the conditions involved the single user and the other condition artificially combined two single users. The rest three conditions were synchronous collaborative search in which location varied from each other, including co-located using same computer, co-located using different computer, and remotely located. A set of measurements were employed to evaluate the synergic effect of collaboration in information seeking, including precision, recall and F-measure, coverage, usefulness, query diversity and cognitive load. They found that two collaborators using the same computer achieved the similar results as the individual users. Two collaborators using different computers, either co-located or remotely located, had a better performance in discovering more and diverse information. These comparison studies between the individual search and collaborative search are mainly focused on search outcomes rather than search processes.

According to Golovchinsky et al. (2008), collaborative search can be classified as implicit or explicit in terms of search intent. The implicit collaboration often occurs in collaborative recommendation and filtering systems where the information from different users is shared without explicit modeling of the collaboration. Explicit collaboration occurs on a smaller scale such as a team of several collaborators. The collaborative querying is a technique that has been widely used in implicit collaborative information retrieval. The technique enables users of an information retrieval system to draw on previous query preferences of other users at the query formulation and reformulation stages of an information search (Foster, 2006). Previously-learned queries and relevant documents are reused in new and similar search sessions to improve the overall retrieval quality (Hust, 2004). Often, the simulated experiments are employed in these studies, rather than user studies involving human subjects. In contrast to the implicit collaborative search, the queries studies in explicit collaborative search are rare (Capra et al., 2012).

Query behavior studies have reached maturity in the context of individuals. However, the studies on query behavior in the collaborative search context were relatively fewer and primarily focused on implicit collaborative search. There were some studies investigating the differences between collaborative and individual search, but they were not particularly focused on the differences in query behavior. Therefore, a comparative study on query behavior in collaborative search and individual search can fill the gap in this research field.

The collaborative search is a form of teamwork. Teamwork in general has been the focus of several research communities, including computer-supported cooperative work (CSCW) (Mishra & Mishra, 2009), computer mediated communication (CMC) (Fletcher & Major, 2006) and computer-supported collaborative learning (CSCL) (Strijbos, Martens, Jochems, & Broers, 2004). The theories and methodologies from these research fields can be transferred to collaborative search studies. For example, González-Ibáñez and collegue (2013) looked into the effects of three different communication medium on the collaborative search. Besides the communication medium, I think that the comunications in a collaborative search process can be affected by other factors , such as the type of search task. Another study focused on the content of communications by analyzing all the chat messages intended for coordination (Shah, 2013). According to the content analysis schema devloped by (Strijbos et al., 2004) for communications, the types of communication include task content, task social or non-task related. The schema have been applied in another study on the effect of communication medium (González-Ibáñez et al., 2013). It will be beneficial to apply this schema for a study on investigating the patterns of communication content in the collaborative search process. Finally, the timing of communications is a very important angle to examine the patterns of communications. Even and Chi (2010) investigated the social interactions involved in the *before*, *during* and *after search* stages in the social search. This motivated me to analyze communications involved in different stages of collaborative search because it can help us to better understand the role of communications in the collaborative search process.

In summary, there is a lack of studies on collaborative search processes in the literature. Particularly, it is worth studying the two key components in the collaborative search process: query behaviors and communications.

1.3 SIGNIFICANCE

In this dissertation, I focus on the automatic methods for analyzing the collaborative information search process using logged user behaviors. The previous studies on investigating the search process using logged data either focused on the observed action level or the manually coded search tactics/strategies level. The connections between the observed actions and search tactics/strategies are missing. To study such connections, I took a two-level view of the basic unit in the search process. The first level is observable actions, which are the manifestation of users' behavior. The second level is unobservable search tactics or strategies. I assume that users can move between different search tactics. In each tactic, users have a list of choices (each choice is an action), and each choice has its probability of being adopted by the user. The observed actions represent the users' adopted choices. Fuhr's theoretical framework for interactive retrieval (Fuhr, 2008), which assumes that a user moves between situations in the interactive information retrieval, supports this assumption.

In order to model the temporal sequence of user behaviors and simultaneously leverage these two levels, I propose using the Hidden Markov Model (HMM) (Baum, Soules, & Weiss, 1970). Because search tactics usually represent the users' internal choices and are difficult to observe, it is reasonable to model the search tactics as the hidden variables. Moreover, unlike the Markov models that have been employed (Chen & Cooper, 2002; Xie & Joo, 2010) to analyze individual search processes, HMM assumes a Markov chain on the unobserved hidden tactics rather than the observed user actions. This approach helps to remove the over-simplistic assumption in Markov models: user's future action depends only upon the present user action, not on the other actions before the present action. HMM consider the holistic view of the entire search process and model search states as hidden variables which can be seen has latent search tactics. One additional benefit of HMM is that rather than manually labeling user actions, HMM is an automatic method that can be easily applied to large datasets.

Although HMM is a well-established model, most its applications focus on predicting future events, such as the weather and stock prices. To the best of my knowledge, the use of HMM in analyzing search processes is rare. No previous works have applied HMM in collaborative web search. Therefore, little available information explains how to categorize the observable user actions, how to choose appropriate parameters and how to make sense and interpret the outputs. All these issues are studied in this dissertation.

The automatic approaches of studying search processes usually miss the content associated with user actions. For example, query actions have query terms as content and communication actions are associated with the messages being sent or received. To complement the search states analysis and gain a more comprehensive understanding of the collaborative search process, I also consider studying the collaborative search process at the content level. Issuing queries is one of the most important steps in the exploratory search process because the query reformulations advance the search process. Communications are unique actions in the collaborative search process. Considering these two reasons, I select **query behaviors** and **communications** as the foci of analyzing collaborative search process at the content level.

In this study, I examine the query behaviors in the collaborative search process through a comparison to the query behavior in the individual search process. The query behavior is an important aspect for studying in exploratory search (Belkin et al., 2001). Queries are representations of users' information needs and users' abilities to transform information needs to queries greatly influence the process of exploratory search (Marchionini, 2006). Researchers found that social inputs may help users to frame their search problems and solving vocabulary problems during the search (Evans, Kairam, & Pirolli, 2010). Other researchers reported that submitting different queries is a very frequently used search strategy used in the collaborative search (Joho et al., 2008). Therefore, it is very important to look at the vocabulary features of the queries such as vocabulary richness and query diversity in the collaborative search. Unlike simple fact-finding search, exploratory search is featured by multiple queries during the search session (White & Roth, 2009). Query reformulations allow users to explore different parts of the information space. The patterns of query reformulation are reflections of users' search tactics employed in the search process (Kelly, 2009). Thereby, the pattern of query reformulation is another angle I select to study the query behaviors involved in the collaborative search performance. The goal of query iterations in an exploratory search task is to satisfy the information needs. Thus it's important to look into the performance of queries. In this study, I look at the success of each of query (whether or not resulting in the saving of relevant documents) as well as the performance of the whole such session such as precision and recall. In addition, I also measure the performance from the users' perspective, including users' satisfaction towards the search performance and users' cognitive load regarding the search experience. In summary, through a comparison between the individual search and collaborative search from three dimensions - query vocabulary features, query reformulation patterns, and query performances, I provide a comprehensive study of query behaviors in the collaborative search.

Through the comparison of the individual search and the collaborative search, we can obtain the differences between these two forms of search. However, we may still be unclear about the causes of the differences. Studying the unique component – communication involved in the collaborative search process may provide us with better understanding of where the differences between the individual search and the collaborative search are coming from. The important role of the communication has been emphasized by many researchers in the collaborative search community (González-Ibáñez et al., 2013; Morris & Horvitz, 2007; Reddy, Jansen, & Krishnappa, 2009b). Communications can be used to discuss the requirement of the search task, coordinate the search efforts of multiple users, share knowledge and provide social support among users. Different types of communications may be triggered by various context throughout the collaborative search process (Reddy & Jansen, 2008). I think it's crucial to study the communications from both timing and content prospects to understand when and what users communicate with each other during the collaborative search process. In this study, I also examine the relationships between communication patterns and search outcomes. The findings can help us to understand the potential benefits and costs of communications in the collaborative search process, which is essential for designing better collaborative search systems.

Another important contribution of this study is that I consider task type as a factor for studying the collaborative search process. Task type has been examined in many research studies for its effect on users' search behaviors. Hsieh-Yee (2001) found that the types of search tasks influence users' search tactics. The study of Toms et al. (2008) indicated that task type has a significant impact on users' query behaviors. Liu and colleagues (2010) found that the query reformulation patterns were affected by task types. Researchers in the CSCW field suggested that an effective collaborative system should be built on the characteristics of the collaboration task (Mennecke, Wheeler, & Iubacs, 1993). The also illustrated the importance of analyzing different task scenarios when evaluating the effectiveness of a collaborative system (Cugini, J., Damianos, L., Hirschman, L., Kozierok, R., Kurtz, J., Laskowski, S., & Scholtz, 1997). Researchers in the collaborative search community have realized the importance of task characteristics in collaborative search (Morris & Teevan, 2010). However, a solo type of search task was used in most collaborative search studies (Paul & Morris, 2010; Shah & Marchionini, 2010b). To overcome this shortcoming, I use two different tasks in the study. From a survey of collaborative search experiences, travel planning and literature search are recognized as two of the top three topics for the collaborative search. Hearst (2014) summarized that information-gathering and decision-making are two representative scenarios for collaborative search. These research findings provide me with the criteria for selecting the two search tasks used in this study. One task is an information-gathering task with the literature search topic, and the other task is a decision-making task with travel planning as the topic. In this study, I consider the task type as an independent variable to study its effects on the search states patterns, query behaviors as well as communication patterns in the collaborative search process.

1.4 RESEARCH QUESTIONS

From the discussion above, it is clear that collaboration search is a new format of search and there is a demanding need for systems that can support collaborative search. Investigating interactions involved in the collaborative exploratory search process is crucial for designing and evaluating systems to support collaborative search. Search state analysis has been widely used in individual search studies to examine the search processes. The basic unit in the analysis varies from study to study. I propose using HMM to model search states as hidden variables. Besides the analysis of search states, I also propose to analyze the query behaviors and communications involved in the collaborative search process. Having identified the focus on investigating the search processes in collaborative exploratory search, the following research questions arise:

RQ1. How to model the search states in the collaborative exploratory search process? What are the characteristics of search states in the collaborative exploratory search process?

1.1 How to apply HMM to analyze search states in the exploratory search process, especially in the collaborative search?

1.2 How to interpret the outputs of HMM? How to determine whether HMM is a valid method for analyzing the individual and the collaborative exploratory search process?

1.3 What are the patterns of search states in the collaborative exploratory search process? What are the differences compared to patterns in the individual exploratory search?

1.4 Are there any differences on the patterns of search states for different search tasks?

1.5 What are the connections between the patterns of search states and the search outcomes?

RQ2. What are the characteristics of query behaviors in the collaborative exploratory search process?

2.1 What are the characteristics of query vocabulary features, query reformulation patterns and the query performance?

2.2 What are the differences on query behaviors between the individual and the collaborative search?

2.3 Are there any differences on query behaviors for different search tasks?

RQ3. What are the characteristics of communications between team members in the collaborative exploratory search process?

3.1 What are the patterns for the content and timing of communications in the collaborative exploratory search process?

3.2 Are there any differences on the patterns of communications for different search tasks?

3.3 What are the connections between the patterns of communications and the search outcomes?

3.4 What are the different communication styles employed by different teams in the collaborative exploratory search process?

1.5 SCOPE DEFINITION

The collaborative information seeking has been studied in various environments including both organizational and web setting (Hansen & Järvelin, 2005; Morris, 2008). Our study focuses on collaborative exploratory search in the web search environment.

Golovchinsky et al. (2008) classified the collaboration in web search using three dimensions: intent, concurrency and location. The collaborative web search can be implicit or explicit in terms of the search intent. On the one hand, the implicit collaboration often occurs in collaborative recommendation and filtering systems, where information from different users is shared without explicitly modeling the collaboration. On the other hand, the explicit collaboration occurs on smaller scales such as in groups of several collaborators. In my study, I focus on the explicit collaboration of a team with two members. In terms of location, collaborative web search can be co-located or remotely located. I am interested in remotely located collaborative searches where a collaborative search system is needed to support both communication and search. Collaboration in web search can also be synchronous or asynchronous in terms of concurrency. In synchronous collaboration, team members can get instant feedback from each other while in asynchronous collaboration only those who search later can benefit from the work of earlier team members. I am particular interested in the synchronous collaborative search in this study.

There are different roles of people in a team that collaborate with each other in exploratory search. For example, a search novice may be collaborating with a search expert. In this study, only teams of two members who are peers are considered, and both of team members are required to be experienced searcher. The dynamics among team members is likely to change for different sizes and different roles of team members. In the user study, the topics for the task assigned to group users were pre-defined. They may not be a true reflection of users' information needs in real life. The nature of this study is a laboratory experiment. The findings and lessons learned in this study should be interpreted with caution.

1.6 OVERVIEW OF THE STUDY DESIGN

My goal is to provide a valuable contribution with proposals and demonstrations of a framework for investigating collaborative search processes. To achieve this goal, I apply the following research design shown in Figure 1.1. According to the research design, I introduce the background, motivations, and significance of this study in this chapter 1. Chapter 2 discusses the related works. I describe the design of user studies in Chapter 3. There are three parts of the result analysis, reported in chapter 4, 5, and 6, respectively. Finally, I discuss the findings, contributions, limitations and future work in chapter 7.

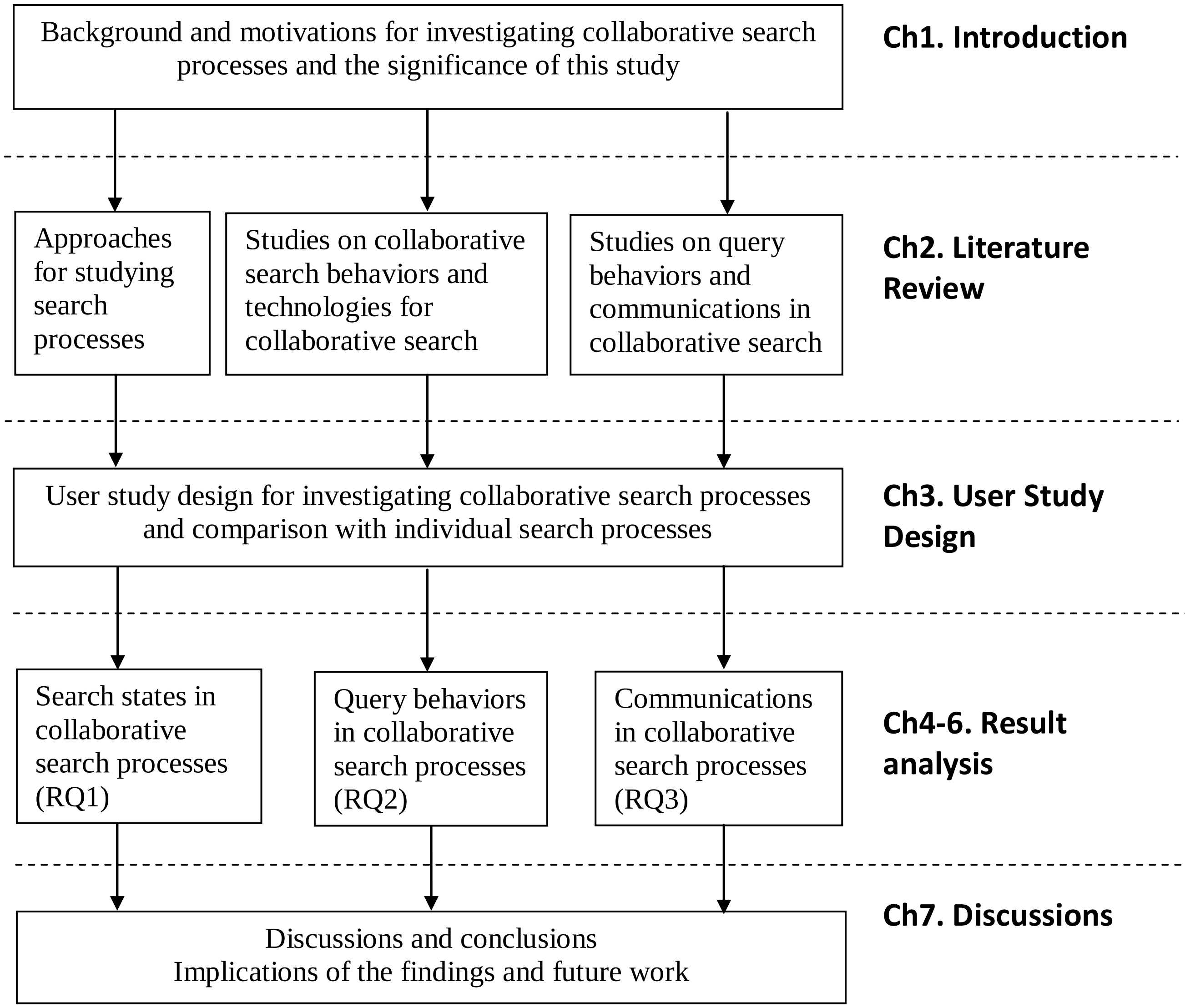


Figure 1.1. Overview of the study

2.0 RELATED WORK

The study of collaborative exploratory search processes can benefit from various research topics including individual information seeking process studies, collaborative information seeking studies, exploratory search and query behavior studies and communications in teamwork. Therefore, the related works in this chapter are organized in four sections. Section 2.1 focuses on information seeking studies in the individual context. Section 2.2 discusses studies which focus on collaborative information seeking. Section 2.3 highlights the query behavior studies in both individual and collaborative context. Finally, Section 2.4 focuses on the communication studies in both general teamwork setting and the collaborative search setting.

2.1 INFORMATION SEEKING

For a long time information seeking study has focused on the individual user, the well-established theory and research findings in the field can provide foundations and useful guidance for the collaborative information seeking study. Two topics in information seeking relevant to this study – information seeking process and exploratory search are discussed in this section.

2.1.1 Information Seeking Process

Information seeking process is one of the major topics in information seeking behavior research. Researchers employed two major approaches to investigate information seeking process. One is modeling macro-level information seeking process, which focuses on qualitative constructs such as stages and context in information seeking process. The other one is modeling micro-level information seeking process by identifying descriptive categories such as user action, search strategies or search tactics and the transition relationships among them (Kim, 2009) .

2.1.1.1 Macro-level Process Studies

Kuhlthau (1991) proposed an information search process model which presents a holistic view of information seeking from the user's perspective in six stages: task initiation, selection, exploration, focus formulation, collection and presentation. Based on the empirical research, the model incorporates the physical, affective, and cognitive aspects of users experience common to each stage. Also derived from empirical study, Ellis (1993) developed a model addressing a series of features of users' behavior involved in information seeking process, including starting, chaining, browsing, differentiating, monitoring, extracting, verifying and ending.

Wilson (1999) did an interesting comparison of Kuhlthau and Ellis's model and found the similarity of them. Typically, the two models share the notion that users start with an information problem. By recognizing the information need, users start searching general topic or perform browsing actions. After analyzing and evaluating the initial results they get, they become more certain about their information problem. Then they start formulating search on more specific area and collect relevant information on their focus. When their information problems have been solved, users feel satisfied and complete the search. The strength of Kuhlthau and Ellis's model is that they are based on experiments and observation in empirical studies and has been tested in many subsequent studies. Wilson also pointed out that Ellis does not present features of information seeking behavior as stages but as elements that may occur in different sequences with different context. It suggests that the sequences of behavioral characteristics may vary as users jump back and forth between different phases. The possibilities of transitions between stages are modeled more explicit by Marchionini (1995). He proposes an information-seeking process model composed of eight stages with possible transitions between each of them: (1) recognize and accept an information problem, (2) define and understand the problem, (3) choose a search system, (4) formulate a query statement, (5)execute search, (6) examine results, (7) extract information, and (8) reflect/iterate/stop. Similar to Kuhlthau and Ellis, the information seeking begins with the recognition and acceptance of the problem and continues until the problem is solved. However, this model highlights the likelihood of a stage calling another stage in three types: most likely transitions, high-probability transitions and low-transition probabilities. Marchionini's model is more suitable for electronic environments as it captures many important elements of information seeking, including knowledge acquisition in extract information, and collection exploration in examine results.

2.1.1.2 Micro-level Process Studies

Realizing the continuous and iterative nature of search behavior, Spink (1997) proposes a model of the search process identifies user judgments, search tactics or moves, interactive feedback loops, and cycles as constituting the search process of a user in interaction with a system. She pointed out that an interactive search process may consist of one or more search strategies made up of a series of cycles. Each cycle is an interactive feedback loop composed of a series of search tactics or moves. The value of this view of search process is that it highlights search strategies and tactics as components of search process. Bates (1979, 1990) defines four levels of search activities from move to strategy. Bates' work identifies 29 search tactics into monitoring, file structure, search formulation and term tactics. Marchionini (1995) also defines moves, tactics and strategies. In his definition, moves are discrete behavioral actions, tactics are discrete intellectual choices manifested as a group of behavioral actions, and strategies are approaches taken to solve problems. He proposed two types of search strategies: analytical strategies and browse strategies. While analytical strategies tend to be more goal-driven, browsing strategies are more informal and interactive.

Incorporating Bates and Marchionini's definitions, Xie and Joo (2010) defines moves as basic thoughts or actions in the information search process, tactics as to a move or moves that users apply to advance their searches, and search strategies as patterns of sequential tactics that imply users' plans for the search process as well as changes occurring in the search process. In the study, they point out that information search process is a complicated and dynamic process, and it is necessary to look into the transition of search tactics to understand the search process. By applying Markov chain, a probabilistic model, Xie and Joo present the most common search strategies representing patterns of tactics transition at the beginning, middle and ending phases in the search process. The value of the study is that the result provides guidance for information search system design to support the most frequently applied tactics and transitions.

Belkin (1995) proposed a faceted classification of interactions between the user and the other components of the IR system. Four dimensions used for the classification includes method of interaction (scanning or searching), goal of interaction (learning or selecting), mode of retrieval (recognition or specification) and resource considered (information or meta-information). He suggest that any single interaction can be described according to its location along these four dimensions, and the information seeking process can be characterized by movement from one interaction to another within the course of a single information-seeking episode. Kim (2009) modified Belkin's model to make it suitable to describe the interactions in web search environment. Then the model was used to analyze the transition patterns in web search process for different task types. Xie (2002) also applied faceted dimensions to classify user interactions. The two dimensions used in the study are methods and resources. Instead of assigning binary value for each dimension, more values for each dimension are considered. For example, the value of methods can be scan, search, acquire, compare, consult, select, track and trial and error.

This line of interaction transition pattern studies are all based on predefined framework of descriptive categories of behaviors such as interactions or search tactics and the data analysis highly rely on manually coding of search transaction logs. Automatic methods have been explored in some work. Chen and Cooper (2001, 2002) used both stochastic model and clustering techniques to examine search tactics in a web-based library catalog. However, they usually missed explain the latent rationale behind the search tactics. Their identified search tactics are simply the aggregation of sequential behaviors while the connections among user actions and search tactics are missing.

2.1.2 Exploratory Search

Exploratory search describe information processes that are opportunistic, iterative, and multi-tactical, in which the query-document matching power of search engines plays a less important role (White et al., 2006). Marchionini (2006) identifies a number of search activities that differentiate exploratory search from look up search. Figure 2.1 shows that exploratory search is especially pertinent to learn and investigate activities. When users' information needs are well defined, look up is sufficient for them to locate information. However, when users' needs are ill-defined, look up search is necessary but not sufficient for users to seek information for learning and investigation. The activities are shown as overlapping clouds because there is generally interplay between them, and some activities may be embedded in others.

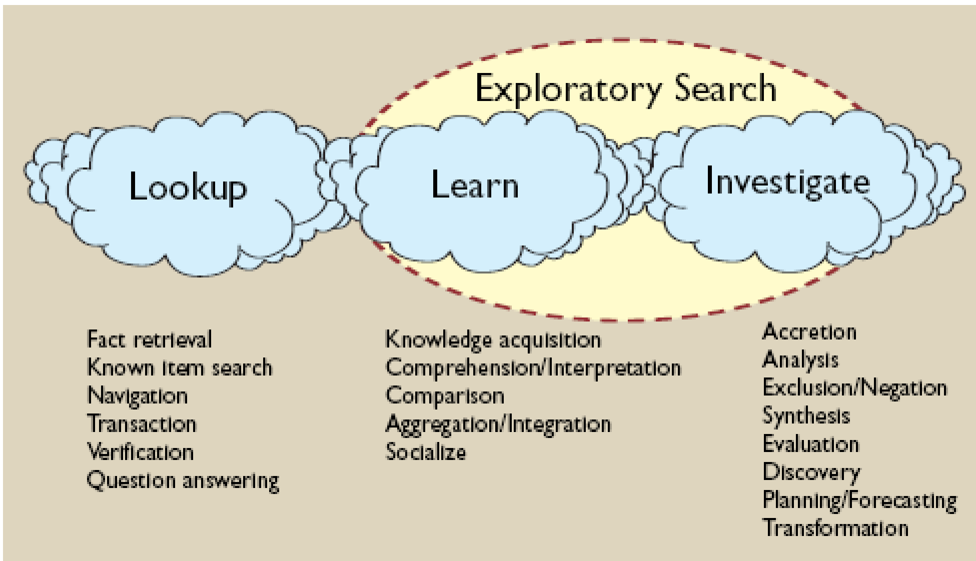


Figure 2.1. Exploratory search activities by Marchionini

Many studies have showed that exploratory search activities are common information seeking behavior exhibited by users. In an investigation of how people performed personally motivated searches in their emails, files, and on the web. Teevan et al. (2004) found that 61% of searches include more exploratory forms of search. In another empirical study, White and Drucker (2007) showed the evidence that 23% searchers are almost entirely exploratory, and only 17% of searches did not exhibit any exploratory behavior. Wilson and Schraefel (2008) studied an interface that supports both searching and browsing and found that around 50% of searches showed the alternatives to keyword search.

To support users' needs for exploratory search, information seeking support systems that provide more than query-response functions are needed. White and Roth (2009) propose a set of features that must be present in system that support exploratory search: (1) support querying and rapid query refinement, (2) offer facets and metadata-based result filtering, (3) leverage search context, (4) offer visualizations to support insight and decision making, (5) support learning and understanding, (6) facilitate collaboration, (7) offer histories, workspaces, and progress update, and (8) support task management. The features of facilitate collaboration are of the most interest to my study. In an exploratory search, the information-seeking problem context is open-ended, persistent, and multi-faceted (White et al., 2006). When people bring diverse perspectives, experiences, expertise and vocabulary to the exploratory search (Golovchinsky et al., 2009), each user's understanding of the problem context can be pooled to identify the salient aspects, and complex problem solving can be more effective as people's ideas are pooled for a coverage of the solution space (White & Roth, 2009).

2.2 COLLABORATIVE INFORMATION SEEKING

In collaborative information seeking, a small group of people share the same information need and they look for information together within the same frame of time (Shah & Marchionini, 2010b).

2.2.1 Collaborative Information Behavior

Collaborative information behavior (CIB) is a relatively new research area compared to individual information behavior research. Poltrock et al. (2003) defined CIB as "activities that a group or team of people undertakes to identify and resolve a shared information need" Two central concept of CIB are included in the definition: one concept is people working together to seek information and the other concept is resolving an information need, which includes seeking, retrieving, and using information to solve a problem (Reddy & Jansen, 2008). This definition provides us a starting point to recognize CIB among all the human information behaviors. Recent studies undertaken across a wide variety of domains showed that the CIB is as common and natural as individual information behavior (Hansen & Järvelin, 2005; McKenzie, 2003; Talja, 2002).

2.2.1.1 CIB Studies in the Web Context

Collaborative information seeking has been studied in the web environment. Morris (Morris, 2008) conducted a survey among 204 information workers about when they used web search tools collaboratively and on what tasks they usually collaborate with others. Evans and Chi (2008) also conducted a survey among 150 people using Mechanical Turk to investigate collaborative search strategies involved in *before search*, *during search* and *after search* stage. The surveys revealed that the collaborative web search is a surprisingly common activity. However, collaborative web search are not well-supported by current web search tools. A most recent survey (Morris, 2013) reported that respondents engaged in collaborative web search on a daily basis has increased from 0.9% in 2006 to 11% in 2012. The author suggested the increased prevalence is a result of the significant change of technology landscape particularly the rise of social networking sites and the growing usage of smartphones. The survey also suggested that users' frustration regarding lack of awareness of collaborators' activities and resulting redundant work are the primary concerns in current collaborative web search practice. Shah and Marchionini (2010) presented a user study to study the awareness in collaborative information seeking. Three instances of the authors' collaborative web system for exploratory search were used in user study which is a between-subject design that involved 14 pairs of participants in each of three conditions. They showed that supporting for group awareness is more significant for effective collaboration than having awareness of personal actions and history.

2.2.1.2 CIB Studies in Academic Settings

Communication and social network among scholars have been recognized and emphasized by researchers since decades ago. Studies of scholarly communication conducted in the 1960s and 1970s established that scholar's social tie and networks profoundly affect their information gathering, reading, awareness and interpretation of documents and literature (Talja & Hansen, 2006). However, only until recently did researchers start to focus on scholar's collaboration during the information seeking and retrieval process.

Based on a comparative qualitative study of scholars across a range of humanistic, social-scientific, and scientific disciplines, Talja (2002) identified four types of information-sharing practice: strategic, paradigmatic, directive and social. Talja (2003) concluded that different kinds of functionalities within existing systems, and different types of IR systems are needed to support different types of information sharing.

In a combined ethnographic and experimental study of physicists, researchers discovered that successful scientific collaboration requires the collection and use of a range of awareness information that updates team members on the current state of their team's activities

(Sonnenwald et al., 2004). The study investigated the types of information and knowledge that need to be shared to support situation awareness and the ways in which technology can be used to facilitate such information sharing.

Blake & Pratt (2002) observed two groups of scientists in public health and biomedical conducting systematic literature review for the Cochrane Collaboration database. They found that scientists actively collaborated as they refined the retrieval, extraction, and analysis phases of a process that they called information synthesis. Based on the characterizations of user behavior during information synthesis, they proposed the design and progress towards implementing a tool METIS, which will support the collaborative, iterative, interactive information synthesis process of scientists.

2.2.1.3 CIB Studies in other Settings

Researchers are studying the collaborative dimensions of information seeking behavior in several different settings other than academic, such as industry, medicine, military and everyday life.

Hansen and Jarvelin (2005) did an empirical study of collaborative activities within information seeking and retrieval process in a real-life and information –intensive setting within the patent domain. The results showed that the patent task performance process involves highly collaborative aspects throughout the stages of information seeking and retrieval process. They categorized the activities into document-related collaborative activities and human-related activities. Finally, a refined IR framework involving collaborative aspects was proposed.

A study of two teams engaged in the software design focused on how team members collectively sought and shared external information acquired within the team (Poltrock, et al., 2003). In the study, they identified five collaborative information retrieval strategies: (1) identifying needs collaboratively, (2) formulating queries collaboratively, (3) retrieving information collaboratively, (4) communicating about information needs and sharing retrieved information, and (5) coordinating information retrieval activities.

Through a study of CIB of two healthcare teams, Reddy and Jansen (2008) proposed a model for understanding CIB in context. They found that collaborative information behavior differs from individual information behavior with respect to how individuals interact with each other, the complexity of the information need, and the role of information technology. They also found triggers for collaboration, including lack of domain expertise.

In a study of information behavior in military command and control teams, Sonnenwald and Pirerce (2000) studied collaboration in dynamic situations with rapidly changing information and a need for continuous information exchange. They found that the commander played an important role in identifying critical information needs. Three types of collaborative information behavior were distinguished: (1) information seeking by recommendation, (2) direct questioning, and (3) advertising information paths.

Within everyday life information seeking (ELIS) studies, McKenzie (2003) found that people routinely assist each other in solving information problems. For example, in representing themselves as information seekers, participants gave accounts that showed them to be active and on guard, attentively receptive, and surrounded by a supportive network of others like them. The findings suggest that information seeking theories and models have limited insight into how information comes or is given through the initiative or actions of another agent.

2.2.1.4 Collaborative Information Seeking Process

In terms of macro-level collaborative search processes, there are several studies attempting to explore Kuhlthau's ISP model in collaborative setting. Hyldegard (2006) explored ISP model in a group educational setting based on a qualitative preliminary case study. She found that collaborative search process cannot be modeled the same way as individual search process. She suggested that the ISP model should be extended to incorporate the impact of social and contextual factors in relation to collaborative information seeking process. Shah and Gonzalez-lbanez (2010) also attempted to map Kuhlthau's ISP model to collaborative information seeking. Through a laboratory study with 42 pairs of participants, they investigated similarities and disparities between individual and collaborative information seeking process. Similar to Hyldgard, they also declared that social elements are missing when applying the ISP model in a collaborative setting.

Very few studies had focused on the micro-level of collaborative search processes. Halvey et al. (2010) investigated frequency and temporal distribution of user interactions by analyzing log data in an asynchronous collaborative search system for online video search.

Based on the above literature review, we can see that there are plenty of investigations on search processes in individual user setting. Approaches from both macro-level and micro-level had been explored to examine search processes. Particularly, search tactics had been recognized as a mean of investigating search processes to bridging the macro-level and micro-level approaches. Search processes were examined in the individual web exploratory search in terms of transitions or sequences of search tactics. However, current investigations on macro-level collaborative search processes are limited to employ Kuhlthau's ISP model in collaborative environment. Studies on micro-level are very few and limited to online video search and implicit collaborative search in which users do not explicitly aware their collaborators.

2.2.2 Collaborative Search System and Evaluation

Collaborative information seeking retrieval activities has been studied in various environments including both organizational and the web setting. This dissertation will focus on the online and web search environment as the context for study collaborative exploratory search. Golovchinsky et al. (2008) classified the collaboration in web search using three dimensions – intent, concurrency and location. Collaborative web search can be implicit or explicit in terms of intent. The implicit collaboration usually occurs in recommendation and filtering systems and it is also called social search because the large scale of collaboration. However, explicit collaboration occurs on smaller scales such as in groups of several collaborators. Collaboration in web search can also be synchronous or asynchronous in terms of concurrency. The collaborative exploratory search is defined as synchronous and explicit collaborative search in this framework.

Table 2.1. Taxonomy of collaboration in web search

	Explicit	**Implicit**
Synchronous	Collaborative exploratory search	Real-time awareness and continual context update Context systems (E.g. Nokia, Imitv)
Asynchronous	Group asynchronous browsing	Collaborative filtering Social search web 2.0 Wisdom of crowds

There are two modes that a collaborative search system can support the collaborative exploratory search process: communication mediation and algorithmic mediation (Golovchinsky et al, 2011). In the communication mediation mode, the system serves as intermediary for collaborators to communicate and share information. In the algorithmic mediation, the search queries, results and relevance feedback are manipulated by the system so that the collaborators can be benefit from each other' search.

2.2.2.1 Systems using Communication Mediation

Recently, several systems have been described in the literature to be designed for supporting explicit collaboration using communication mediation.

SearchTogether (Morris & Horvitz, 2007) is a prototype that enables remote users to synchronously or asynchronously collaborate when searching the web. The system aims to support collaboration with several mechanisms for awareness, division of labor and persistence. SeachTogether's collaboration features include group query histories, split searching, page-level rating and commenting, automatically-generated shared summaries, peek-and-follow browsing, and integrated chat. An updated version of SearchTogether, called CoSense (Paul & Morris, 2010) added several new features for collaborative information sense-making, including search strategies view, timeline view, workspace view and chat-centric view.

CoSearch (Amershi & Morris, 2008) is a tool that provides explicit support for groups of co-located people to search the web when gathered around a single computer. The primary design goal for CoSearch was to enhance the experience of co-located collaborative web search in settings where computing resources are limited, by enabling distributed control and division of labor while maintaining group communication and awareness level.

Coagmento (Shah, 2010) is a system supporting multiple people work together conducting online information seeking tasks. Coagmento is designed as a plug-in for Firefox. It allows one to perform various information seeking and communication activities from right within the browser. There are two components of the system, a toolbar and a sidebar. The toolbar helps user collect information and be aware of the progress in a given collaboration while the sidebar provide collaboration features such as chat window history of queries, saved pages, and snippets.

Results space (Capra et al., 2012) is designed to support asynchronous collaborative web search. The system implements a set of collaborative awareness features that are embedded in the search results list. Users can use the system to share ratings on search results and share queries histories.

HeyStaks (Mahony et al., 2009) is a collaborative search tool that utilize the shared interests with a community of users. Community preferences, rather than individual preferences are used to re-rank the search results from mainstream search engines.

2.2.2.2 Systems using Algorithmic Mediation

Cerchiamo (Pickens et al., 2008) implements a form of algorithmic mediation, while each team member searches and browses results independently, the system coordinates their judgments of relevance, and offers search term suggestions based on team partners' actions. Furthermore, the two team members act in different roles – Prospector to discover potentially relevant documents, and Miner to explore such groupings – and therefore use different interfaces. The system mediates their activities, enabling the team to discover more, and different, relevant documents than they would by working separately in parallel.

Querium (Golovchinsky et al, 2011) implements both algorithmic mediation and communication mediation components. The communication components include chat and note-taking facility, documents and queries sharing, and commenting on documents. The algorithmic mediation components include query fusion and relevance feedback that operate on queries and documents.

2.2.2.3 Evaluation

Evaluation in a collaborative information seeking environment can be a huge challenge due to the variety of interactions among system and users. A few efforts had been made to evaluate various parameters in a collaborative information seeking environment by using traditional IR or HCI measures (Shah, 2010). Baeza-Yates and Pino (1997) presented an initial attempt to evaluate performance measures in collaborative IR. They tried to extend the performance measure in single-user IR system and treat the performance of a group as the summation of performance of individuals. In a later work (Baeza-yates & Pino, 2006), they evaluated the relationships among quality of the outcomes, number of people involved and time spent on the overall task, and total work done. As both works only use measures for evaluating performance, how well the system support user in the process of collaboration was not evaluated.

There are several studies focused on the usability of the collaborative interface. Wilson and Schraefel (2008) proposed an analytical inspection evaluation for information seeking interface which incorporate information seeking models in HCI usability evaluation method. And later (Wilson & Schreafel, 2009) they extended the framework for application of evaluating collaborative search interface. This method was designed for HCI experts to evaluate the usability of the interface; no real users are involved in the evaluation. Morris and Horvitz (2007) evaluated their SearchTogether system with a user study of fourteen subjects in 7 pairs. They collected log, observation and questionnaire data from the study. The evaluation showed the effectiveness of their interface by analyzing the usage of certain features and asking user how they feel about the features in helping them accomplish the task. In the evaluation of CoSearch system, Amershi and Morris (2008) recruited 36 subjects in 12 groups to use the system. Subjects were asked to comment on the usability of CoSearch by answering 5-point Likert scale questions. Shah (2010) evaluated the Coagmento system using a set of objective and subjective measures in a user study involved 42 pairs of subjects. Objective measures include effectiveness and efficiency which are based on analyzing search outcome of individual and group. Subjective measures such as awareness, effort, ease of use and satisfaction, engagement were evaluated through questionnaire.

Capra et al. (2012) used the TREC Robust corpus for a collaborative search user study so that standard recall and precision measures can be computed. However, when the collection is the open web, there is no ground truth can be used to calculate recall and precision. Shah and González-Ibáñez (2011) proposed precision and recall that can be used in an open-web collection context. Recall is defined as the ratio of relevant web pages collected by a single team to the relevant web pages collected by all the teams. Precision is defined as the ratio of relevant web pages collected by a single team to all the web pages viewed by that team. In addition, the authors also proposed other measurements such as query diversity, useful webpages and likelihood discovery. Lavenshtein distance is used to compute the distance between pairs of queries for each team to measure the query diversity. Useful webpages are defined as webpages that a user spends at least 30 seconds on it. Likelihood of discovery is used to measure hard to find information, which is measured by the inverted frequency that each webpage is visited by all the teams.

2.3 QUERY BEHAVIOR STUDIES

Complex and explorative web searches often involve iterative interaction with retrieval systems, so that query behaviors have been important topics in individual explorative searches. However, as a much more complex form of explorative search, collaborative web searches have seldom been the focus for query behavior studies. A few studies on query behaviors in collaborative information retrieval have been based on implicit collaborative search where information from a community of like-minded searchers is shared without explicitly modeling the collaboration (Balfe & Smyth, 2005). In this section, query behaviors in both individual and collaborative context are discussed.

2.3.1 Query Behaviors in Individual Search

Researchers have investigated the effect of various factors on users' query behavior. Bates (1979) proposed the notion of search tactics and a set of term tactics referring to the search tactics for reformulating queries in search. Contextual factors such as search experience and domain knowledge affect search tactics (Ingrid Hsieh-Yee, 1993). Task type is the focus of many research studies looking at its effect on users' search behavior. Toms et al. (2008) classified tasks into three different types: decision–making , fact-finding, and information-gathering. Two types of task structure -- hierarchical and parallel -- were also considered. They found that the query length in fact-finding and information-gathering tasks with a hierarchical structure tended to be longer than those with parallel structure. In information-gathering tasks, users are more likely to use additional and unprompted terminology. Liu et al, (2010) examined the effect of task type on query reformulation patterns. Three types of tasks are recognized including simple, hierarchical, and parallel. They also classified query reformulation into five categories: Generalization, Specialization, Word substitution, Repeat and New. They found that specialization is used more often in simple and hierarchical tasks while word substitution is used more often in parallel tasks. Other taxonomies were used to classify query reformulation patterns. Jansen et al. (2009) summarized six different types of query reformulation patterns: New, Assistance, Content change, Generalization, Reformulation, and Specialization. Lau and Horvitz (1999) and He et al. (2002) used the same taxonomy and, depending upon the changes in query content and query length, four types of patterns can be distinguished: Generalization, New, Reformulation, and Specialization.

Previous research pointed out that successful assistance to query reformulations must be designed based on the understanding of users' query behavior (Jansen et al., 2009). Various techniques had been used to generate query suggestions. Depends on whether or not a query log is available, there are two lines of research on query suggestion algorithms. If a query log is available, the goal is to find good query suggestion candidate in terms of both similarity and diversity. One approach is to use query cluster – given a query, first identify the cluster of the query belong to, and then the rest queries in the same cluster can be presented as query suggestion (Cao et al., 2008). Another approach optimizes the query suggestion using the users' implicit feedback such as hitting time (Mei, Zhou, & Church, 2008). These techniques require a large scale of existing query log. A combination of semantic clustering and pseudo-relevance feedback method was used to generate terms for suggestion when query log is not available (D. Kelly, Gyllstrom, & Bailey, 2009). Another approach to generate query suggestion without query logs is to use anchor text (Dang & Croft, 2010).

Besides the query suggestion algorithms, there are many studies focused on the query suggestion presentation. Joho et al. (2002) compared a list and a menu hierarchy display of query expansion terms. The authors found that although there were no differences on search performance, users select more terms from the menu hierarchy. Kelly et al. (2009) investigated the differences between term suggestion and query suggestion. A user study was conducted and the authors found that subjects prefer query suggestion to term suggestion while there was no significant difference on search performance. Another study (Kelly, Cushing, Dostert, Niu, & Gyllstrom, 2010) investigated the effects of usage statistic information on the use of query suggestion. In the user study, fake usage information of each suggestion query is provided to the user. The researchers found that subjects were able to distinguish high quality and low quality queries and were not influenced by the usage information. Kato et al. (2012) proposed a novel structured presentation interface for query suggestion which can support two popular query reformulation actions – specialization and parallel movement. Categories with labels are used in the query suggestion presentation. In addition, new entities as alternative are shown as alternatives to current entity. Through a task-based evaluation, the results showed that the structured query suggestion presentation increase the search performance than a flat list presentation of query suggestions.

2.3.2 Query Behaviors in Collaborative Search

Collaborative querying is a technology that has been widely used in implicit collaborative information retrieval. Collaborative querying enables users of an information retrieval system to draw on previous query preferences of other users at the query formulation and reformulation stages of an information search (Foster, 2006). Previously-learned queries and relevant documents are reused in new and similar search sessions to improve the overall retrieval quality (Hust, 2004). Often, simulated experiments are employed in these studies, rather than user studies involving human subjects. Walkderine & Rodden (2001) described the design and evaluation of a prototype environment that supports community use of query recommendation.

Smyth et al. (2005) introduced a community-based search engine I-SPY. The system implements a collaborative ranking function based on similar query-document pairs and suggests similar queries to users. The evaluation results showed that the system offers potential improvements in search performance, especially when communities of searchers share similar information needs and use similar queries to express their needs. Another study incorporate I-SPY search engine with a social navigation function. The integrated system allows users to effectively combine their search and browsing activities. The findings from the study indicate that subjects found the query suggestions were useful during the browsing as it provides the "community wisdom".

A study that investigated query formulation and reformulation in explicit collaborative search is conducted by Capra et al. (2012). They designed an asynchronous collaborative search user study using the system Results Space. In the study, subjects who did the search later were provided with query histories of the participants who did the search earlier. They found that although only 4 participants actually clicked on the provided queries from previous participants, 10 out of 11 participants reported that they indeed looked at the query history and made use of it. Four motivations of using the query history were summarized from the interview. The first motivation is to write different queries from what the previous participants had already done. The second one is to get an overall sense of what the previously participants had searched for. The third motivation is trying to figure out where to start their search by examining the train of thought of previous participants through query history. The last motivation is that the query history can inspire participants to get new ideas for issuing their quires.

From the literature, it can be seen that the query behavior and reformulation studies have reached maturity in the context of individuals. However, the studies on query behavior in the collaborative search context were relatively fewer and primarily focused on implicit collaborative search. A comparative study on query behaviors in collaborative search and individual search can help researchers to understand how users' query behaviors are affected in the collaboration setting.

2.4 COMMUNICATION STUDIES

Communication is the process of sending and receiving information. It is vital to the success of two or more individuals working as a team (Dickinson & McIntyre, 1997). Although the studies of communication in collaborative searches is a relatively new topic, researchers in other domains, such as computer-supported cooperative work (CSCW), computer mediated communication (CMC) and computer-supported collaborative learning (CSCL), have studied communications for a long time. In this section, I first review the studies of communication in a general teamwork setting, and then I focus on the communication studies in collaborative search.

2.4.1 Communications in Teamwork

There is a stream of work investigating the medium of communications. A well-known media richness theory (Daft & Lengel, 1984) recognized four different types of communication medium according to the varying degree of richness: face-to-face, video, audio and computer-mediated text transfers. Different tasks are best mediated by different mediums. For example, video is good for judgment task but too rich for generating ideas. Text messaging is good for generating ideas but not rich enough for negotiation (McGrath & Hollingshead, 1993). Researchers examined the collaborative performance among team members through different communication medium (Stone & Posey, 2008). They found that the perceived performance was lower in computer-mediated text groups than that in face-to-face groups when the groups were not trained. But with training, there is no difference on perceived performances between the groups using two different communication medium.

Two types of communication styles were recognized in the literature: task oriented versus socially oriented (Bass, 1990). Task oriented communication focuses on fulfilling the responsibilities while socially oriented communication focuses on satisfying the emotional needs of interpersonal relationships. In a study of investigating communication in CSCL environment (Strijbos et al., 2004), the researchers proposed a framework of coding communication messages, which can be used to distinguish socially oriented communication from task oriented communication. There is also a line of work investigate the emotions involved in the text-based communication. For example, Brooks and colleagues (2013) proposed a machine learning technique that can automatically detect and classify affections in the chat logs.

The theories and methodologies from communication studies in general teamwork settings can be borrowed by researchers in collaborative search studies to investigate the role of communication in the collaborative search process.

2.4.2 Communications in Collaborative Search

Many collaborative search strategies and tactics have been identified to be related to communications between team members in the collaborative search process. Foley and Smeaton (2010) proposed division of labor and sharing of knowledge as two important strategies of successful collaboration in search. Both strategies can be facilitated by the communication between team members. Through a study of library users, Twidale (1997) identified a set of search tactics that may require the communication with others. Examples include, users may seek for help from the reference librarian or brainstorm with others to generate new approach for search. Reddy and colleagues (2009) identified three reasons for communication among team members while looking for information: consulting, brainstorming and team cognition. Based on the identified importance of communication in collaborative search, most existing collaborative search systems have implemented instant message as the function to support the communication among team members (Morris & Horvitz, 2007; Shah, 2010).

Instant message is the simplest way of supporting communication and it offers high user freedom. How to design advanced support for communications should be based upon the understanding of cost and benefits of communications in the collaborative search process (González-Ibáñez et al., 2013). Hertzum (2008) found that communications could be effective in establishing common ground between team members. However, other researchers also reported that communication could introduce extra workload or distract users from their search tasks (Carroll et al., 2006). González-Ibáñez and colleagues (2013) investigated the cost and benefit of three different communication mediums: face-to-face, computer-mediated text, and audio plus the text. They found that the face-to-face medium allows users to interact effortlessly, but it also generated more non-task related communications which are at the risk of hurting the search performance. The communication through text medium was more focused on the task-related conversations but also limit the social aspects of communication in collaborative search. The audio plus text medium was able to provide the right level of social presence and at the same time did not distract team members from the task too much. Another study focused on the usages of communication for coordination (Shah, 2013) in the collaborative search process. The study presented the effects of three different awareness conditions on the coordination through chat messages. Their findings showed that a lower level of awareness support increases the cost of coordination in the collaborative search process.

The research community of collaborative search has realized and emphasized the importance of communication in collaborative search process. I think additional studies of investigating the patterns of communication, especially the relationship between communication patterns and search outcomes are needed. These studies can help researchers to understand the benefits and costs of communication, and can help to design systems to support effective communications in the collaborative search process.

3.0 METHODOLOGY

The data used in this study was collected from a laboratory-based user study. Participants were recruited to our lab to use a collaborative search system I designed. The participants were required to work on exploratory search tasks either collaboratively with a partner or individually. In this chapter, I introduce the experiment design of the user study, including system design, participants and tasks, experiment conditions and procedures, and data analysis methods.

3.1 SYSTEM DESIGN

3.1.1 System Features

In this study, I need a system that could help team users conduct web search collaboratively. One option is to use an integrated collaborative search system that have both search and collaboration features. Another option is to use one system for search and the other system for communication, such as using both Google and Skype in the study. The reason I chose an integrated system is that I need to study the activity and information flow during the collaborative search process. If the activities are logged in different systems, it would be difficult to examine the activity and information flow. In addition, dealing with multiple systems may be an extra workload for the users. A good collaborative search system for this study should meet two requirements. First, the system should have basic functions that make the collaborative search possible. Second, the system should not be too complicated so that users can easily learn how to use the system and at the mean time have the flexibility in exploring various search tactics themselves. Third, the features in the system should have been commonly used and accepted in previous studies, so that the findings based on the user behavior of using the system can be generalized.

Recently, several systems have been described in the literature to be designed for supporting explicit collaboration, including SearchTogether (Morris & Horvitz, 2007), Coagmento (Shah & Marchionini, 2010), Cerchiamo (Pickens et al., 2008) and Querium (Golovchinsky et al., 2011). The prototype system CollabSearch[1] was built upon the examination of features in these systems. Some features that have been reported to be very important, such as chat and shared workspace were implemented in CollabSearch. As shown in figure 1, the left side of the system's interface is the space for chat. And the main interface contains three frames: topic statement, web search and team workspace. The topic statement frame shows the task description on which the user is currently working. Users can also post their comments below the task description. The search frame connects the user's query to Google, and displays the Google search results. Users can also see their search histories (queries) as well as those of their teammates. Users examine search results for relevant information, and can save a whole web page or a snippet of the page. All the saved web pages and snippets, collected by the user and the teammate, are stored in the team workspace frame. All the features implemented in CollabSearch are well studied and commonly used in other collaborative search studies. Therefore, the generalizability of observed user behavior using this system can be achieved.

---

[1] http://crystal.exp.sis.pitt.edu:8080/CollaborativeSearch

3.1.2 Design Rational for Process Collaboration

Coordinated searching is an important search strategies observed by (Twidale, 1997). Using CollabSearch, users in the same team can communicate with each other by sending instant text messages to coordinate their search processes. I didn’t implement advanced features such as split search in SearchTogether because the coordination process can be accomplished through communication and users can be creative in how they want to complete the search tasks collaboratively. In addition, implementing uncommonly used features would result in unique behaviors observed in this particular collaborative search system. The shared search history provide support for the process collaboration as team members can be aware of each other’s search progress by checking the search history.

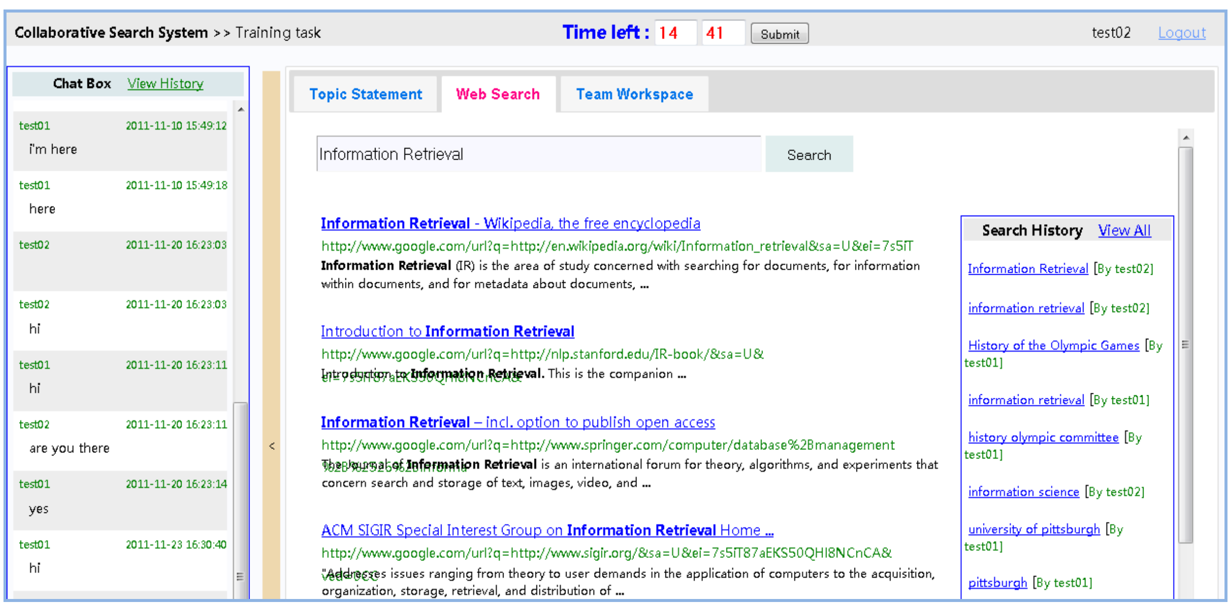


Figure 3.1. The web search frame of CollabSearch

3.1.3 Design Rational for Products Collaboration

In addition to the collaboration on search process, sharing search products have been recognized as very important search strategies. The team workspace is designed for users to share the relevant search results. All of the saved web pages and snippets, collected by the users in the same team, are saved in the team workspace. A notice is displayed at the top when new items are saved to the team workspace. Users can click on the title of an item to view more details about the item in the workspace. Users can also decide whether a particular item is visible to other team members or not. The items saved by the user him/herself and the teammates are displayed in different colors and the user can choose to view a particular sets of items by using the filter.

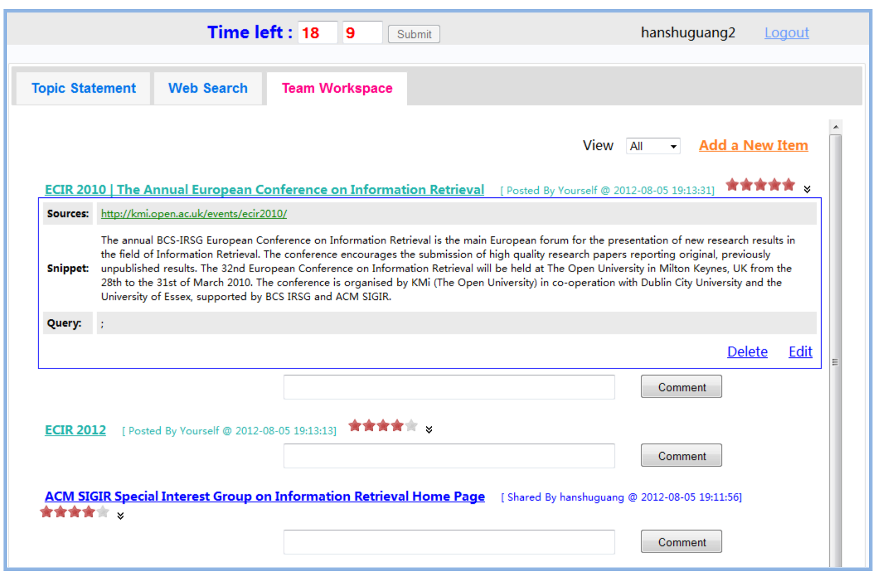


Figure 3.2. The workspace frame of CollabSearch

For each item saved in the workspace, the user need to assign a rating to indicate the quality of the saved item. One- star means that the item is not relevant and has low quality and five-star means the item is highly relevant and has high quality. Users also have the options to assign tags to the items in the workspace saved by themselves or they can comments on the items saved by themselves and the partners.

3.2 EXPERIMENT DESIGN

3.2.1 Experiment Conditions

I adopted a mix-method experiment design with one within-subject factor: search task; and one between-subject factor: search condition, which refers to two search modes:

Collaborative search condition (COL). In this condition, two participants formed a team, and they worked on the same task simultaneously. As I was trying to simulate remotely-located collaboration, the team members could only communicate with each other by sending instant messages or reading each other's search histories. The collected results are shared in the team workspace, but no face-to-face communication was allowed.

Individual search condition (IND). This condition was devised as a baseline. In this condition, participants worked on the exploratory search tasks individually. When used by individual users, the chat function of CollabSearch was hidden.

3.2.2 Participants and Tasks

Fifty-four participants including 26 females and 28 males were recruited from the University of Pittsburgh. Among all of the participants, 36 signed up in pairs and thus formed 18 teams, which were assigned to the COL condition. Two participants work as a team know each other before they sign up for the study because it’s uncommon for strangers to do collaborative search together. The remaining 18 individual participants were assigned to the IND condition. All participants are students and they use computers and conduct web searches on a daily basis. Twenty-four participants are graduate students whereas the other 30 are undergraduates. According to a question asking them to rate their search experiences from 1-7 (with 1 as the least experienced and 7 as the most experienced), the responses ranged from 4 to 7. Thus most of our participants were experienced searchers.

Two exploratory web search tasks were used in this study. Both of them have been used in other collaborative web search studies (Paul & Morris, 2010; Shah & Marchionini, 2010). The topic of one task is literature search, asking the participants to collect information for a report on the effect of social networking service and software. The topic of the other task is travel planning, asking the participants to collect information for planning a trip to Helsinki. Morris (2008) noted that literature search and travel planning are two common collaborative search tasks. Therefore, both of the tasks are appropriate to study collaborative web search. The description of each task is shown in Figure 3.3 and Figure 3.4 respectively.

The reason that I chose these two tasks is that they represent two different types of exploratory web search tasks. First, the T1 is a recall-oriented information-gathering task, whereas T2 is a utility-based decision-making task. Second, the relevance criteria in these two tasks are different according to Saracevic’s relevance theory (2007). Topical relevance is probably the most important criterion in T1 because the topic is more objective in relevance judgments, whereas T2 involves users’ subjective judgments and even personal preferences, so the relevance criteria contain many subjective and personal flavors.

Task 1: Literature search [2]
The College Network News Channel wants to do a documentary on the effects of social networking services and software. You are responsible for collecting various relevant information about this topic from the web. Your goal is to collect information for preparing a report on this topic and it should address the following issues: *Emergence and spread of social networking sites, such as MySpace, Facebook, Twitter, and del.icio.us, statistics about popularity of such sites (How many users? How much time they spend? How much content?), impacts on students and professionals, commerce around these sites (How do they make money? How do users use them to make money?), and examples of usage of such services in various domains, such as health-care and politics."* *To prepare this report, search and visit any website that you want and look for specific aspects as given in the guideline above. As you find useful information, highlight and save relevant snippets. Later, you can use these snippets to compile your report. You may also want to save the relevant websites as bookmarks. Remember your main objective here is to collect as many relevant snippets as possible.*

Figure 3.3. Information-gathering task (T1)

Task 2: Travel Planning [3]
You and your friend are planning a four-day vacation in Helsinki, Finland from Dec 23th - 26th. You want to search for information about how you will spend your vacation in Finland. Assume that your flights are booked (leaving the US on the 22th of Dec and returning to the US on the 27th of Dec) and your hotels are booked too. But you have not yet planned the activities for your vacation. Your goal is to come up with a travel plan of things you will be doing on your vacation. You have certain constraints as follows: *You can only spend 200 Euros (100 Euros per person). Of all the activities your group chooses for the vacation, one has to be an outdoor activity, the other is a dining activity, and the third is a cultural activity. You are free to choose any other types of activities in addition to these three.* *As you find useful information, highlight and save relevant snippets. Later, you can use these snippets to compile your travel plan. You may also want to save the relevant websites as bookmarks. Remember you main objective is to collect as many relevant snippets as possible.*

Figure 3.4. Decision-making task (T2)

[2] From (Shah, 2010) with minor modifications.
[3] From (Paul, 2010) with minor modifications.

3.2.3 Experiment Procedure

Each team in COL worked on both tasks. The order of the two tasks was rotated to reduce the learning and fatigue effect. During the experiment, participants were introduced to the study and the system, and completed an entry questionnaire to establish their background. Then, participants worked on a training task for 15 minutes to become familiar with the system. They went on T1 or T2, depending on the task order assigned to each team. They had 30 minutes for each task. At the end of each task, participant completed a post-search questionnaire about their satisfaction on the performance and the cognitive load of the search experiences. At the end of the experiment, I conducted a short interview with both of the participants in the team.

The experiment procedure in IND is identical to the COL condition except that only one participant undertaking the entire process. The questionnaire used in the IND was modified to remove the questions related to the collaboration, and no interview was conducted at the end.

3.3 DATA ANALYSIS METHODS

3.3.1 Building the Groundtruth

When the participants were saving documents in the workspace, they rated the relevance of the saved documents using a 5-point Likert scale with 1 being not relevant and 5 being highly relevant. I built a pool that contains all the saved documents from the 54 participants for each task. Documents that have the same URL are considered as the same documents. One document could be saved by multiple participants. In order to determine the relevance of each document, I adopted the IMDB's Weighted Ranking method, whose purpose is to determine the top 250 rated movies in IMDB (Wikipedia, 2014).

For a given saved document *di*, a simple way of computing the relevance *r̂(di)* is through the average of all ratings. IMDB's Weighted Ranking method also takes into account the confidence of the averaged rating. In this method, the relevance score of each document *r̂'(di)* is computed based on Equation (3.1). C_m is the average rating for all documents in the pool, which is 3.99 in my study. In the formula, v denotes the number of voters and in my study is the number of participants that had saved the documents. In IMDB method, m is the minimum votes to be displayed for top 250 movies. Here I set it to 1.

$$\hat{r}'(d_i) = \frac{\hat{r}(d_i)v + Cm}{v + m} \qquad \text{Eq. (3.1)}$$

The thread-hold for a relevant document is set to be *r̂'(di)* greater than 3.5. The value is determined based on the principle that at least one participant had rated the document as great than 3.

3.3.2 Performance Measurements

Precision and recall are commonly used measurements for search performance. Based on the method introduced in Section 3.3.1, I defined the pool of the relevant webpages (Ground-Truth data denoted by G). Then, for each participant *u*, the precision *P(u)* and recall *R(u)* were computed using Equation (3.2) and Equation (3.3), in which *S(u)* are a set of webpages saved by participant *u*.

$$P(u) = \frac{|G \cap S(u)|}{|S(u)|} \quad \text{Eq. (3.2)}$$

$$R(u) = \frac{|G \cap S(u)|}{|G|} \quad \text{Eq. (3.3)}$$

User satisfaction *Sat* is a subjective measurement which reflects the participants' perception of the search outcome (Spink, 2002). In this study, I measure the participants' satisfaction based on their responses to three questions asking them to evaluate their satisfaction on the search outcome and performance using 7-point Likert scale. A higher score indicates a better satisfaction.

For participants in COL condition, the questions were asked as follows:

1. *I am satisfied with the amount of the information collected by our team.*
2. *I am satisfied with the quality of the information collected our team.*
3. *I am satisfied with the overall performance of our team.*

For participants in IND, the questions were asked as follows:

1. *I am satisfied with the amount of the information I collected.*
2. *I am satisfied with the quality of the information I collected.*
3. *I am satisfied with my overall performance.*

Cognitive load (Cog) can measure how hard one have to work for solving a complex problem, which can be used as a subjective measurement to evaluate the participants' perception towards their search experience. I used the instrument which has been used in another collaborative web search study (Shah & González-Ibáñez, 2011) to measure participants' cognitive load, which is a simplified version of NASA's Task Load index (TLX) (Hart & Staveland, 1988). The instrument includes the following five questions.

The participants responded to these questions in the post-task questionnaire on a 7-point Likert scale from very low to very high. A higher score indicates a higher cognitive load, and yet a negative user perception to the search experience.

1. *How mentally demanding was this task?*
2. *How physically demanding was this task?*
3. *How hurried or rushed was the pace of the task?*
4. *How hard did you have to work to accomplish your level of performance?*
5. *How insecure, discouraged, irritated, stressed, and annoyed were you?*

3.3.3 Statistical Model

Since my study contains both within-subject and between-subject factors, and data maybe correlated, I adopted generalized estimating equation (GEE) to fit the model to the data, and analyzed the relationships between the independent variables and dependent variables, as well as the correlations. $p \leq .05$ was used to test any significant differences. GEE is a flexible statistical tool which deals with repeated measure and non-normal distributed data.

3.4 SUMMARY

In this chapter, I introduced the experiment design of the user study. A collaborative web search system that could support both web search and collaboration was developed and used in the user study. The experiment was designed with one within-subject factor *task type* and one between-subject factor *search condition* (individual search or collaborative search). Eighteen pairs of participants were recruited to work in the collaborative search condition, and another eighteen individual participants were recruited to work in the individual search condition. Participants in both search conditions worked on two tasks. One task is a recall-oriented information-gathering task and the other task is a utility-based decision-making task. Participants' behaviors were logged in the system and their perceptions of the search experiences were collected using questionnaires.

The data collected in this user study was used for the analysis in the following three chapters. Chapter 4 provides the analysis of the overall picture of search states involved in the collaborative search process. Chapter 5 concentrates on the query behaviors. Chapter 6 is a deep dive into the communications between team members in the collaborative search process.

4.0 SEARCH STATES IN COLLABORATIVE SEARCH

There are two approaches to study search process. The first approach is modeling information seeking process from top-down, focusing on qualitative constructs such as stages and context in information seeking process. The second approach is modeling information seeking process from bottom up by identifying descriptive categories such as user action, search strategies or search tactics and the transition relationships among them (Kim, 2009). In my study, I adopted the bottom-up approach which generates data-driven search process model based on the analysis of log data. The data was collected from the user study described in chapter 3. This chapter addresses the first research question RQ1 - How to model the search states in collaborative exploratory search process? The Hidden Markov Model (HMM) method is used to model the search states in the search process as hidden variables. I detailed this process in section 4.1. The procedures to apply HMM are shown in section 4.2 (RQ1.1). Section 4.3 introduces the HMM results for individual search process and collaborative search process. The validity of HMM and the comparison between individual and collaborative search process are addressed in this section (RQ1.2, RQ1.3). The applications of HMM outputs in analyzing the connections between patterns of search process and task differences or search performances are discussed in section 4.4 (RQ1.4, RQ1.5).

4.1 MODELING SEARCH STATES USING HMM

A popular method for examining the search process is to analyze the sequence of user action transitions. The Markov chain has been applied in many research works to model user's action or tactic sequence. The differences among these studies are the units in the Markov Chain. Chen and Cooper (2002) directly use the actions recorded in a library catalog system as the unit and apply Markov Chain to identify user action patterns. Chapman (1981) recognized nine states as the basic units and calculated the probability of search-state transition using Markov Chain. Using Markov Chain analyses, Xie and Joo (2010) first manually coded the transition logs into 13 search tactics and then adopted a five-order Markov chain to do the analysis. Most above-mentioned works use the Markov model on the observed action level, which made the over-simplistic Markov assumption – each action in the sequence is only related to the previous one action. One way to overcome the inappropriate assumption is to model the sequence at the unobserved search states level. The Hidden Markov Model (HMM) is a well-established model with mature techniques for parameter estimation, which can be used to model the unobserved hidden search states and the observed user actions simultaneously.

The HMM model is described in Figure 4.1. There is a sequence of user actions from A_1 to A_M. Using HMM, it is assumed that there is also a sequence of hidden search states, from H_1 to H_M. HMM assumes that each action is generated by a corresponding hidden search state, but different actions can be generated by the same search state with different probabilities. In this case, each action is corresponding to only one search state, and the search state sequence forms a Markov Chain.

A HMM model has several parameters: the number of hidden states N, the start probability of each state π, the transition probabilities among any two hidden states A_{ij} and the emission probability from each state to each action B_{ij}. By only defining the N and π, a Baum-Welch algorithm (Baum, Soules, & Weiss, 1970) can be used to estimate the emission and transition probabilities.

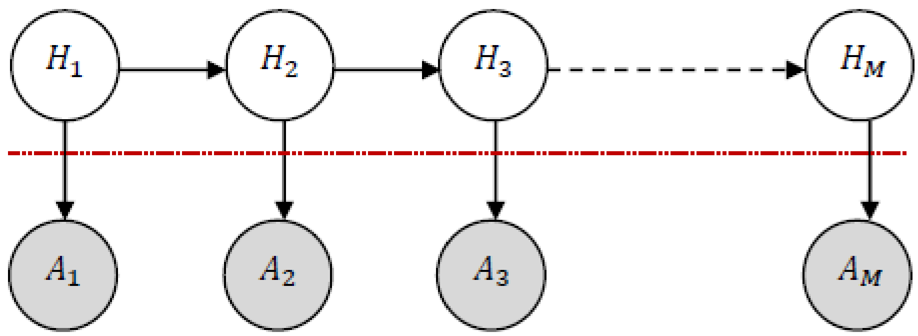


Figure 4.1. A Hidden Markov Model for search states

4.2 PROCEDURES OF APPLYING HMM

4.2.1 Categorizing User Interactions

Before using HMM, I preprocessed user actions by classifying them into meaningful categories. Belkin and colleagues (1995) classified user interactions using four dimensions: method of searching, mode of retrieval, goal of retrieval, and resource considered. The combination of dimensions defines multiple user interactions. In his model, each dimension was presented as binary values. Later Kim (2009) expanded some dimensions with more than two values and removed some dimensions and values that do not apply to web search environment. Xie (2010) used two dimensions—methods and resources to classify user interactions, and she defined 8 values for methods and 6 values for resources.

For team users, the interactions are more complex than individual users. For example, when team users use CollabSearch for a collaborative web search, the items saved in the workspace are both the ones saved by user him or herself and the partner. Therefore, it is useful to distinguish the interactions in which the user clicks the workspace to check on his/her own saved items from the interactions where the user checks on the partners' items.

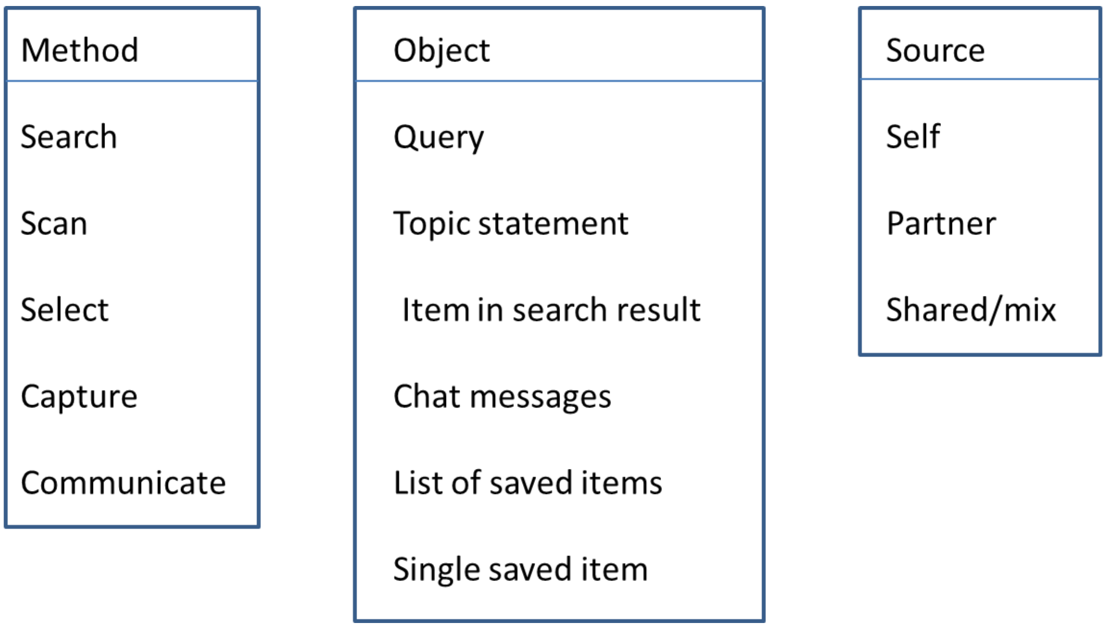


Figure 4.2. Three dimensions for classifying user interactions

Inspired by those ideas of classifying interactions using dimensions, I employed the following three dimensions to categorize user interactions in collaborative web search: method, object and source, as shown in Figure 3. Some of the values of the method dimension, like search, scan, select and capture were also used in Kim's model (Kim, 2009). However, I added another value communicate, which is unique in collaborative search. The values of the object dimension include all the possible objects that may exist in the collaborative web search process, including query, topic statement, single item in search result, chat messages, list of saved items, and single saved items. The source dimension is unique in collaborative search context because it is important to distinguish the source of a particular object in collaborative process, whether it is from the user him/herself or from the partner or it is a shared/mix object.

Table 4.1. User action categorization

Actions	Description
Search – query – self (Q)	A user issues a query
Select- item-self (V)	A user clicks on a result in the returned result list
Capture-item-self (S)	A user saves a snippet or bookmarks a webpage
Scan-list of saved item – mixed (Wm)	A user checks the workspace without clicking on any particular item.
Select – single saved item –self (Ws)	A user clicks on an item in the workspace saved by him/herself
Select – single saved item – partner (Wp)	A user clicks on an item in the workspace saved by the partner
Scan-topic -shared (T)	A user clicks on the topic statement for view
Communicate- messages-self (Cs)	A user sends a message to the other user
Communicate-message-partner (Cp)	A user receives a message from the other user

Using the combination of the above three dimensions, the following observable user interactions are defined. Search-query-self represents user issue a query while search-query-partner represents user issue a query originally proposed by the partner (user issue the query by click a query in the search history). In terms of the actions related to workspace, user can scan the whole workspace without clicking on any particular item; this kind of interaction is the scan-list of saved item-mix. If user click on a particular item; depends on whether the item is saved by the user or the partner, the interaction can be select-single saved-item-self or select –single saved item- partner. All the possible combinations of the three dimensions that can be observed in the CollabSearch system are listed in Table 4.1. There are other possible combinations like select – item – partner, which means user can click on an item in the partner's search result. However, this interaction is not supported in CollabSearch because team users do not share the screen and they cannot see the process when the partner issuing a query and get a returned results list. The process is not shared in CollabSearch.

4.2.2 Model Selection

It is still an open issue for determining the number of hidden states. Determining number of hidden states N is a model selection problem in learning the Hidden Markov Model. A complex model with large number of states will help to increase the sequence likelihood because there are more parameters that can be used to describe the model more precisely. But it has high risk to cause over-fitting. A simple model is less likely to over-fit on the given dataset, but it may not be able to uncover the natural feature of datasets. In model selection, the information criterion such as the Akaike Information Criterion (AIC) or its variants (Akaike, 1974) and Bayesian Information Criterion (BIC) (McQuarrie & Tsai, 1998) can be used to determining the optimal number of states. In this paper, I used BIC because it also considers the sample size.

$$BIC = -2 \times log(L) + \log(s) \times p \qquad \text{Eq. (4.1)}$$

The number of parameters in HMM is p, and the number of total samples is s. The BIC is defined in Equation (3.1), in which L denotes the log-likelihood of all samples. The p can be calculated using $p = (N-1) + (N-1) \times (N-1) + N \times (M-1)$, considering the summation of all probabilities is 1. The *M* denotes the number of action types. A large log-likelihood and less parameter are preferred for BIC.

Figure 4.3 plots the *BIC* values against the number of hidden states in the IND condition. We can see that *BIC* has the optimal value when the number of hidden states is set to 4.

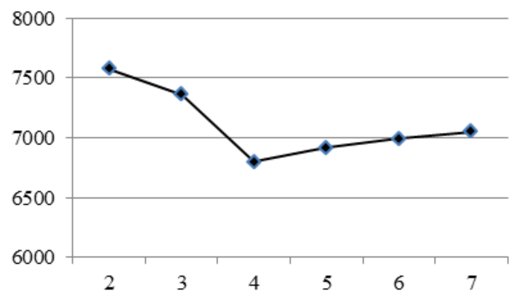


Figure 4.3. BIC Evaluation of HMM parameters in IND

In Figure 4.4, we can see that the BIC has the optimal value when the number of hidden states in the COL condition is set to 6.

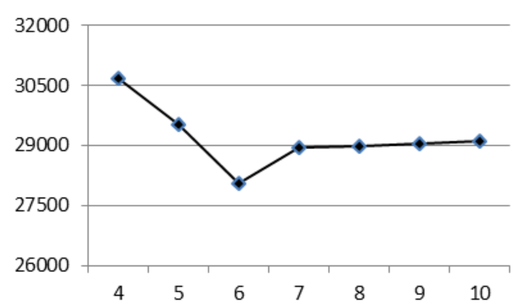


Figure 4.4. BIC Evaluation of HMM parameters in COL

4.3 HMM RESULTS

4.3.1 HMM Results for Individual Search

Hidden states of HMM are represented by the emission probability distribution over observable user actions. The results of emission probability distribution in IND are shown in Table 4.2, in which I removed the probabilities that are smaller than 0.05 for better visualizing each hidden state. The first hidden state has a very high probability (0.99) of generating the interaction Q (defined in Table 1). Therefore, I termed it HQ. Using the same naming criteria, I defined the second and third hidden states as HV and HS, respectively. It is clear that these three hidden states are directly related to search. The fourth hidden state is the most interesting one; it has a 0.57 probability of generating Ws and a 0.42 probability of generating T. I think that this hidden state is related to sense-making, which is the process of bridging a knowledge gap that prevents the user from accomplishing the task (Dervin, Foreman_Wernet, & Lauterbach, 2003). In the exploratory search, participants may lack knowledge about the information problem, result space or the needed vocabulary for search (Qu & Furnas, 2007). In this hidden state, the participants were trying to evaluate the current search stage and define the current search problem in order to advance the search. Therefore, I named it the hidden state of defining search problem (HD).

Table 4.2. Hidden states and emission probability in IND

	Q	**V**	**S**	**Ws**	**T**
HQ	0.99				
HV		0.91			
HS			0.96		
HD				0.57	0.42

In HMM, each observed action corresponds to a hidden state in Table 4.2. To compare the differences between two tasks (in Section 4.4.1), I computed the mean transition probabilities from each hidden state to any of the four (including itself) hidden states across all the participants. The transition probabilities are visualized in Figure 4.5 (probabilities lower than 0.05 are omitted). There is a pattern of high transition probabilities on HQ→HV→HS, which represents a typical search pattern – a query is issued and results are viewed and saved if they are relevant. After saving an item, the participant may continue view another item HS→HV, issue another query HS →HQ, or transitioned to the sense-making states before issuing another query HS→HD→HQ.

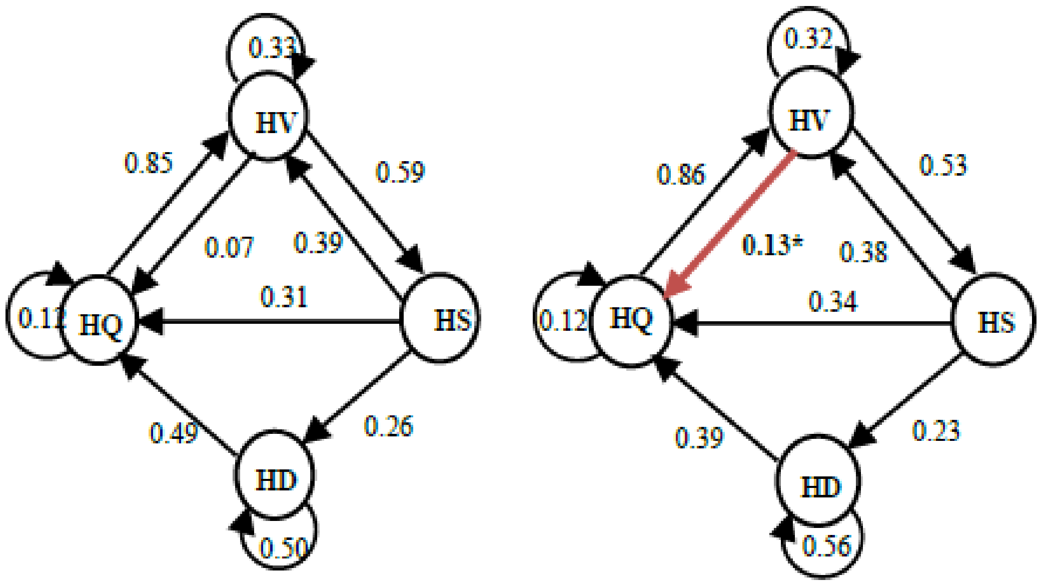


Figure 4.5. Comparison of transition probabilities of hidden states in IND for two tasks (left: T1, right: T2; a red arrow indicates significant difference: *p<0.05)

To validate HMM, I compared its output with Marchionini's information search process (ISP) model (Marchionini, 1995), which is a well-established model in the information seeking field. I found that the transitions among hidden states were very similar to the transitions among sub-processes in the ISP model. The default transitions in the ISP model can be mapped into HD→HQ→HV→HS→HD (Table 3), which is also the pattern of the highest transition probabilities in Figure 6. The ISP model also described the high and low transition probabilities among different sub-processes. For example, “extract information” (HS) had a high probability of transitioning to “examining results” (HV) and “formulate query” (HQ). Those transitions were also represented in the HMM output, with more details on the probabilities. Another model that can be used to validate the HMM result is the model of sense-making loop (Russell, Stefik, Pirolli, & Card, 1993). The sense-making loop is also reflected in the HMM output (transitions between sense-making related hidden states and search related hidden states) with more details on the transition probabilities.

Table 4.3. Mapping from sub-process in Marchionini’s ISP model to the hidden states

Sub-processes in the ISP model	HMM
Define Problem	HD
Select Source, Formulate Query, Execute Query	HQ
Examine Results	HV
Extract Information	HS
Reflect/Iterate/Stop	HD

4.3.2 HMM Results for Collaborative Search

The emission probabilities of each hidden state over observable interactions are shown in Table 4.4. The first three hidden states have high probabilities of generating Q, V and S respectively, which are similar to the first three hidden states in the IND condition. Therefore, I assigned them with the same names as in IND. These hidden states are directly related to the search while the rest three are related sense-making.

Table 4.4. Hidden states and emission probability in COL

	Q	V	S	Wm	Ws	Wp	T	Cs	Cp
HQ	0.82							0.13	
HV		0.87							0.1
HS			0.88						
HD				0.36			0.36	0.21	
HW					0.37	0.44			0.12
HC								0.44	0.47

HD has a 0.36 probability of generating Wm, a 0.36 probability of generating T and a 0.21 probability of generating Cs. I think that this is a sense-making hidden state in which the participants define the current search problem. Besides looking at the information in workspace and topic statement, the participants may also communicate with their partner to discuss the current search problem. The remaining two hidden states HW and HC are related to the communication between team members during the sense-making stage. HW represents the state of checking the saved item details in the workspace whereas HC represents the continuous communication between team members.

The transition probabilities were visualized for each search task respectively in Figure 4.6 (probabilities lower than 0.05 are omitted). The results show that sense-making in the collaborative exploratory search (HD+HW+HC) are more important and complex than that in the individual search (HD only). I also recognized different types of sense-making states, such as chat-centric sense-making (HC) and workspace-centric sense-making (HW). These results are consistent with the sense-making types mentioned in (Paul & Morris, 2010). In addition, our HMM outputs were consistent with Evans and Chi's model (Evans & Chi, 2008). Their model consists of three phases: *before search*, *during search* and *after search*. In the before-search stage, users mainly focus on gathering requirements, which can be mapped to the HD in the HMM output. The *during search* stage for informational tasks highlights the fact that "the foraging and sense-making loops are tightly coupled," which is also reflected in the HMM output. The sharing of information with others in the after-search stage is also reflected in the HMM output with more details on what follows the sharing. The HMM output shows that after sharing, users could explicitly communicate about it or continue to the next round of defining a search problem.

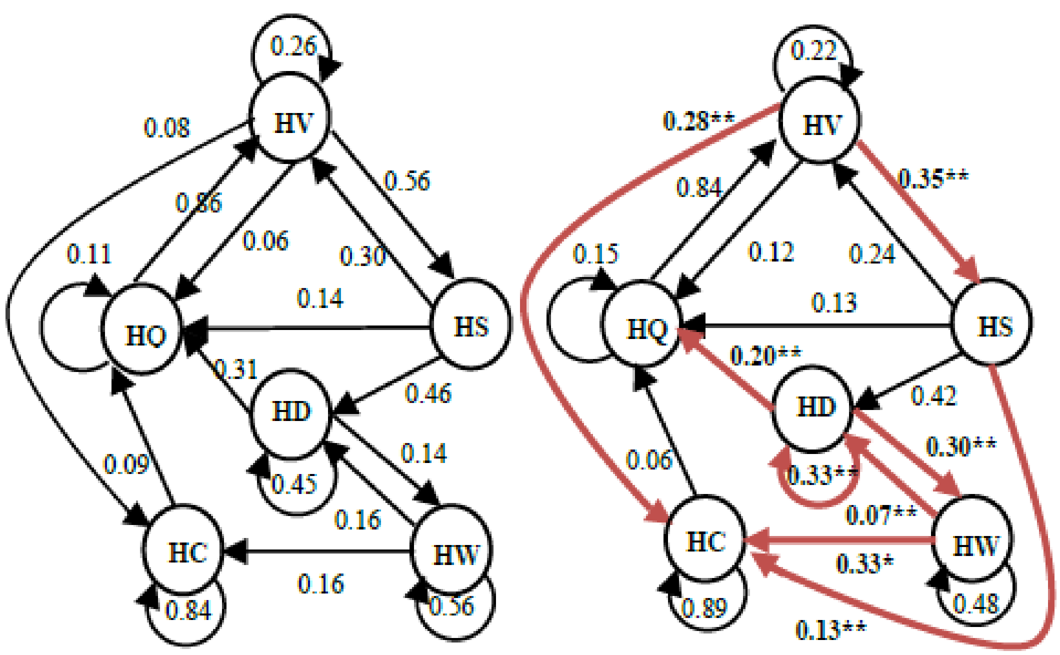


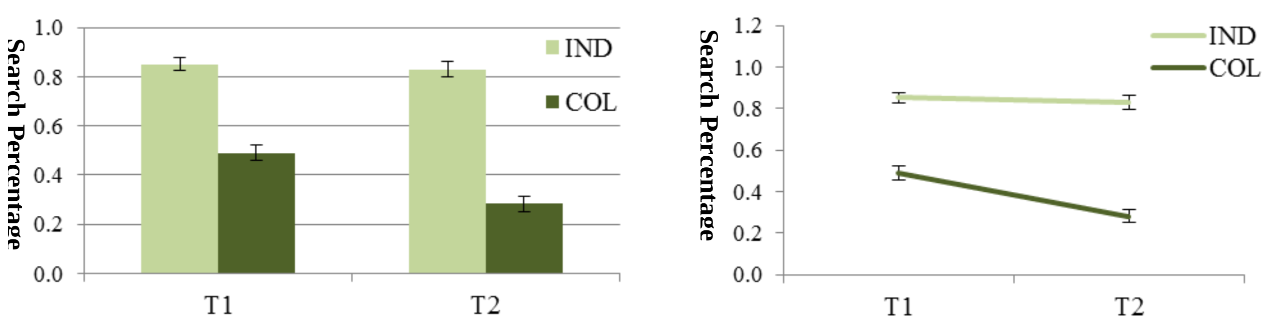
Figure 4.6. Comparison of transition probabilities of hidden states in COL for two tasks

(left: T1, right: T2; red arrows indicate significant difference: *p<0.05, **p<0.01)

The consistency of our HMM results with that of previous search process models in both individual search and collaborative search demonstrate the validity of HMM. The HMM results not only reveal the patterns found by previous models, but also provided more detailed information than previous model such as probabilities of transitions among different hidden tactics, which can be utilized to better understand users' search behavior.

4.3.3 Comparison of IND and COL

When comparing the hidden states in IND and COL, it is clear that they both have search related and sense-making related hidden states. The three search related hidden states (HQ, HV and HS) are similar in both IND and COL. Although there is a similar sense-making state HD, it is slightly different in IND and COL. HD in COL has a certain probability of generating Cs, indicating that explicit communication is also a way for defining search problem in COL. In addition, there are two more sense-making related hidden states HW and HC in COL. This shows that sense-making is more complex in COL. the participants not only need to make sense of their own information but also the partner's information.



(a) (b)

Figure 4.7. Percentage of search related hidden states (a) and Interaction effect (b)

I further examined the differences using statistical test. The mean percentage of search related hidden states (HQ+HV+HS) in compared in IND and COL on the two tasks (Figure 4.7(a)) and found significant differences (Table 4.5). The percentage of search related hidden states in IND is significantly higher than that in COL (Mean diff = .46, SE=.03, $p<.001$). The participants in IND had more activities on the search and fewer activities on sense-making compared to the participants in COL. Comparing to COL, the sense-making is relatively easier in IND because there is only one person's information. The percentage of search related hidden states is significantly higher in T1 than in T2 (Mean diff = .11, SE=.02, $p<.001$). This might indicate that in a recall-oriented information gathering task, sense-making is less critical than in utility-based decision making task, in which users need to negotiate on what kind of information is relevant.

The interaction of condition and task is shown in Figure 4.7(b). There is no significant difference on search percentage between the two tasks in IND. However in COL, search percentage is significantly higher in T1 than in T2. This suggests that the task difference is more sensitive in COL. The participants were more likely to take different search strategies in COL for different tasks.

Table 4.5. Analysis of search related hidden states

	Wald $\chi 2$	**df**	**p-value**
condition	188.143	1	<.001
task	24.000	1	<.001
condition *task	16.079	1	<.001

In terms of transition probabilities, there are also similarities and differences between COL and IND (Figure 4.5 and Figure 4.6). The similarity is that transitions within search related hidden states and within sense-making hidden states are higher than between them. The difference is that the transition between search hidden states and sense-making hidden states is higher in COL than in IND, which means that the participants in COL needed to switch between search and sense-making more often.

4.4 APPLICATIONS OF HMM

The benefit of HMM is that it provides detailed information on the transition probabilities among different states in the search process. In this section, I show the applications of such information through two cases.

4.4.1 Task Differences

Evans and Chi's model (Evans & Chi, 2008) built different search processes for three different types of user needs: informational, navigational and transactional. However, their model cannot distinguish two tasks within the same category. In this study, I showed that the HMM outputs can be used to reveal task differences.

In HMM, each observed action is corresponding to a hidden state (Table 4.2; Table 4.4). To compare the differences between two tasks, I computed the mean transition probabilities from each hidden state to any of the four (including itself) hidden states across all the participants. The task comparison of individual search and collaborative search using HMM outputs are visualized in Figure 6 and Figure 8, respectively.

In individual search, the patterns in the two tasks are very similar except HV→HQ, which I found it is significantly lower in T1 than in T2 (Mean diff = -.06, SE=.02, p=.012). In T2, participants were more likely to issuing another query after viewing a result, which might because the item was irrelevant. This may reflect the differences of task requirements. T2 is a decision making task, the participants are more concerned about the integration of information rather than collecting information. Therefore, they may be more selective on what information to save.

In the collaborative search, we can see that there are several significant differences between the two tasks, especially for the transitions between search related hidden states and sense-making related hidden states. HV→HC is significantly lower in T1 than in T2 (Mean diff = -.20, SE=.03, p<.001), so does HS→HC (Mean diff = -.10, SE=.03, p=.001). These differences suggest that when working on decision-making task T2, the participants were more likely to communicate with each other after they viewed or saved an item. Also, HW→HC is significantly lower in T1 than in T2 (Mean diff = -.17, SE=.07, p=.013). After viewing an item saved in the workspace, the participants were more likely to discuss what they think about the saved item in decision-making task T2. The transitions from HD are also different in the two tasks. HD→HQ is significantly higher in T1 than in T2 (Mean diff =.11, SE=.03, p<.001) whereas HD→HW is significantly lower in T1 than in T2 (Mean diff = -.16, SE=.06, p=.003). These results may indicate that in the information-gathering task such as T1, the participants preferred to have an overview of the workspace when they need to make sense of the current search problem whereas the users in decision-making task such as T2 preferred to look at the details of each saved items.

In both of the individual search and the collaborative search process, HMM recognized two types of hidden tactics, i.e. the search related tactics and the sense-making related tactics. The search related tactics remain similar in both search conditions, but sense-making related tactics are more complex in the collaborative search than that in the individual search. In terms of task difference, the collaborative search process exhibits more sensitivity on task differences. The ability of HMM on detecting task differences can be used for intelligent system design. When certain task type is detected, the system can provide support that is more suitable for the task.

4.4.2 Connections between Search Processes and Search Outcomes

The ultimate goal of studying search process is to locate the core factors that influence search outcomes and provide better support for those factors. I am interested in locating those factors in collaborative web search process from real user behaviors, particularly how sense-making tactics influence the overall search performance.

In this study, I am particularly interested in how sense-making are related to search performance. Therefore, I examined the correlation of the following transitions with the search performance, including HS→HD, HS→HC, HV→HC, HD→HQ and HC→HQ. These transitions are chosen based on two criteria: 1) the probability in either task is higher than 0.05; 2) it represents a transition between search and sense-making. I also considered HW→HC because it represents the transition between two different types of communication: from implicit communication to explicit communication.

Table 4.6. Correlation of search processes and search outcomes
(↓ denoting negative and ↑ denoting positive correlation)

	HS→HD	HD→HQ	HW→HC	HC→HQ
Precision	-	-	-	-
Recall	↓($p<0.001$)	↑($p=0.002$)	-	-
Satisfaction	-	↑($p<0.011$)	-	↓($p=0.007$)
Cognitive load	-	↓($p=0.002$)	↑($p<0.001$)	-

The results are shown in Table 4.6. ↑ means that the transition is positively related to the performance and user perception while ↓ represents a negative relationship. I didn't find any significant differences on HV→HC and HS→HC, thus they are not shown in the table. I found that the transition from sense-making to search (HD→HQ) is positively related to performance and user perception. However, the transition from search to sense-making (HS→HD) is negatively related to performance and user perception. This might be caused by the fact that when the participants were facing knowledge gap during exploratory search, they need to transit to sense-making states; and when the problems were solved, they transited back to the search states. Another interest finding is about HC→HQ, which is negatively related to the satisfaction. It might suggest that the explicit communication maybe triggered by a problem in search; which makes the participants feeling less satisfied with their performance. In addition, I found that HW→HC is positively related to cognitive load, which means that a transition from implicit communication to explicit communication increases the participants' efforts. This might indicate that team members had something to negotiate through explicit communication, which increases the cognitive load.

4.5 SUMMARY

In this chapter, I adopted a novel approach HMM to automatically model search process using hidden states. The HMM outputs on search process were used to compare the search process in collaborative exploratory search and individual exploratory search. Through the analysis, I demonstrated that HMM is a valid method for automatically analyzing search processes. Different patterns of hidden states were recognized and compared in both individual and collaborative search. In addition, the patterns of hidden states between two types of tasks were quite different in collaborative search. I also discovered the relationships between search processes and search outcomes.

Through the analysis of search processes in exploratory search using HMM, I have several important findings. First, two types of hidden states are recognized in both individual and collaborative search processes: the search related hidden states and the sense-making related hidden states. This is consistent with previous studies that exploratory search can be regarded as an intertwine process of search and sense-making (Qu & Furnas, 2007). Second, by using HMM in analyzing the individual search process and the collaborative search process, I obtained similar transition patterns as defined in several well-established information seeking process models, demonstrating the validity of our model. Third, I found that the search related states are similar in both individual and collaborative search. However, sense-making related states are more complex in collaborative search. This again is consistent with previous findings. The ability to capture different types of sense-making demonstrates the generalizability of our model.

With regards to task type, the collaborative search is more sensitive to the task difference. I didn’t find many differences on the search process between two tasks in the individual search. However, the search processes between the two tasks in collaborative search are quite different.

There are more transitions between search and explicit communications in the utility-based decision-making task. It indicates that this type of task requires users to be more active in the collaboration, a fact that might be caused by the need for negotiation and achieving agreement.

Based on the analysis of relationship between search processes and search outcomes, I found that the transition from search to sense-making has a negative relationship with the performance while the transition from sense-making to search has a positive relationship with the performance. I think that when sense-making is needed, it means the user has to spend time on absorbing information or on resolving problems. If we can make the transition smoother, it may improve the search performance.

5.0 QUERY BEHAVIORS IN COLLABORATIVE SEARCH PROCESSES

The goal of information seeking is to find relevant information. In this process, issuing queries is a very important component. This chapter focuses on the analysis of query behavior involved in the search process. The data are transaction logs including user queries and user actions collected from the user study in Chapter 3. To serve as a baseline for testing the effect of collaboration on users' query behaviors, individual search is included in the comparison. The previous studies indicate that task type has a significant impact on users' query behavior (Tom et al., 2008). Therefore, I consider the task as an independent variable. Query behavior can be measured from many aspects. In this study, I focus on three dimensions of query behavior: query vocabulary features, query reformulation patterns and successful query rate. Section 5.1 introduces the measurements for these three dimensions of query behaviors. The effects of search condition and task type on query behaviors are discussed in Section 5.2. RQ2 including RQ2.1-RQ2.3 are addressed in this section. Section 5.3 summarizes the findings in this chapter.

5.1 QUERY BEHAVIOR MEASUREMENTS

The data was analyzed in three dimensions: query vocabulary features, query reformulation patterns and the query performance. The details of measurements in each dimension are introduced in this section.

5.1.1 Query Vocabulary Features

In order to complete a task, users need to formulate or reformulate a set of queries. Because the exploratory web search tasks in this study require the participants to explore different aspects of a topic, it is critical to determine whether the participants can employ a goodly number of queries and query terms. Therefore, I relied on the following set of methods in order to measure the vocabulary features of queries in a search session:

- The number of unique queries (NQ) of a user during the process of completing one task.
- The query vocabulary richness (QVR) is the ratio of the number of unique query terms to the number of queries, and QVR implies the vocabulary richness of a user's queries. QVR is defined in Equation 5.1, where Γ(*S*) denotes the number of elements in the set *S*.

$$\mathrm{QVR} = \frac{\Gamma(\text{Unique Query Terms})}{\Gamma(\text{Queries})} \qquad \text{Eq. (5.1)}$$

Common search strategies employed by team members include submitting different queries and avoiding viewing duplicate retrieved results (Joho et al., 2008). Therefore, a group level measurement for examining query features is to look at the query diversity within a team. The more diverse the queries issued by two participants in a team, the higher the chance that the team will be more efficient. The following two measurements were proposed to measure the diversity of queries within a team.

- One way is to measure query diversity (QD) using the Levenshtein distance (Shah & González-Ibáñez, 2011) to calculate the difference between a pair of queries. The average Levenshtein distance between any pair of queries from two participants is used to measure the query diversity of the group.

- Another way is to measure query result similarity (QRS) (Kromer, Snasel, & Platos, 2008), which looks at the overlap in corresponding returned top N documents between two queries. The calculation is shown in Equation 5.2, where $\psi(p_1)$ denotes the aggregated result set retrieved in response to all the queries issued by one of the users on a team and $\psi(p_2)$ denotes the aggregated result set retrieved in response to all the queries issued by the other user in the same team. Here, I use the top 10 returned results as the corresponding results set for each query.

$$QRS\ (p_1, p_2) = \frac{|\psi(p_1) \cap \psi(p_2)|}{|\psi(p_1) \cup \psi(p_2)|} \qquad \text{Eq. (5.2)}$$

5.1.2 Query Reformulation

Based on the query log obtained from this study and the classification of query reformulation types in the literature (Jansen & Pooch, 2000), I defined the four types of query reformulation patterns as: *New, Generalization, Specialization* and *Reconstruction* (Table 5.1). Q_{i-1} and Q_i are two consecutive queries in the same search session.

Table 5.1. Definition of query reformulation types

Type	**Definition**
New (N)	Q_i is the first query or does not share any common terms with Q_{i-1}
Generalization (Ge)	Q_i shares common terms with Q_{i-1} ; and Q_i contains fewer terms than Q_{i-1}
Specialization (Sp)	Q_i shares common terms with Q_{i-1} ; and Q_i contains more terms than Q_{i-1}
Reconstruction (Rc)	Q_i shares common terms with Q_{i-1} ; and Q_i has the same length as Q_{i-1}

5.1.3 Query Performance

Precision and recall introduced in Section 3.3.1 are two performance measurements. User satisfaction and cognitive load are also two measurements related to users' perceptions of the search performance and efforts put into the search. In addition, I propose another measurement for analyzing the success of each query. The success of a query is measured by whether an item or several items are saved after the query was issued. This measurement reports the number of queries with items collected normalized by the number of queries issued, which is termed as a successful query rate (SQ):

$$SQ = \frac{\Gamma(Queries\ with\ items\ collected\ )}{\Gamma(Queries)} \qquad \text{Eq. (5.3)}$$

Table 5.2. Measurements used for query behavior analysis

<table>
<tr><td rowspan="1">Query features</td><td colspan="2">S: Number of queries (NQ)
S: Query vocabulary richness (QVR)
P: Query diversity (QD)
P: Query results similarity (QRS)</td></tr>
<tr><td>Query reformulation</td><td>S: Pattern of query reformulation</td><td>New
Generalization
Specialization
Reconstruction</td></tr>
<tr><td>Performance</td><td colspan="2">S: Precision & Recall
S: Satisfaction (Sat)
S: Cognitive load (Cogload)
S: Successful query rate (SQ)</td></tr>
</table>

Table 5.2 summarizes all of the measurements for query behavior used in this study. Some of the measurements such as query diversity and query results similarity cannot be computed for single participants. In order to perform a comparison between COL and IND, I artificially created pairs of participants for IND. All possible pairs of the 18 participants in IND are generated, which is 153 in total. Therefore, for the single participant measurements, the sample sizes were COL (36) and IND (18), whereas for the paired participants' measurements, the sample sizes were COL (18) and IND (153). Therefore, the analysis unit of some measurements is a single participant (e.g. NQ, SQ), whereas other measurements use a pair of participants as the analysis unit (e.g. QD, QRS). Two different prefixes, S (single) and P (pair), are used to distinguish between these two sets of measurements.

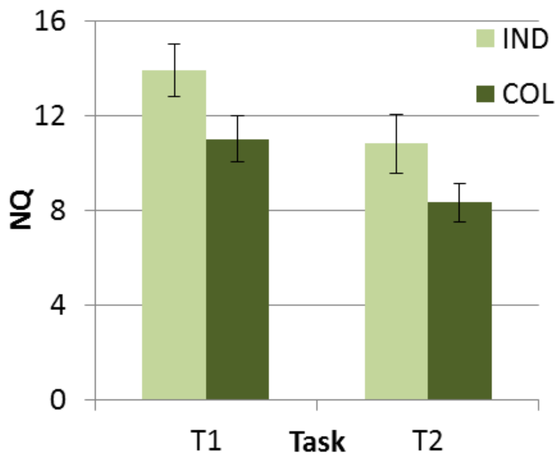
5.2 RESULTS

The analysis results of measurement in three dimensions are reported in this section: query vocabulary features, query reformulation patterns and query performance.

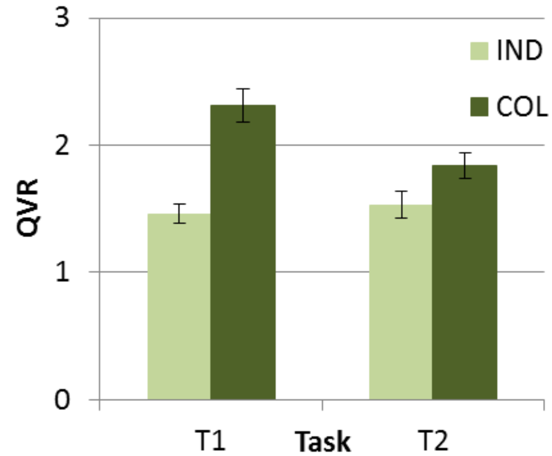
5.2.1 Query Vocabulary Features

I first present the query features that are measured at a single participant level: number of queries (NQ) and query vocabulary richness (QVR). I then offer two measurements of query features on the paired participants' level: query diversity (QD) and query results similarity (QRS). For the statistical analysis, I included the following in the model: main effect of condition, main effect of task, and interaction of condition and task (condition * task).

The mean and standard error of number of queries and query vocabulary richness are shown in Figure 5.1. Significant differences are reported in Table 5.3 and Table 5.4.



(a)



(b)

Figure 5.1. Number of queries (a) and query vocabulary richness (b)

5.2.1.1 Number of Queries (NQ)

There is a significant effect of condition (Table 5.3) on the number of queries (Mean diff = -2.71, SE=1.28, p=.035). Participants in COL issued fewer queries than participants in IND. This might be caused by the fact that participants in COL had to spend time on collaboration; thus, they had less time for search.

Table 5.3. Analysis of Number of queries

	Wald $\chi 2$	**df**	**p-value**
condition	4.469	1	.035
task	17.751	1	<.001

There is a significant effect (Table 5.3) of task on the number of queries (Mean diff = 2.90, SE=.69, p<.001). The participants issued more queries in T1 than in T2. This indicates that participants tend to issue more queries for recall-oriented tasks, which is intuitive.

5.2.1.2 Query Vocabulary Richness (QVR)

There is a significant effect of condition (Table 5.4) on query vocabulary richness (Mean diff = .58, SE=.11, p<.001). The participants in COL had a higher level of query vocabulary richness than those in IND.

Table 5.4. Analysis of query vocabulary richness

	Wald $\chi 2$	**df**	**p-value**
condition	28.490	1	<.001
task	4.455	1	.035
condition *task	8.115	1	.004

There is a significant effect of task (Table 5.4) on query vocabulary richness (Mean diff = .20, SE=.09, p=.035). The query vocabulary richness is higher in T1 than in T2, which might indicate that a rich vocabulary is not necessary in the travel planning task because the goal was to find the specific results of most interest to the participants, rather than being recall-oriented as in T1.

The interaction of condition and task on query vocabulary richness is shown in Figure 5.2. The participants in COL have significantly higher query vocabulary richness in T1 than in T2; however, the participants in IND have no significant difference in query vocabulary richness between the two tasks. This indicates that recall-oriented tasks may benefit from collaboration among team participants by more effectively generating rich search vocabularies.

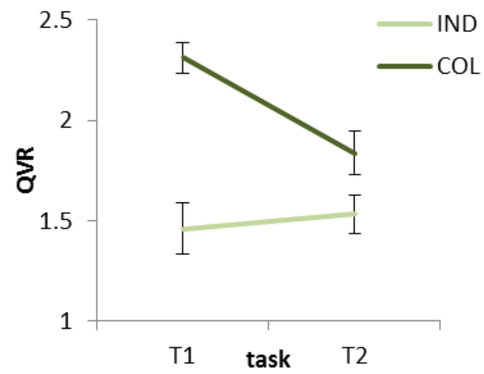
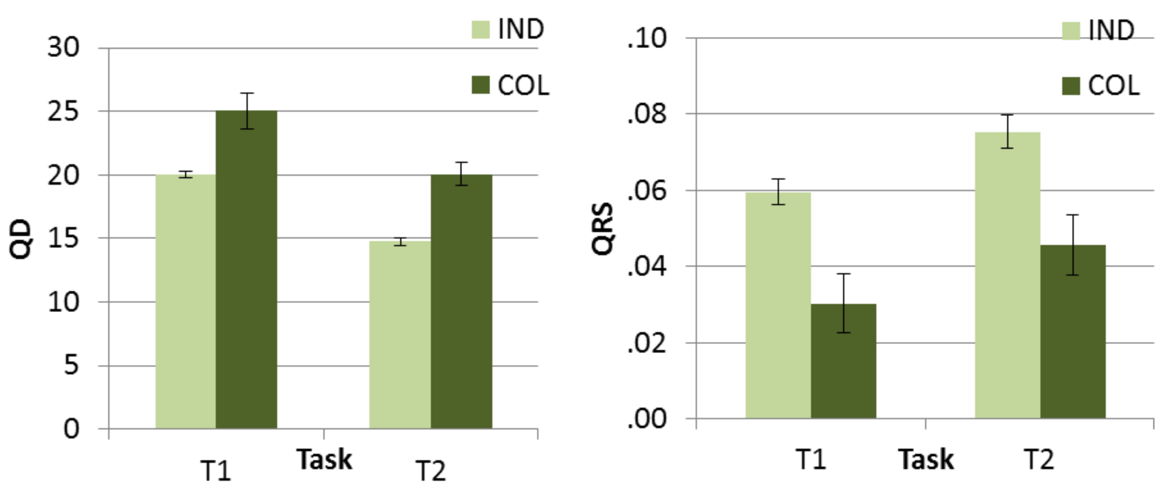


Figure 5.2. Effect of condition *task on QVR

5.2.1.3 Query Diversity (QD)

The mean and standard error of query diversity and query results similarity are shown in Figure 5.3. Significant differences are reported in Table 5.5 and Table 5.6.



(a)

(b)

Figure 5.3. Query diversity (a) and Query results similarity (b)

There is a significant effect of condition (Table 5.5) on query diversity (Mean diff = 5.18, SE=.85, p<.001). Two team members in COL issued more diverse queries than two random individuals in IND. In other words, participants in COL were able to avoid similar queries being submitted by members of the same team.

There is a significant effect of task (Table 5.5) on query diversity (Mean diff = 5.11, SE=.85, p<.001). Query diversity between two participants is higher in T1 than in T2. This might indicate that the information needs of T1 are expressed more diversely by the participants.

Table 5.5. Analysis of query diversity

	Wald $\chi 2$	**df**	**p-value**
condition	37.010	1	<.001
task	35.984	1	<.001

5.2.1.4 Query Results Similarity (QRS)

There is a significant effect of condition (Table 5.6) on query results similarity (Mean diff =.03, SE=.01, p<.001). Two team members in COL have less similarity than two random individuals in IND. This shows another benefit of collaboration in search, in that it helps to avoid the same document being seen by the participants on the same team.

Table 5.6. Analysis of query results similarity

	Wald $\chi 2$	**df**	**p-value**
condition	24.030	1	<.001
task	6.699	1	.010

There is a significant effect of task (Table 5.6) on query results similarity (Mean diff = .02, SE=.01, p=.01). Query results similarity between the two participants is lower in T1 than in T2, which matches the findings about query diversity.

Table 5.7. Summary of statistical test results on query features

	Statistical test results
NQ	COL<IND; T1>T2
QVR	COL>IND; T1>T2; Interaction
QD	COL>IND; T1>T2
QRS	COL<IND; T1<T2

Table 5.7 summarizes all of the findings about basic query features. It seems that although the participants in COL issued fewer queries, they were able to issue more different queries than two random individual participants. In COL, the participants were able to divide the whole search topic into subtopics and each took charge of a set of subtopics. Therefore, their queries reflect a different focus on the information needs.

5.2.2 Query Reformulation

In order to compare the distribution of different types of query reformulations, query reformulation type is included as a predictor in the statistic model. I also considered the interaction of condition and type (condition * type) and the interaction of task and type (task * type). Significant differences are reported in Table 5.8. There are significant effects of type and two interaction effects, and the details are discussed in the following section.

Table 5.8. Analysis of query reformulation pattern

	Wald χ2	df	p-value
type	30.024	3	<.000
condition*type	20.862	3	<.000
task*type	9.085	3	.028

As shown in Figure 5.4, *New* (29.7%) was the most frequently used reformulation type, followed by Reconstruction (26.0%) and *Specialization* (24.9%). *Generalization* (19.4%) was the least used reformulation type. The percentages of four types of query reformulation are significantly different. Pairwise comparison of types with the Bonferroni adjustment shows that the percentage of *Generalization* is significantly smaller than the other three types (Ge vs N: Mean diff=-.10, SE=.02, p<.001; Ge vs Sp: Mean diff=-.05, SE=.01, p<.001; Ge vs Rc: Mean diff=-.11, SE=.03, p<.001). The comparison also shows that the percentage of *Specialization* is significantly smaller than *New* and *Reconstruction* (Sp vs N: Mean diff=-.05, SE=.02, p=0.05; Sp vs Rc: Mean diff=-.06, SE=.03, p=0.05).

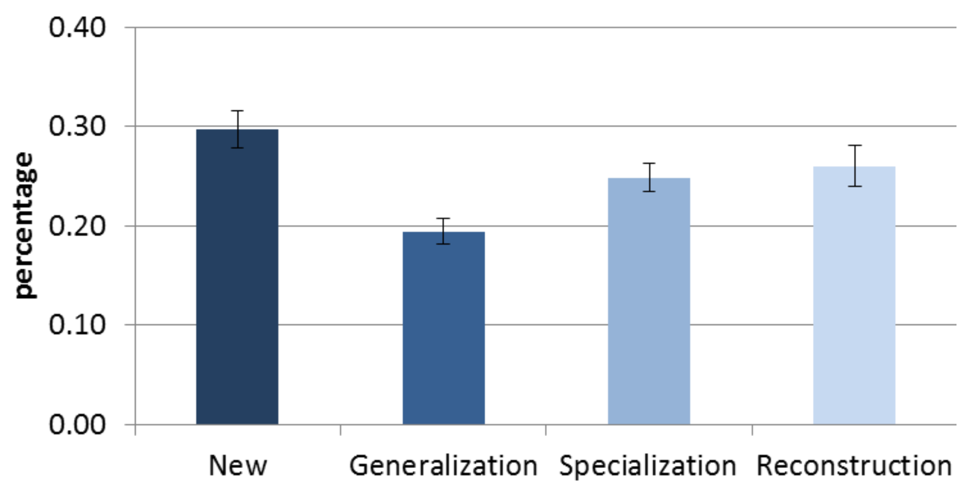
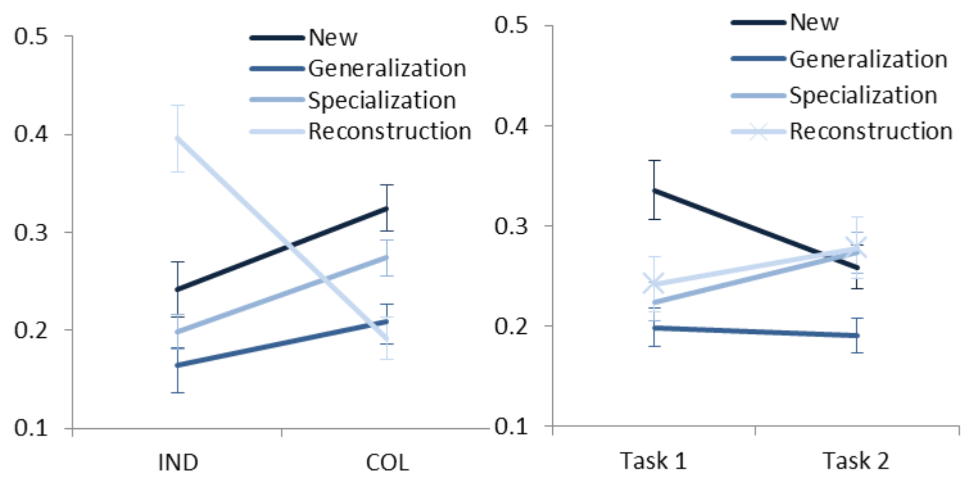


Figure 5.4. Query reformulation patterns

There is a significant interaction effect of condition *type (Figure 5.5 (a)). The participants in the COL condition used more *New* than those in the IND condition (Mean diff=-.08, SE=.03, p=0.026). *Specialization* was also used significantly more often in COL than in IND (Mean diff=-.07, SE=.02, p=0.009). However, the participants in the IND condition used *Reconstruction* significantly more often than those in the COL condition (Mean diff=-.19, SE=.04, p<0.001).



(a) (b)

Figure 5.5. Effect of condition*type (a) and effect of task*type (b) on query reformulation

There is a significant interaction effect of task*type (Figure 5.5 (b)). The participants used *New* significantly more often in the T1 than in T2 (Mean diff=-.08, SE=.03, p=0.026). This might be due to the fact that many queries in T2 contained any of the two terms "Helsinki" or "Finland". Therefore, most query reformulations share common terms.

Table 5.9. Summary of statistical test results on query reformulation pattern

	Statistical test results
New (%)	COL>IND, T1>T2
Specialization (%)	COL>IND
Reconstruction (%)	IND>COL

Table 5.9 summarizes all the significant findings of query reformulation patterns. The results suggest that the participants in COL tended to use the *New* and *Specialization* patterns, while those in IND were more likely to use *Reconstruction*. One possible explanation is that in collaborative search, most teams split the topic into subtopics. Because each team member focused on only a subset of the subtopics, they were able to explore each subtopic in depth. However, in the individual search, the participants need to cover all facets of a topic, leading to a situation that they use the *Reconstruction* strategies more frequently to explore the topic in depth.

5.2.3 Query Performance

In the previous two sections, I have compared the vocabulary feature and reformulation patterns of the queries in both collaborative search and individual search. Since the goal of query iteration in an exploratory search is to satisfy the information need, it's important to examine the search performance and users' perception on their search experience. Here I compared the precision, recall, satisfaction, cognitive load as well as successful query rate between the collaborative search and individual search.

The mean and standard error of satisfaction and cognitive load are shown in Figure 5.6. Significant differences are reported in Table 5.10 and Table 5.11.

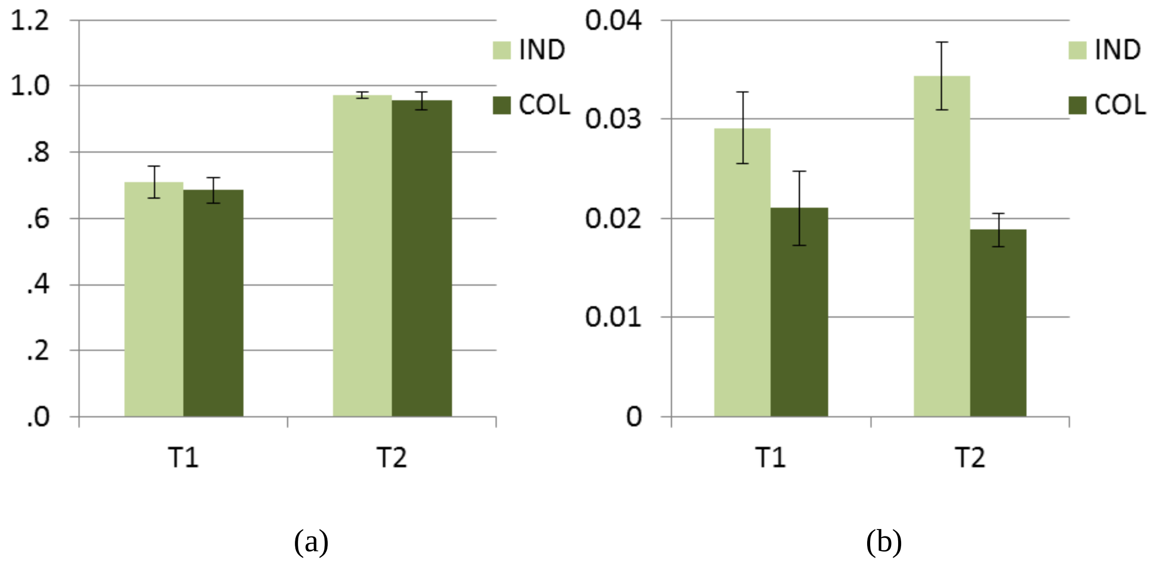


Figure 5.6. Precision (a) and Recall (b)

The precision in the information-gathering task T1 is significantly lower than that in the decision-making task T2 (Mean diff =-.21, SE=.03, p<.001). It might because that the participants were more selective for the information collected for the decision-making task while in the information-gathering task they are more open to somewhat relevant documents.

Table 5.10. Analysis of precision

	Wald $\chi 2$	df	p-value
task	92.97	1	<.000

The recall in the IND is significantly higher than that in COL (Mean diff =-.011, SE=.004, p=.005). One possible reason for the low recall in COL is that team members frequently communicated with each other to share thoughts and findings so they ended up spending less time on collecting relevant results.

Table 5.11. Analysis of recall

	Wald χ2	df	p-value
condition	9.051	1	.005

The mean and standard error of satisfaction and cognitive load are shown in Figure 5.7. Significant differences are reported in Table 5.12 and Table 5.13.

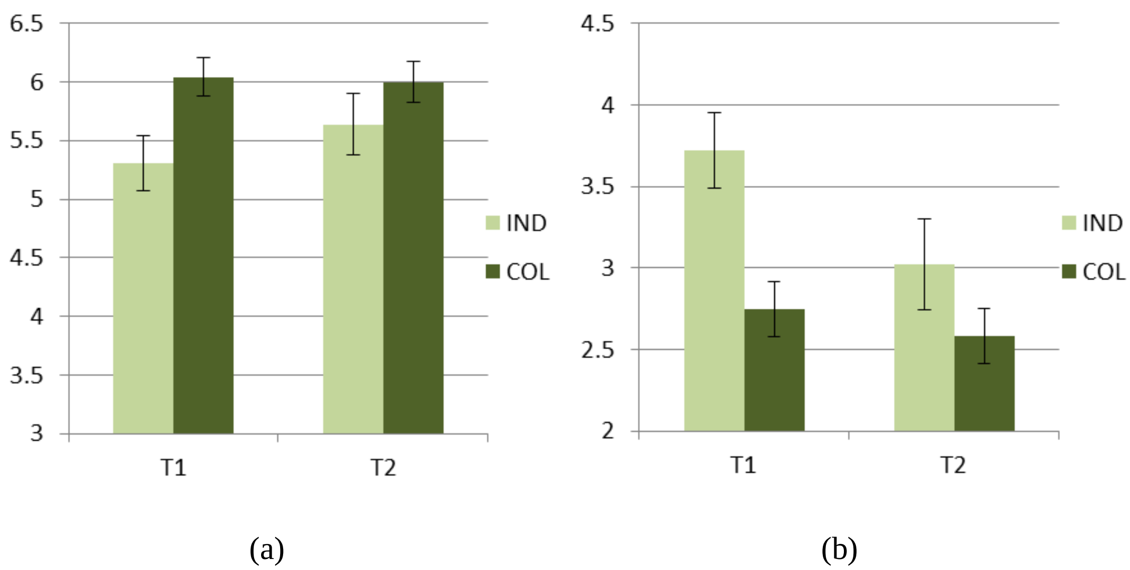


Figure 5.7. Satisfaction (a) and cognitive load (b)

It's interesting that there is no significant difference on precision and recall in collaborative search is significantly lower than that in individual search, the participants in collaborative search are significantly more satisfied with their search performance (Mean diff =.55, SE=.26, p=.032).

Table 5.12. Analysis of satisfaction

	Wald χ2	df	p-value
condition	4.596	1	.032

I also found that the cognitive load in collaborative search is significantly lower than that in individual search (Mean diff =.70, SE=.26, p=.007), which indicates that although in collaborative search conditions, participants had to do extra work to facilitate the collaboration, the collaboration work seems lower their cognitive load for the whole exploratory search task. In terms of task difference, the participants' cognitive load is significantly higher in the information-gathering task than the decision-making task (Mean diff =.43, SE=.14, p=.002). This might because that the topic of the information-gathering task is academic while the topic for the decision-making task is leisure.

Table 5.13. Analysis of cognitive load

	Wald χ2	df	p-value
condition	7.191	1	.007
task	9.579	1	.002

The total average successful query rate is 66.0%, which indicates that about two-thirds of queries issued by the participants were followed by at least one saved item. I examined the effect of condition, task, query reformulation type and their interactions on successful query rates. Significant results are shown in Table 5.14.

The average successful query rate is 61.3% in COL and 75.1% in IND, the difference of which is significant (Mean diff =-.14, SE=.04, p=.001). There is also a significant effect of task on successful query rates (Mean diff =.19, SE=.03, p<.001). T1 has a higher successful query rate (77.7%) than T2 (58.7%).

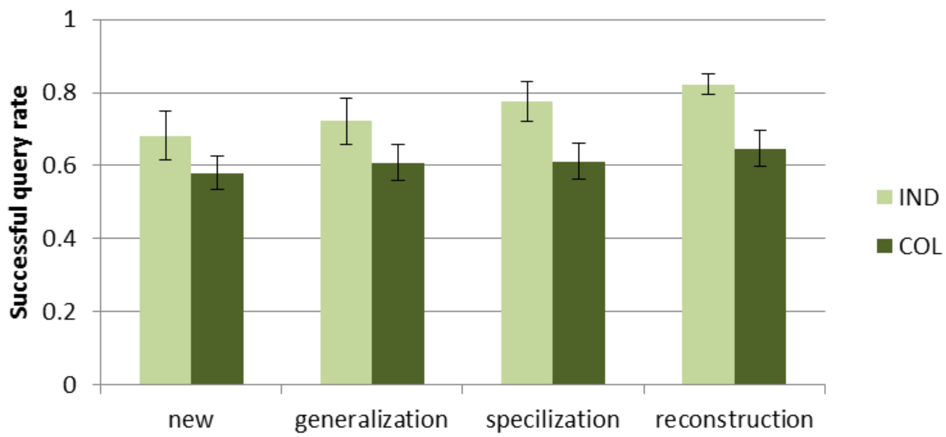
Table 5.14. Analysis of successful query rate

	Wald $\chi 2$	**df**	**p-value**
condition	10.273	1	.001
task	29.911	1	<.000
task*type	8.750	3	.033

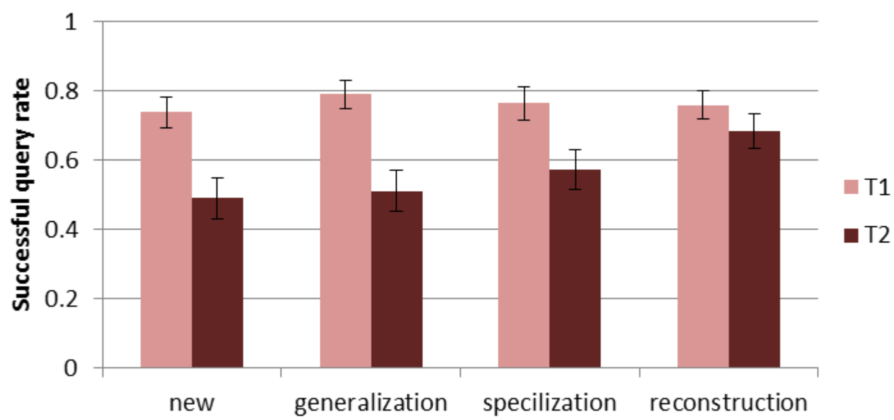
The fact that T2 has a lower successful query rate might be due to the difference in relevance criteria. In T2, user subjective relevance is more important than topic relevance; therefore, although some items were relevant to the topic, they did not meet the participant's personal interest. The participants were less likely to save items in this situation.

The low successful query rate in COL might also be caused by more stringent relevance criteria. When saving an item, the participant not only needs to consider his/her own judgment about the relevance, but also consider the needs of their partner. Therefore, the participants in COL were more cautious when they saved webpages.

I also find a significant interaction of task and type (Figure 5.9). *New*, *Generalization*, and *Specialization* have significantly higher successful query rates in T1 than in T2, but that is not the case for *Reconstruction*. Pairwise comparison with the Bonferroni adjustment shows that in T2, *Reconstruction* has a significantly higher successful query rate than that of *Generalization* and *New* (Rc vs Ge: Mean diff=-.18, SE=.06, p=.009; Rc vs N: Mean diff=-.19, SE=.07, p=.007). This indicates that *Reconstruction* is a more useful reformulation strategy in T2.



(a) Effect of condition



(b) Effect of task

Figure 5.8. Successful query rate

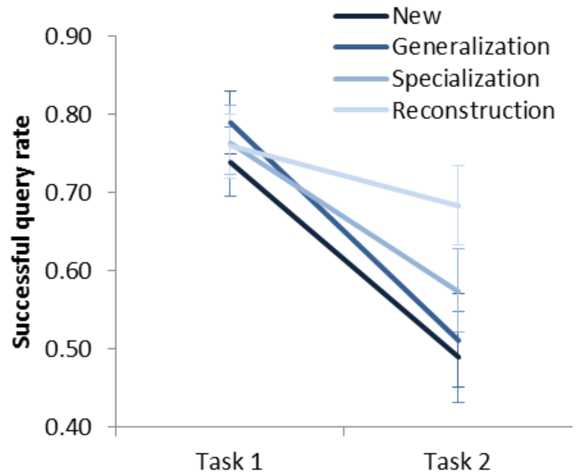


Figure 5.9. Effect of task*type on successful query rate

5.3 SUMMARY

In this chapter, I report the analysis on examining the effect of collaboration and task type on users' query behaviors. The participants worked on two different exploratory web search tasks using our CollabSearch system under two conditions: the collaborative search and individual search. I examined the effects of search conditions and task type on users' query behavior from three dimensions: query vocabulary features, query reformulation patterns and query performance.

Through the analysis of the results, I have following major observations. The participants in the collaborative search issue fewer queries than those in the individual search. One possible reason is that participants in collaborative search need to spend time not only on search, but also on collaboration. Therefore, they have allocated less time to search than someone undertaking individual search. However, the effort on collaboration has benefits. The participants in collaborative search are able to issue queries with a wider range of vocabulary for recall-oriented tasks. In addition, because they can coordinate on the search, they are able to issue more diverse queries and avoid overlapping of query results in both tasks. This finding is consistent with Joho et al. (2008) and Shah & González-Ibáñez (2011). Regarding task differences, the participants issue more queries, use a richer vocabulary, and expresse their information need in more diverse ways for recall-oriented tasks, a fact that is intuitive.

For the query reformulation, *Generalization* was used less frequent than other types of query reformulation. In exploratory search, users usually start with general queries and then start exploring the topic in more depth (Jansen et al., 2009). This might be the reason why *Generalization* is less frequently used. For the effect of collaboration on query reformulation, I found that the participants in collaborative search tend to use *New* and *Specialization* more often than those in individual search. I believe that this is because the participants in collaborative search usually split the topic and each focuses on only part of it. Since the scope of the topic they worked on became smaller, they were able to explore the topic more deeply. In contrast, the participants in individual search employ *Reconstruction* more frequently. This suggests that they may need to explore multiple facets of the topic at the same level. Another explanation is that *New* and *Specialization* are higher cost reformulation types than *Reconstruction*. The participants in collaborative search were able to afford higher cost reformulation. This hypothesis needs further study to confirm.

By analyzing the query performance, I found that the successful query rate is higher and precision is significantly lower in the recall-oriented information-gathering task than that in the utility-based decision-making task. I noted that for the decision-making task, participants' personal judgment matters more than the topical relevance. Therefore, the participants were more selective in saving relevant items. Similarly, the lower successful query rate in collaborative search might also be caused by more stringent relevance criteria. The participants in collaborative search need to consider their partner's opinion, and they both need to agree on the relevant items. Although there is no significant difference on precision and the recall is significantly lower in the collaborative search than that in the individual search, participants felt more satisfied with their search performance and have less cognitive load in the collaborative search. This suggests two possible benefits of collaboration – making people happen and less stressed.

6.0 COMMUNICATIONS IN COLLABORATIVE SEARCH PROCESSES

One essential difference between collaborative search and individual search is that the former involves communications among team members. On the one hand, communication could be effective in establishing common ground between team members; on the other hand, communication could also introduce extra workload or distract users from their search activities. In order to understand the role of communication in collaborative search, I conducted the analysis of chat messages from two aspects – content and timing of communications. Section 6.1 introduces the content and timing analysis methods of chat messages. The results of content and timing analysis of chat as well as the relationship between communications and search performance are discussed in section 6.2. RQ3 including RQ3.1-RQ3.4 are addressed in this section. Section 6.3 summarizes the findings in this chapter.

6.1 CHAT MESSAGES ANALYSIS METHODS

The chat messages were generated by all the 36 participants in the COL condition. I retrieved all the messages from the chat log in the CollabSearch system. The basic unit for chat message analysis is a sentence or part of a compound sentence (Strijbos et al., 2004). In the chat log, each message was generated as the participant press the “Send” button. Thus, a message may contain multiple sentences or a single sentence may be distributed in a set of consecutive messages. I manually applied a pre-processing procedure to merge or split chat messages into the analysis units as defined. After the pre-processing, 36 participants (18 teams) generated 676 cleaned messages in the information-gathering task (T1) and 1137 cleaned messages in the decision-making task (T2).

6.1.1 Content Analysis Method

One way to look into the characteristic of communications is to analyze the content of communications. A coding schema of text messages was adapted from a framework developed in a CSCL study (Strijbos et al., 2004). The framework was also used in a collaborative search study (González-Ibáñez et al., 2013). It includes four main categories – task social (TS), task coordination (TC), task content (TN) and non-task related (NT). A summary of each category in the coding schema is depicted in Table 6.1.

Table 6.1. Coding schema for the content analysis of chat messages

Code	Description
Task social (TS)	All types of statements concern group effort or attitude as well as opinions in regards to information obtained or information resources
Task coordination (TC)	All types of statements regarding coordination of the search task, which include division of labor and checking task status
Task content (TN)	All types of statements related to the content of the search task, which involve task requirement assessment and information sources
Non-task related (NT)	All types of statements that are not related to the search task or regarding the issues of the user study itself

Two coders went through all the chat messages and manually assign a category for each message. A training process was applied at the beginning to make sure the two coders have a common understanding of the coding framework. The first round of coding was conducted by each of the coders independently. The agreement between the two coders is 86.1% for T1 and 83.3% for T2. Then a second round of coding was conducted to resolve the discrepancies between the two coders. After the two rounds of coding, the two coders made agreement on the categories of all the chat messages.

A combination of qualitative and quantitative analysis methods is adopted. The content of the communication is coded and then the frequencies are used for statistical comparisons.

6.1.2 Timing Analysis Method

Another angle to examine the characteristics of communications in collaborative search process is analyzing the timing of communications. All the chat messages are categorized into *before search*, *during search* and *after search* in terms of the timing. The boundaries among these three categories are determined based on the first and last search actions of a participant. Issuing a query, viewing a search result and saving a result are considered as search related actions. Any communications before the first search action is *before search* while any communications after the last search action is *after search*. The rest of the communications are categorized as *during search*.

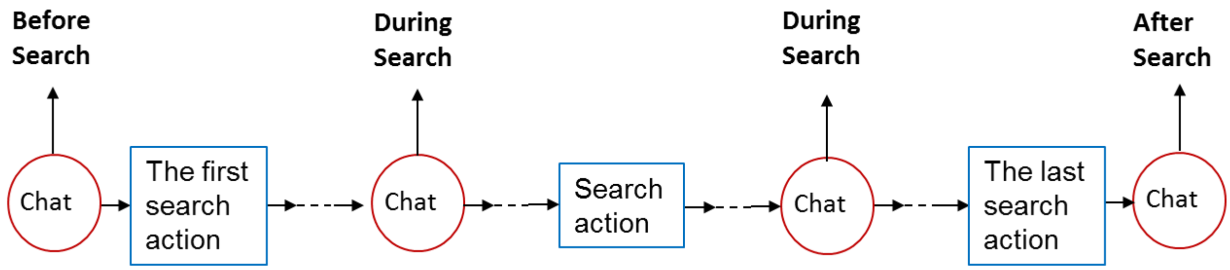


Figure 6.1. Communication timing

The *before search* communications are not affected by any of the search activities while the *during search* communications might be influenced by the search results. The reason to have an *after search* category is that unlike the *before search* and *during search*, the *after search* communications do not have impact on the search activities.

When calculating the time spent on communication, I use the following strategies: first, both sending and receiving a chat message were labeled as chat, and the rest of the actions in the log data were labeled as non-chat. Then the time intervals from a chat action to another chat action or from a chat action to a non-chat action are counted as the communication time. The two participants in the same team may start of end their search actions at different time. Therefore, the *before search*, *during search* and *after search* communication times may be different for the two team members.

6.2 RESULTS OF CONTENT ANALYSIS

6.2.1 Characteristics of Communication Content

Using the content analysis method introduced in section 6.1.1, the 676 messages in T1 and 1137 messages in T2 were classified into four categories. I use both the number of messages (Table 6.2) and percentage of messages (Table 6.3) to show the results.

Table 6.2. Task effects on the communication content (number of messages)

Number of messages	Mean (SD)		Statistical test
	T1	T2	
Task social (TS)	5.94 (5.26)	8.17 (6.03)	$\chi 2$=3.80, p=.051
Task coordination (TC)	10.94 (6.60)	8.83 (4.48)	$\chi 2$=3.47, p=.062
Task content (TN)	9.06 (9.01)	37.00 (20.80)	$\chi 2$=71.46, p<.001
Non-task related (NT)	7.22 (8.44)	9.17 (14.57)	$\chi 2$=0.96, p=.327

Table 6.3. Task effects on the communication content (percentage of messages)

Percentage of messages	Mean (SD)		Statistical test
	T1	T2	
Task social (TS)	16.31 (13.77)	13.11 (8.09)	$\chi 2$=1.98, p=.159
Task coordination (TC)	37.52 (22.15)	14.51 (6.27)	$\chi 2$=30.89, p<.001
Task content (TN)	26.94 (19.26)	59.95 (20.95)	$\chi 2$=60.01, p<.001
Non-task related (NT)	19.23 (20.74)	12.34 (15.89)	$\chi 2$=3.72, p<.054

We can see that the communication patterns are very different in the two tasks. Among the four types of communication content, the number of task content is significantly higher in T2 than in T1 (Mean diff=-27.94, SE=3.31, p<.001). With regards to the percentage, there are significantly more task coordination messages (Mean diff=.23, SE=.04, p<.001) in the information-gathering task (T1) while the decision-making task (T2) has more task content messages (Mean diff=-.33, SE=.04, p<.001). This reveals the nature of the differences of these two tasks. For the information-gathering task, the criteria of what information is relevant are objective and participants didn't have much discussion on the assessments of information obtained. However in the decision-making task, the relevance criteria are subjective, which depends on personal opinions of each team member. Therefore, participants were more involved in the discussion of their information need and search results.

In order to provide a clearer vision on how team members communicate with each other in the search process, I provide some examples of chat messages in each of the four categories.

6.2.1.1 Task Social

The main purposes of task social messages are initializing the task and providing social support. Chat messages fell into the task social category include the greetings between team members at the beginning. And sometimes participants may joke about the topic of the task.

S0301:" well hello there"
S0302:" helsinki!"

S0701: "is yodeling a thing people do in finland?"
S0702: "hahaha"

Another typical type of chat messages for task social is to express attitude or opinions on the information obtained or shared.

S0302: "this one is way more fun than the other"

Participant may also comment about the group functioning and effort. I found that most of the expressions are positive. It seems that participants are more likely to encourage each other for the group efforts.

S1601: "everything looks great so far!"

6.2.1.2 Task Coordination

The most common task coordination is the division of labor between team members. The exploratory search task in this study contains several sub-topics. Participants may want to divide the whole search into several sub-topics and assign each sub-topic with an owner.

S1802: "okay how would you like to split this up?"
S1801: "you do stats and I"ll do impacts on students and professionals, commerce around these sites"

Participants may also inform the partner their current status or progress on the sub-topic they own. Or they may ask for their partners' status.

S0401: "have you done impact yet?"
S0402: "I think I got impact done"
S0402: "going for econ now"

6.2.1.3 Task Content

Participants communicate with each other on the requirement of the task, especially when there is particular constraint. For example there are two constrains in the decision-making task, budget limit to 200 euros and time of travel is during Christmas. These two constrains generated many discussions between the team members.

S1801: "we each get 100 euros so let's set aside 25 euros each for dining"

S1601: "The climate is very cold in December"

S1602“ok so outdoor activities will be hard”

S0701: “the only one i could find is the nutcracker because the city of Helsinki is like practically shut down between Dec. 22-25 for Christmas”

There are many communications related to the assessment of information resources and information obtained. These communications enable team members to share knowledge with each other.

S0401: “visitfinland isn’t much help”
S0401: “I think I found one site to cover all of the usage stuff”
S0402: “okay, if you see anything about the value of a site(s), pass it off to me”

S1601: “what’s the Christmas Market?”
S1602: “in December they set up tons of markets and stuff in the streets”

It’s also possible that a participant may ask the partner for a question related to the task or talk about the difficulties encountered in the search. Getting a response from the partner may help the participant to better understand the context of the task.

S1502: “What is del.icio.us?
S1501: “saves bookmarks. it’s now delicious”

S1401: “all these websites I try to go on are in what I can only assume is Finnish”
S1402: “put "English" in the search?”

6.2.1.4 Non-task Related

Participants sometimes talked about random things that were not related to the search task. These communications could also be viewed as social interactions. But they are different from the task social because the content of the communication has nothing to do with the search topic.

S1001: “Can we eat after this?”

Another typical type of non-task related communications are about the user study itself and the system being used in the study.

S1401: "I wish there was a notification every time we saved a page"

In a few cases, the team members may also discuss about the time constrains of the study. I consider these communications as non-task related because the 30 minutes time limitation was not a naturalized constrain. It's a requirement specially designed for this particular lab-based user study.

6.2.2 Coordination Strategies

Division of labor was recognized by many previous collaborative search studies as an import collaborative search strategy (Foley & Smeaton, 2009; Halvey et al., 2010; M. R. Morris & Horvitz, 2007). Researchers also reported that the simplest form of coordinating divided labor is through communication (Kelly, Kingdom, & Payne, 2013). Through the analysis of task coordination chat messages, I recognized four different ways of coordinating search among the 18 teams in the study. Table 6.4 shows the names of the teams that take each coordination strategy for the two tasks respectively.

The first coordination strategy is *pre-defined division of topics*. Teams using this strategy made a complete and detailed division of labor topic wise before the search. Team members split the search topic into sub-topics and each team member take part of it. Using this strategy, they can avoid redundant work. Sometimes they may find it hard to divide the subtopics; they would propose some strategies like using search history to coordinate. (*"The first one is pretty large - maybe both do it and keep an eye on the search history?" – S0301*). The second strategy of coordination is *evolving division of topics*. The difference of this coordination strategy from the first one is that the team members didn't well-planned everything before the search. They usually quickly start the search and inform each other what subtopic they pick to start with. As the search going on, they would further coordinate the on the topic depending on the progress. The benefit of this strategy is that they can quickly start working on the search without spend too much time on the planning. However, team members need to monitor each other's progress to coordinate in the middle of their search process.

Table 6.4. Coordination strategies

	T1 (team names)	**T2 (team names)**
Pre-defined division of topics	03, 04, 13, 14, 15, 17, 18	03, 13, 14, 15, 17, 18
Evolving division of topics	06, 09, 10, 16, 21, 22	04, 07, 09, 16, 19, 21, 22
Division of roles	08	08
No division of labor	05, 07, 19, 20	05, 06, 10, 20

Previous research (Pickens et al., 2008) recognized different roles of prospector and miner in collaborative search. In my study, I only find one team using this coordination strategy of *division of roles*. In team 08, one of the participants took the role of prospector and in charge of exploring the information. The other participant in the same team worked as a miner to examine the information found by the prospector in detail. The minor keep updating the prospector what had been found and what were still missing. There are also teams which do not divide the labor explicitly through communication. Teams taken this strategy may need to monitor each other's progress through other means like checking the shared workspace to avoid repeated work.

Through the comparison of coordination strategies in the two tasks, I found that most teams stick to the same coordination in both tasks. Therefore, the coordination strategy is a reflection of the team's collaboration style, which is not very likely to be affected by the task.

6.2.3 Correlation between Communication Content and Search Outcomes

From the results in Table 6.2 and Table 6.3, we can see that the variance for each type of communication is large. It indicates that the content of communication is very different across different teams. In order to better understand the benefit and cost of communication in the collaborative search process, I conduct the analysis of correlation between communication content and the search outcomes.

Table 6.5. Correlations between communication content and search outcomes

Time	Satisfaction	CogLoad	Precision	Recall	QVR
Task social (TS)	↑(p=0.017)	↓(p=0.022)	-	↑(p=0.018)	-
Task coordination (TC)	-	-	-	↓(p=0.009)	-
Task content (TN)	-	↑(p=0.008)	-	↓(p=0.004)	-
Non-task related (NT)	-	-	-	↓(p<0.001)	-

Table 6.5 shows the correlations between time spent on each type of communication content and the five indicators of search outcomes. ↑ means the communication time is positively related to the performance and user perception while ↓ represents a negative relationship.

The previous section showed that the recall in collaborative search is significantly lower than that in individual search. One of the reasons might be the communications take time and thus the participants had less time devoted to the search. The results in Table 6.5 evidence that the longer a participant spent time on task coordination, task content and non-task related communications, the lower the recall is. In addition, the time spent on task content communication is positively correlated to the cognitive load. It requires additional effort from the participants discuss the matters of task content through explicit communication.

An interesting finding is on the task social communications. Unlike other types of communication, the time spent on task social is positively correlated with the recall and satisfaction and negatively correlated with cognitive load. For teams with more communications on task social, it's more likely that they perform better, and the team members were more likely to be satisfied with the results and feel less stressed. This might because that the task social communications promoted the social ties between team members and their engagement to the search task.

6.3 RESULTS OF TIMING ANALYSIS

The previous section introduced what the characteristics of communication in terms of content, which reveals what the team members communicated with each other during the collaborative search process. In this section, I focus on investigating when they communicate.

6.3.1 Communication Timing Patterns

As shown in Table 6.6, the participants communicated more in the decision-making task (T2) than in the information-gathering task (T1) (Mean diff=-253.61, SE=58.62, p<.001). Particularly, there are more communications in the *during search* (Mean diff=-172.94, SE=56.04, p=.002) and the *after search* (Mean diff=-101.75, SE=47.06, p=.031) stages in the decision-making task than in the information-gathering task. This may indicate that the participants generated more discussions based on the information found in the search process for the decision-making task. However, the information-gathering task has significantly more communications in the *before search* stage than the decision-making task (Mean diff=21.08, SE=8.63, p=.015). According to Evans and Chi (2008), the *before search* stage involves context framing and understanding the details of the task. The topic of T1 is academic while the topic of T2 is leisure. The requirement in an academic search topic might require the participants spending longer time to communicate in order to understand the details.

Table 6.6. Task effects on the communication timing

Chat time (seconds)	**Mean (SD)**		**Statistical test**
	T1	**T2**	
Total	487.4 (330.7)	741.1 (281.3)	$\chi 2$=18.72, p<.001
Before search	82.8 (76.4)	61.7 (60.0)	$\chi 2$=5.97, p=.015
During search	324.3 (284.1)	497.2 (240.6)	$\chi 2$=9.53, p=.002
After search	80.3 (199.8)	182.1 (212.1)	$\chi 2$=4.68, p=.031

In order to understand what the participants communicated in each stage, I analyzed the percentage of each communication content type within each stage. Figure 6.1 and Figure 6.2 plot the distribution of communication content for the *before, during* and *after search* stage in T1 and T2 respectively.

We can see that the majority of communications in the *before search* stage are task coordination. This is more obvious in T1, for which 59.2% of the *before search* communications are task coordination. The percentage of task coordination in the *before search* stage of T2 is 43.0%, which is lower than T1 but still dominate the *before search* communications.

The percentage of coordination is lower in the *during search* stage (32%.7 in T1 and 13.0% in T2). Instead, the majority type of communication is task content in the *during search* stage (35.6% in T1 and 66.2% in T2). This represents that as participants started the search exploration, they communicated with each other about the information obtained and information resources.

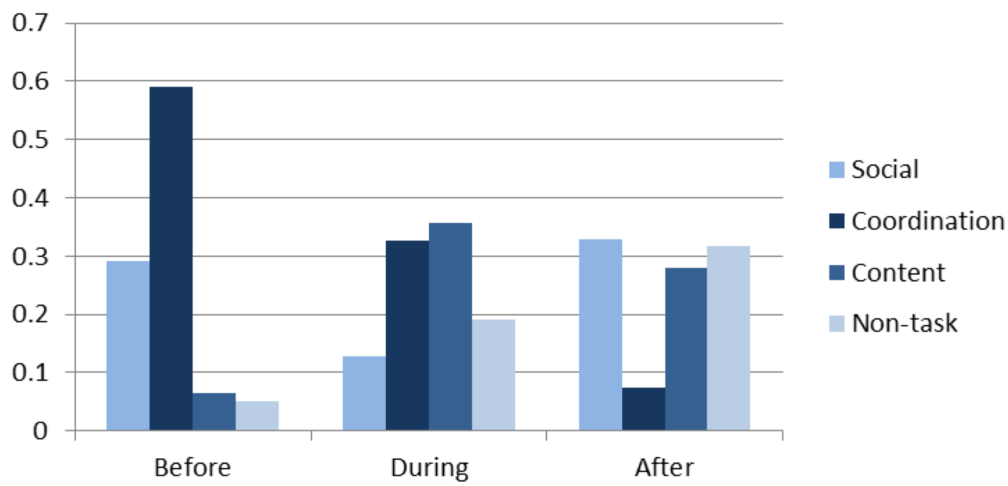


Figure 6.2. Proportion of each communication content type within stage (T1)

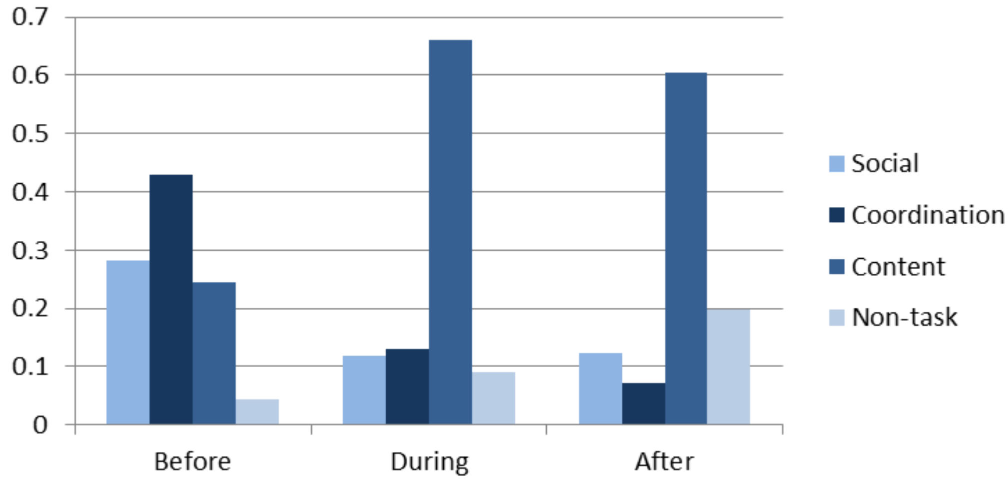


Figure 6.3. Proportion of each communication content type within stage (T2)

The percentage of task content is the highest (60.4%) among the four types of communications in the *after search* stage of T2. The participants may communicate with each other to come out with a decision – the travel plan after they finished the search. In the information gathering task, the percentage of task social is relatively higher than the other types of communication in the *after search* stage. This might because that participants commented on the group effort or express their opinions on the information obtained in the *after search* stage.

Another interesting finding is that task social is relatively higher in the *before* and *after search* stage while task content is relatively higher in the *during search* stage. While the participants were performing search, their communication were more focused on achieving the goal of the task. The fact that the percentage of task coordination is the highest in the *before search* stage and the lowest in the *after search* stage indicate that coordination through communication is more important in the beginning of the collaborative search process. The non-task related communication is more likely to happen in the *after search* stage. This is intuitive as the participants may talk about irrelevant stuff after they finished the task.

6.3.2 Team Differences on Communication Timing

The large variance of communication time in each stage shown in Table 6.6 suggests the communication patterns are very different across teams. When analyzing the chat logs, I also noticed that some teams communicated a lot in the *after search* stages while some other teams didn't communicate at all in the *after search* stage, especially for T1. The participants were given instructions to collect information that could be used for writing a high quality report, but they didn't need to actually write the report. In the *after search* stage, some team still discussed about issues around crafting the report while some other teams talked about random things that were not related to the task.

Here I am more interested in the *before search* and *during search* communications as these communications have potential impact on the search activates. Through the analysis of communication time in *before search* and *during search*, I identified four different communication patters. Depending on whether the *before search* communication time for a particular team is larger or smaller than the average *before search* communication time, the team can be classified as more planning or less planning. Depending on whether the *during search* communication time for a particular team is larger or smaller than the average *during search* communication time, the team can be classified as more dependent or less dependent. The combination of the two dimensions generates four different patterns (shown in Table 6.7).

Team members having the *more planning and more dependent* pattern are more engaged to each other through communications in both *before search* and *during search* stages. It represents a pattern of continuous communication. Team members using the *more planning and less dependent* communication style focused more on the planning of the search but later became more independent from each other during the search. In contrast, team members taking the *less* *planning and more dependent* communication style teams may spend less time on planning the search but they are more engaged with each other through communications during the search. The last communication pattern *less planning and less dependent* is featured by less than average communication in both *before* and *during search* stages. The team members who took this communication style may work more independently on the search tasks throughout the whole process.

Table 6.7. Patterns of communication timing

	T1 (team names)	**T2 (team names)**
More planning + More dependent	03, 05, 14	03, 05, 10, 14, 18, 21
More planning + Less dependent	04, 17, 18	13, 17
Less planning + More dependent	08, 10, 20	04, 06, 07, 15
Less planning + Less dependent	06, 07, 09, 13, 15, 16, 19, 21, 22	08, 09, 16, 19, 20, 22

An interesting finding is that most of the teams have different communication styles in the two tasks. This may suggest that the timing of communication is greatly influenced by the task.

6.3.3 Correlation between Communication Timing and Search Outcomes

The communication in different stages play different roles in the collaboration process and they may have different impact on the teams' search outcomes. Therefore, I conducted an analysis of the correlations between communication timing and search outcomes.

Table 6.8. Correlations between communication timing and search outcomes

Chat time	Precision	Recall	QVR	Satisfaction	CogLoad
Total	-	↓(p=0.001)	↑(p=0.045)	-	-
Before search	-	↓(p=0.022)	-	-	-
During search	-	-	-	-	-
After search	-	↓(p<0.001)	-	-	-

The results in Table 6.8 suggest that longer the total communication time, the lower the recall is. However, the communication indeed brings some benefit as we can see that the total communication time has a positive correlation with the vocabulary richness (QVR). The communications may promote participants to employ wider range of vocabularies for the search. The results also suggest that the *before search* and *after search* have a negative correlation with the recall. When the team members spent more time on planning the search through communication, they were also at the risk of shortening their time on the search and thus have a lower recall. This explanation also applies to the relationship between the *after search* communication and the recall.

6.4 SUMMARY

In this chapter, I report the analysis on communications in the collaborative exploratory search process from two aspects: the content of communication and the timing of communication. I applied a content analysis method to manually classify all the chat messages into four categories: task social, task coordination, task content and non-task related. In terms of timing, all the chat messages were categorized as *before search*, *during search* and *after search* stage communications. First, communication is an essential component in the collaborative search process. Team members may communicate with each other in any of three stages. Second, the communication content varies in the three stages. The *before search* stage communication is more focused on the task coordination. In the *during search* stage, team members are more involved in the task content communication. Task social communication is more common in the *before search* and *after search* stage than in the *during search* stage.

The communication patterns in the information-gathering task are very different from the decision-making task. There is more task coordination in the information-gathering task while there is more task content in the decision-making task. This reflects the different nature of the two tasks. For the information-gathering task, the criteria of what information is relevant are objective and participants didn't have much discussion on the assessments of information obtained. However in the decision-making task, the relevance criteria are subjective, which depend on personal opinions of each team member. Therefore, participants were more involved in the discussion of their information need and search results. The communication timing patterns are also very different in the two tasks. The *before search* communication is longer in the information-gathering task while the *during search* and *after search* communications are longer in the decision-making task. The participants may need longer time to plan the search through communication for the information-gathering task. In the decision-making task, more discussions were generated based on the search results.

Through the analysis of task coordination, I identified four different coordination strategies. Some teams did a complete division of search topics *before search* while some other teams only did an incomplete division of topics at the beginning and they did follow-up coordination through the search process. There are teams which didn't divide the labor through explicit communications. I only found one team using the coordination strategy of taking different roles in the search – one act as the prospector while the other one act as the minor. Through the analysis of *before* and *during search* communications, I also identified four different communication styles: continuous communication in both *before search* and *during search* stages, more engaged in the planning *before search*, more engaged in the communication during search, and relatively independent in both *before search* and *during search* stages.

The analysis on the correlation between communication patterns and search outcomes reveals the benefit and cost of communications. The results suggested that communication can promote participants to explore a wider range of vocabularies for the queries. However, the communication also takes time and additional effort from the participants, thereby decreasing the recall and increase the cognitive load. An interesting finding is that task social communication actually has a positive correlation with the recall and satisfaction, suggesting that the social interaction may engage participants to the search task. However, there is indeed cost for other types of communications. Task coordination, task content and non-task related communications have negative relationships with the recall, and task content also has a positive correlation with the cognitive load. Therefore, there are both benefits and cost of communications in the collaborative search processes.

7.0 DISCUSSIONS AND CONCLUSIONS

The previous three chapters (Chapter 4-6) present the results analysis in response to each of the three research questions raised in the introduction (Chapter 1) respectively. In this chapter, I discuss and conclude all the findings and implications of the entire study. Section 7.1 provides a comprehensive discussion of the results from previous three chapters. Then in Section 7.2 I discuss the contributions and implications that can be drawn from the findings of this study. Limitations of this study are discussed in Section 7.3. Finally, Section 7.4 presents the conclusions and future work.

7.1 DISCUSSIONS OF RESULTS

7.1.1 Application of HMM for Analyzing Search States

When users seeking for information, they often apply a series of search tactics (Bates, 1979). These tactics then guide the users to take certain search actions. However, it is not straightforward to infer users' search tactics by only observing users' actions, particularly in collaborative searches where users' tactics may be affected not only by their own searches but also by that of their team members. Because of this, I think that it is desirable to model tactics as hidden states in analyzing the collaborative search process. The Hidden Markov Model (HMM) is the method that can satisfy this need.

The application of HMM for analyzing search states has proven to be successful in this study. I demonstrated its validity based on the finding that the HMM outputs on hidden states are consistent with several existing well-known information seeking models. More importantly, HMM can provide more detailed and richer information than existing models on the search states involved in exploratory search processes. The search states expressed as hidden variables in the HMM model are represented by emission probabilities to different user actions. Thus the relationship between the search states and user actions can be clearly interpreted by the model. The HMM method also provides transition probabilities between any two search states, which can be used to identify various patterns in the search process.

In summary, there are several benefits of using HMM: 1) search processes are temporal sequential behaviors and HMM is a well-established method for temporal pattern recognition; 2) HMM assumes a Markov process with unobserved/hidden states, the unobserved search tactics in search process can be modeled as hidden variables. The Markov process with hidden states in HMM overcomes the disadvantage in Markov-chain which assumes a Markov process with the observable actions, i.e. the next action depends only on the current action and not on the sequence of actions that preceded it; 3) HMM can model both the observed action and the latent states, therefore it uncover the relationships between users' actions and search tactics. In the Markov chain method, the meaning of an observable action is the same no matter where it occurs in the sequence. However, users may take the same action for different purposes. In HMM, the same action can be generated by different hidden states and a hidden state can also generate several different actions. While the hidden states that are dominated by a single action can also be found using Markov-chain method, the hidden states that are represented by multiple actions cannot be discovered without using HMM; 4) HMM is an automatic method that can be applied to a large dataset and thus avoid the labor of manually coding. Although the manually labelling method can also recognize hidden search tactics in a search process, such method is time-consuming. A possible future work is to use manually labeled data as training dataset for a supervised HMM method.

7.1.2 Comparison of Search States Patterns

Based on the HMM output, I discovered two different categories of hidden states that exist in both individual search and collaborative search, which I summarized as the search related hidden states and the sense-making related hidden states. Within the search related hidden states, users' interactions are focused directly on search activities, such as specifying a query, viewing a result or saving a result, whereas the sense-making related hidden states tend to support the search in terms of evaluating and defining search problems, or making sense of the information through communications.

The search related hidden states are similar in the individual search and collaborative search. However, the sense-making related hidden states are quite different. Individual searches only have one type of sense-making related hidden state, but there are three different types in collaborative search. In addition, sense-making related hidden states have occurred significantly more in the collaborative search than in the individual search. Between the two tasks in collaborative search, the percentage of sense-making is significantly higher in the decision-making task than that in the information gathering task. These findings suggest that the demand of sense-making is higher in the collaborative search and especially in the decision-making task. Moreover, people are utilizing multiple approaches for sense-making in the collaborative search.

The comparison also showed that cross-category transitions, i.e. the transitions between search related states and sense-making related states are different. There are more cross-category transitions in the collaborative search than in the individual search. In particular, the cross-category transitions occurred more often in the decision-making task. These findings indicate that the search and sense-making are more tightly connected with each other in the collaborative search.

The cross-category transitions in the collaborative search also have impacts on the search outcomes. The transition from the sense-making to search has a positive correlation with the search outcomes while the transition from search to sense-making has a negative correlation with search outcomes. This may imply that the timing of sense-making in the collaborative search process matters for the search outcomes.

The analysis of hidden states through HMM provides us a holistic picture of the collaborative search processes. The findings suggest that there are great differences between the individual search and the collaborative search. Task type also plays an important role for the differences in the search process. The results highlight the importance of sense-making in the collaborative search, leading to the investigation on communications, which is one of the most important methods of sense-making in collaborative search. Moreover, the impact of sense-making to search is likely to be reflected on query behaviors due to high transition probabilities from sense-making to query hidden states. Therefore, I've selected query behaviors and communications as two important aspects for further investigations on the collaborative search processes.

7.1.3 Effects of the Collaboration

The comparison between the individual search and the collaborative search suggests possible benefits and costs of the collaboration in information search. The study on the unique component in the collaborative search, which is the communication, provides us a deeper understanding of the factors that accounts for the benefits and costs.

One important benefit of collaboration in information search is that it makes people happy and less stressed. Although the recall is significantly lower in the collaborative search, the user satisfaction on the search performance is significantly higher and the participants' cognitive loads are significantly lower in the collaborative search. The analysis on the relationships between communication content and the search outcomes showed the time spent on task social communication has a positive correlation with the search outcomes, a fact that provide a possible explanation to the benefit of collaboration. Researchers in small group research also found that social interactions can make the teamwork more effective (Harrison, 2006). Another possible explanation is that people have higher confidence in the quality of their search outcomes in the collaborative search (Morris, 2008).

The low recall in the collaborative search also implies a potential cost of the collaboration – it takes time and effort. A piece of evidence from the HMM results is that the percentage of search related hidden states is significantly lower in collaborative search than that in individual search. The participants in the individual search only need to concentrate on the search activities while the participants in the collaborative search need to allocate part of their time and effort on the collaboration. As a consequence, the participants in the collaborative search end up with the lower recall given the same amount time. The analysis on the relationships between communication content and the search outcomes confirms this finding – the time spent on task coordination, task content and non-task related communications have negative correlations with the search outcomes. However, the low recall doesn't imply that collaboration has no value to the search outcome. The measurements used in this study might not capture all the aspects of search outcome quality. Other measurements such as passage-level evaluation of the search outcome can demonstrate the benefit of collaboration. The 30 minutes time limit for each search task is another factor. The benefits of collaboration on search outcome might be reflected in a much longer search session since the individuals may run out of ideas for exploration while team users can keep on generating new ideas for the explorative search. In addition, if the task involves more brain storming, complex problem-solving and requires domain expertise, collaboration might be more effective.

The above benefit and cost of collaboration reveals that the social-oriented communications are beneficial to the search outcomes of collaborative search whereas the task-oriented communications may have placed extra burden on the users. The previous research recognized two types of communication styles: 1) the task-oriented communication which focuses on fulfilling the responsibilities; and 2) the social-oriented communication which focuses on satisfying the emotional needs of interpersonal relationships (Bass, 1990). In my study, it is possible that the social-oriented communications contribute to the search outcome by increasing the user engagement to the search task. My study does not imply that the task-oriented communications are not important in the collaborative search. However, it seems that communications through chat messages may not be the best way to attain collaboration on fulfilling task responsibilities in the collaborative search. This might be an opportunity for collaborative search systems to step in and facilitate the collaboration.

Another benefit of collaboration is that the participants in the collaborative search were able to employ wider range of vocabularies for the queries and the queries between team members were more diverse than two artificially combined individuals. This finding is consistent with previous studies on the collaborative search (Joho et al., 2008; Shah & González-Ibáñez, 2011). Previous research (Furnas, Landauer, Gomez, & Dumais, 1987) highlight that human-to-human communication may serve as cognitive aids during search which can help users to transform concepts into query keywords. Through an analysis on the relationship between the communications and the query behaviors, I indeed found a positive correlation between the total chat time and the query vocabulary richness. However, breaking down chats into three stages didn't provide more insight on which parts of communications contributing to the rich vocabulary.

Collaboration also affects the patterns of query reformulations, the benefit or cost of which is unclear. The participants in the collaborative search often split the search takes into subtopics and each person takes charge of parts of the subtopics, resulting in a higher percentage of *New* and *Specialization* query reformulation patterns. In contrast, there is higher percentage of *Reconstruction* query reformulation pattern in the individual search. In the collaborative search, the participants were able to explore the spited subtopics in depth while the participant in the individual search owns the entire search topic and the coverage maybe the first priority. A study on social search (Evans et al., 2010) reported that the searching in large databases contributes to the *scope* of the search while a social interaction contributes to the *depth* of the search. My study suggests similar findings - the information exploration in the collaborative search focuses on depth while the exploration in the individual search focuses on scope. The effects of the different information exploration styles were not captured by the search outcome measurements used in this study. Further studies are needed to gain insights on the influences of query reformulation patterns to the search outcomes.

7.1.4 Effects of the Task Type

My study demonstrated that task type can greatly affect users' search processes and search outcomes. I chose two representative exploratory search tasks to use this study: the information-gathering task and decision-making task. I found that the participants indeed exhibit very different behaviors during the search process and achieved different search outcomes for the two tasks.

During the search process, the participants showed more sense-making activities in the decision-making task than that in the information-gathering task, and their search activities are more tightly coupled to the sense-making activities in the decision-making task. This suggests that the decision-making task requires the team members to be more engaged with each other during the search process. Particularly, the participants need to consider the utility problem in the decision-making task, i.e. the constraints on price for the travel planning, which may require communications between team members on the negotiation and achievement for agreements.

With regards to the search outcomes, the participants achieved a significantly higher precision in the decision-making task while their query successful rate is significantly higher in the information-gathering task. The HMM outputs are consistent with the query successful rate finding, which showed that the transition from HV to HS is significantly lower in the decision-making task than in the information gathering task. This reflects an important impact of the task type. Participants are more selective on what information to save in the decision-making task, resulting in a low query successful rate and high precision. For the information-gathering task, the relevance criteria are objective while that in the decision-making task are more subjective. The team members may need to make agreement on the relevance of the information obtained in the decision-making task. This can be supported by the fact that the transition from HV to HC is much higher in the decision-making task. I also found that the participants' cognitive loads are significantly higher in the information-gathering task than that in the decision-making task. This may be caused by two reasons: 1) the topic of the information-gathering task is academic while the topic for the decision-making task is leisure and the participants may feel more stressed for the academic topic; 2) the participants may feel more overhead cognitive loads for the information-gathering task because it's recall-oriented.

7.2 IMPLICATIONS AND CONTRIBUTIONS

7.2.1 For Researchers in Collaborative Search

Researchers who are interested in the collaborative search should be able to draw research questions from the findings in my study for their own work in the collaborative search. The methodologies including data analysis methods and measurements can also be applied to other studies in the collaborative search.

First, researchers can study the relationship between search activates and sense-making activities in the collaborative search. My results highlight different types of sense-making states and how each of them is connected to the different search states. This provides researchers a method on investigating the interactive influences of search and sense-making in the collaborative search process. For example, my analysis of search state transition indicates that the probability of transition from viewing or saving a Webpage to chat is higher in the decision-making task than that in the information-gathering task. Researchers can examine the reason that viewing and saving activities trigger communication and whether the content of the web pages plays a role for eliciting the communication.

Second, researchers can study the implicit communications involved in the collaborative search process. Although my analysis in this study mainly focuses on the explicit communications, the search state analysis through HMM implies the important role of implicit communications (e.g., the activity of checking the shared team workspace) in collaborative search process. Researchers may look into the different roles of explicit and implicit communications in the collaborative search. In addition, researchers studying asynchronous collaborative search can benefit from the results on implicit communications and how they are connected to the search activities. My study provides the patterns of implicit communications in the synchronous collaborative search. Other researchers can conduct a comparison study to examine the differences of implicit communication in the synchronous and asynchronous collaborative search.

Third, an important taken-away message from this study is that the studies of collaborative search should not just concentrate on the effectiveness of search, but also on the users' perception of their search experiences, particularly their satisfaction and cognitive load. My results suggest that the search performance measured by precision and recall are not consistent with users' perception of the search performance and their search experiences. Therefore, if I only look at the traditional search effectiveness measures such as precision and recall, I may not be able to find any benefit of the collaboration. Furthermore, researchers should explore other measurements that can be used to examine the social benefits introduced by collaboration to the information searching.

Fourth, the results of this study also suggest that the wider vocabulary in collaborative search did not necessarily lead to a more effective search outcome. Researchers have similar findings in evaluating different query expansion techniques (Harman, 1992). The findings in that study indicate that although different query expansion algorithms were able to suggest different sets of query terms, these terms lead to similar set of documents in the results. Linking this to my study, the wider range of vocabulary used for queries in collaborative search may not necessarily lead to very different search results. We know that human-to-human communications can aid the users to specify their information needs into query keywords. How to best utilize this potential benefit and transform it to more effective search outcomes is a question that well-worth investigation for the collaborative search community. Furthermore, researchers may also take into account of the query reformulation patterns in collaborative search and find out the connections between query reformulation and search outcomes.

Finally, my findings suggest that researchers may study how the factors related to team members could affect the collaborative search process. I found that the communication styles and collaboration strategies are quite different across all the teams in my study. Factors such as personality composition in a team, collaboration skills of team members, relationships between team members all could have impact on their collaborations in the search task. These are interesting research questions for the collaborative search community.

7.2.2 For Designers of Collaborative Search system

The findings of this study have several implications for how to design collaborative search systems to better support team users. There are two different ways of implementing support for collaboration in the search system: the interface-mediated and the algorithm-mediated (Golovchinsky et al., 2011b). This study provides implications for the collaborative search system design in both ways.

First, it's important to design interface-mediated support for the coordination among team members as the coordination through communication is costly. Team members in the collaborative search often need to make a division of labor on topics, the system should be able to provide support for them to divide the topics in the search task and take ownerships of sub-topics. Also, the team members need to be aware of the progress on the sub-topics so that they can make adjustments to the coordination as the search is going on. The system should provide support for such awareness and the mechanism for adjustment. It may be helpful for the system to visualize the information space that has been explored by the team members so that they can evaluate the status of the search task.

Second, the system should have a good mechanism for organizing saved items, which can help the team members to make assessment on the information obtained. In the information gathering task, team members need to decide which parts of the search topic have been explored thoroughly and which parts still need further exploration based on the information obtained. In the decision-making task, team members usually need to pay attention to the constrains in the search tasks. It's very important for the system to highlight constrains. For example, the price is a constrain in the travel-planning task. The system should allow users to specify their requirement on the price, organizing their saved items using the price and make the price on the each saved item easily noticeable to all the team members to facilitate the decision-making.

Third, the collaborative search system can provide targeted algorithm-mediated query suggestions based on my findings of how users reformulate queries in the collaborative search. The low successful query rate in the collaborative search indicates a need for query assistance. Team members in the collaborative search tend to use *New* and *Specialization* more often because they coordinate the search on subtopics. Adaptive query suggestions can be generated based on the coordination strategies of the team members. It is also worth investigating whether providing query suggestions in collaborative search can help to increase the successful query reformulation rate. In addition, providing support for search history awareness along with query suggestions might help team users to select from the suggested queries. In this case, users are able to evaluate the current search status based on the search history and then make a decision on the direction of the following search.

Fourth, another way of algorithm-mediated collaboration support is to automatically filtering and re-ranking the search results based on the information shared among team members. For example, the system could provide different search results for users in the same team based on their different roles in the search (Pickens et al., 2008). My study suggests that the role-based collaboration is not commonly used among the participants in this user study. However, future work can look into other user groups or other search tasks to see how the role-based collaboration is employed by team users. Furthermore, teams with more than two team members may be very different from teams with only two team members. It is possible that team members are more likely to take different roles in a team with three or more members.

Finally, an important lesson learned from this study is that designers need to make a balance between the support for fulfilling the search task and the support for social interactions among team members. Many efforts have been dedicated to increase the search effectiveness and efficiency of collaboration through intelligent and automatic mediation of the collaborative search system (Diriye & Golovchinsky, 2012; Morris & Horvitz, 2007). However, my study suggests that the key for success in collaborative search might be the interpersonal social interactions among the team members, which provide social support and increase team members' engagement to the search. Therefore, the collaborative search system should not take over all the collaboration mediation which results in removing the personal interactions among team members. Instead, the collaborative search system should design for opportunities supporting team members to provide social support for each other.

7.2.3 For Researchers in other Fields

Researchers from other fields can also benefit from the methodologies and findings from this study.

Researchers who need to analyze user log data may find the HMM method useful. I demonstrated that HMM is a valid method for model users' intent or hidden search tactics without input from a theoretical model or manual label. Collaborative search is one scenario for applying HMM because collaborative search tactics have not been well-defined in literature. Researchers can also apply HMM to other scenarios of log analysis. I recommend researchers to try HMM in their studies if they are analyzing complex interactive process in a time sequence, particularly when there is not a theoretical model for them to generate a pre-define data analysis framework. The researchers may also try HMM if they want to get a quick examination of the patterns in their data before applying time-consuming qualitative annotation. HMM method can be extremely useful if the researchers are interested in the hidden strategies or tactics underneath the observable user interactions. The important procedures I identified for applying HMM are also benefit to other researchers. Categorizing user actions and conducting model selection are two important components in HMM. My approach of categorizing user interactions using three dimensions: method, object and source can be applied to other studies. Future applications of HMM can follow the rules and methods I provided.

The findings from this study are based on the collaboration in exploratory search tasks. However, the findings can also be generalized to collaboration tasks in other settings. Researchers in CSCW and CSCL can get some insights from this work for their own studies. For example, sense-making may be a common activity that exists in many collaborative works. Researchers should consider how the sense-making activities are intertwined with the activities that directly aim for fulfilling the task requirements. Another insight is that when evaluating the team effectiveness, it is important to not only measure the objective outcomes, but also consider the social gain and emotional support. The different task types studied in this dissertation: information-gathering and decision-making may also exist in other types of collaboration work. Researchers can learn from the findings of the differences between these two types of collaborative tasks.

7.3 LIMITATIONS

There are several limitations of this study. First, the search topics used in this study were pre-defined and assigned to the participants. It may be different for the participants to bring their own information needs from their daily life. Second, this study only considered a team with two team members, and both of the team members were experienced searchers. The dynamics among the team members is likely to change for different sizes and different roles of team members. Third, the sample size in this study is relatively small and the participants were limited to the population of students. Fourth, the measurements for search effectiveness in this study on were at document level whereas a passage level relevance may be a more true reflection of users' efforts on the information exploration. Finally, my study only employed two exploratory search tasks, one for each type (information-gathering and decision-making). In my study, the topic for the information-gathering task is literature research while the topic for the decision-making task is travel planning. It's unknown whether changing the topics of the search task still give us the same findings.

7.4 CONCLUSIONS AND FUTURE WORK

Given the complex nature of the information needs, exploratory searches may require the collaboration among multiple people who share the same search goal. Therefore there are demands for collaborative search systems that could support this new format of search (Morris, 2013). Despite the recognized importance of understanding search process for designing successful search system (Bates, 1990; M. Hearst, 2009), it is particularly difficult to study collaborative search process because of the complex interactions involved. In this dissertation, I propose and demonstrate a framework of investigating search processes in collaborative exploratory search. I designed a laboratory-based user study to collect the data, compared two search conditions: individual search and collaborative search as well as two task types through the study. I first applied a novel Hidden Markov Model approach to analyze the search states in the collaborative search process, the results of which provide a holistic picture of the collaborative search process. I then investigated two important components in the search process – query behaviors and communications. The findings suggest that there are differences between individual search and collaborative search, and reveal the characteristics of communications in the collaborative search. The results of this study not only provide implications for designing effective collaborative search systems, but also show valuable research directions and methodologies for other researchers.

I plan to conduct future studies in the following two directions. The first one is to study the supports for collaborative search process, which include implementing and evaluating interface-mediated or algorithm-mediated supports for collaborative search. For example, I want to investigate whether or not providing the awareness of search history along with query suggestion can increase the effectiveness of query suggestion. I also want to examine how personalized search can be achieved by extracting information from what are shared by the team members.

The second direction of the future work is to study the factors that affect the collaboration styles within teams; particularly I am interested in the factors such as the collaboration skills of team members, personality composition of the team and relationships among team members. Future studies are needed to fully understand the effects of such factors on the collaborative search processes and outcomes.

In conclusion, I conducted a comprehensive investigation on the collaborative search processes and discovered differences between the individual search and the collaborative search. The study of the collaborative search is a joint effort of multiple communities, including information retrieval (IR), computer supported cooperative work (CSCW) and human-computer interaction (HCI). I hope that my study provides some contributions to a more holistic understanding of collaborative search.

APPENDIX A

ENTRY QUESTIONNAIRE

1. Your age: ___

2. Gender: __Female __Male

3. Your program of study: __Undergraduate __Graduate __Other:______

4. What is your major course of study or profession? ___________________

5. Which operating system do you use most frequently?

__Mac __Windows __Linux __Other: _________

6. Which browser do you use most frequently?

__Firefox __Internet Explorer __Chrome __Safari __Other: _____

7. How often do you search the web?

__Occasionally

__1-3 searches per day

__4-6 searches per day

__7-10 searches per day

__More than 10 searches per day

8. How would you describe your search experience?

(Very Inexperienced) 1 2 3 4 5 6 7 (Very Experienced)

APPENDIX B

POST-TASK QUESTIONNAIRE

Q1. Experience with the search process and outcome

Q1.1 I understand the topic.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q1.2 It was easy to find relevant information for this topic.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q1.3 I found it easy to formulate queries for this topic.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q1.4 I have enough time.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q1.5 During the process of conducting the search task, it is necessary to check what the other team member has done.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q1.6 During the process of conducting the search task, it is necessary to compare what the other team member has done with what I have done.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q1.7 I am satisfied with the amount of the information collected by our team.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q1.8 I am satisfied with the quality of the information collected our team.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q1.9 Overall, I am satisfied with our team performance.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q2. System usability

Q2.1 It was easy to learn to use this system.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q2.2 I can effectively complete my work using this system.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q2.3 I can efficiently complete my work using this system.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q2.4 I found the workspace useful to keep tracking of the information I had collected.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q2.5 I found the search history useful to see what queries I had issued.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q2.6 I found the workspace useful to keep tracking of the information the other team member had collected.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q2.7 I found the search history useful to see what queries the other team member had issued.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q2.8 Overall, I am satisfied with this system.

(Not at all True to Completely True) 1 2 3 4 5 6 7

Q3. Cognitive load

Q3.1 How mentally demanding was this task?

(Very low to Very high) 1 2 3 4 5 6 7

Q3.2 How physically demanding was this task?

(Very low to Very high) 1 2 3 4 5 6 7

Q3.3 How hurried or rushed was the pace of the task?

(Very low to Very high) 1 2 3 4 5 6 7

Q3.4 How hard did you have to work to accomplish your level of performance?

(Very low to Very high) 1 2 3 4 5 6 7

Q3.5 How insecure, discouraged, irritated, stressed, and annoyed were you?

(Very low to Very high) 1 2 3 4 5 6 7

APPENDIX C

INTERVIEW QUESTIONS

1. What kind of strategies do you use to work on the web search tasks collaboratively?
2. Are your collaboration strategies same or different for the two search tasks?
3. Did you use the workspace? How did you use it? In what circumstance would you check the workspace? Did it affect the way you conduct search?
4. Did you notice the search history? How did you use it? In what circumstance would you check the search history? Did it affect the way you conduct search?
5. Did you use the chat? In what circumstance would you talk to each other through chatting? Did it affect the way you conduct search?
6. What are the features that you like about the system? What are the features you dislike? Can you tell me more details on the reasons? Any suggestions improving the system?
7. Will you use this system in your daily life? If yes, in what kind of situations will you use it?
8. Any other comments from the study?

BIBLIOGRAPHY

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723.

Amershi, S., & Morris, M. R. (2008). CoSearch: a system for colocated collaborative web search. In *Proceeding of ACM SIGCHI* (pp. 1647–1656). Florence, Italy.

Baeza-Yates, R., & Pino, J. A. (1997). A first step to formally evaluate collaborative work. In *Group* (pp. 56–60).

Baeza-yates, R., & Pino, J. A. (2006). Towards formal evaluation of collaborative work. *Information research - and international electronic journal. 11 (4).*

Balfe, E., & Smyth, B. (2005). A Comparative Analysis of Query Similarity Metrics for Community-Based Web Search. In *ICCBR* (pp. 63–67).

Bass, B. M. (1990). *Stogdill's Handbook of Leadership: Theory, Research, and Managerial Applications* (3rd ed.). New York: Free Press.

Bates, M. J. (1979). Information search tactics. *Journal of the American Society for Information Science,* 30(4), 205-214.

Bates, M. J. (1989). The design of browsing and berrypicking techniques for the online search interface. *Online Review*, *13*, 407–424.

Bates, M. J. (1990). Where should the person stop and the information search interface start? *Information Processing & Management*, *26*(5), 575–591.

Belkin, N. (1995). Cases, Scripts, and Information-Seeking Strategies: On the Design of Interactive Information Retrieval Systems. *Expert Systems with Applications*, *9*(3), 379–395.

Belkin, N. ., Cool, C., Kelly, D., Lin, S.-J., Park, S. ., Perez-Carballo, J., & Sikora, C. (2001). Iterative exploration, design and evaluation of support for query reformulation in interactive information retrieval. *Information Processing & Management*, *37*(3), 403–434.

Blake, C., & Pratt, W. (2002). Collaborative information synthesis, *Proceedings of the American Society for Information Science and Technology*, 39(1), 44-56.

Brooks, M., Aragon, C. R., Kuksenok, K., Torkildson, M. K., Perry, D., Robinson, J. J., Harris, P. (2013). Statistical affect detection in collaborative chat. In *Proceedings of the 2013 conference on Computer supported cooperative work - CSCW '13* (p. 317). New York, New York, USA: ACM Press.

Cao, H., Jiang, D., Pei, J., He, Q., Liao, Z., Chen, E., & Li, H. (2008). Context-aware query suggestion by mining click-through and session data. In *Proceeding of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD 08* (p. 875). New York, New York, USA: ACM Press.

Capra, R., Chen, A. T., Hawthorne, K., Arguello, J., Shaw, L., & Marchionini, G. (2012). Design and evaluation of a system to support collaborative search. *Proceedings of the American Society for Information Science and Technology*, *49*(1), 1–10.

Carroll, J., Rosson, M., Convertino, G., & Ganoe, C. (2006). Awareness and teamwork in computer-supported collaborations. *Interacting with Computers, 18*(1), 21–46.

Chapman, J. (1981). A state transition analysis of online information-seeking behavior. *Journal of the American Society for Information Science*, *32*(5), 325–333.

Chen, H.-M., & Cooper, M. D. (2001). Using clustering techniques to detect usage patterns in a Web-based information system. *Journal of the American Society for Information Science and Technology*, *52*(11), 888–904.

Chen, H.-M., & Cooper, M. D. (2002). Stochastic modeling of usage patterns in a web-based information system. *Journal of the American Society for Information Science and Technology*, *53*(7), 536–548.

Cugini, J., Damianos, L., Hirschman, L., Kozierok, R., Kurtz, J., Laskowski, S., & Scholtz, J. (1997). Methodology for Evaluation of Collaboration Systems. *The Evaluation Working Group of the DARPA Intelligent Collaboration and Visualization Program*.

Daft, R., & Lengel, R. (1984). Information richness: A new approach to managerial behavior and organizational design. In B. Straw & L. Cummings (Eds.), *Research in organization behavior*. Greenwich, CT: JAI Press.

Dang, V., & Croft, B. W. (2010). Query reformulation using anchor text. In *Proceedings of the third ACM international conference on Web search and data mining - WSDM '10* (p. 41). New York, New York, USA: ACM Press.

Dervin, B., Foreman_Wernet, L., & Lauterbach, E. (2003). *Sense-Making methodology reader: Selected Writings of Brenda Dervin*. NJ: Hampton Press, Inc.

Dickinson T. L., & McIntyre, R. M. (1997). A conceptual framework of teamwork measurement. In M. T. Brannick, E. Salas, & C. Prince (Eds.), *Team performance assessment and measurement: théory, methods, and applications* (pp. 331–356). Taylor & Francis.

Diriye, A., & Golovchinsky, G. (2012). Querium: a session-based collaborative search system. In *Proceedings of the 34th European conference on Advances in Information Retrieval* (pp. 583–584).

Diriye, A., Golovchinsky, G., Dunnigan, T., & Alto, P. (n.d.). Querium : A Session-Based Collaborative Search System, 2–3.

Ellis, D. (1993). Modeling the information seeking patterns of academic researchers: a ground theory approach. *Library Quarterly*, *63*(4), 469–486.

Evans, B. M., & Chi, E. H. (2008). Towards a model of understanding social search. *Proceeding of the 2008 ACM Workshop on Search in Social Media - SSM '08*, 83.

Evans, B. M., & Chi, E. H. (2010). An elaborated model of social search. *Information Processing & Management*, *46*(6), 656–678.

Evans, B. M., Kairam, S., & Pirolli, P. (2010). Do your friends make you smarter?: An analysis of social strategies in online information seeking. *Information Processing & Management*, *46*(6), 679–692.

Fletcher, T. D., & Major, D. A. (2006). The Effects of Communication Modality on Performance and Self-Ratings of Teamwork Components. *Journal of Computer-Mediated Communication*, *11*, 557–576.

Foley, C., & Smeaton, A. F. (2009). Synchronous Collaborative Information Retrieval : Techniques and Evaluation. In *ECIR*, 42–53.

Foley, C., & Smeaton, A. F. (2010). Division of labour and sharing of knowledge for synchronous collaborative information retrieval. *Information Processing & Management*, *46*(6), 762–772.

Foster, J. (2006). Collaborative information seeking and retrieval. *Annual Review of Information Science and Technology*, *40*(1), 329–356.

Fuhr, N. (2008). A probability ranking principle for interactive information retrieval. *Information Retrieval*, *11*(3), 251–265.

Furnas, G. W., Landauer, T. K., Gomez, L. M., & Dumais, S. T. (1987). The Vocabulary Problem in Human-System Communication. *Communications of the ACM*, *30*(11), 964–971.

Golovchinsky, G., & Adcock, J. (2008). Cerchiamo: a collaborative exploratory search tool. *Proceedings of the Computer Supported Cooperative Work*.

Golovchinsky, G., Diriye, A., & Pickens, J. (2011). Designing for collaboration in information seeking. In *HCIR2011*.

Golovchinsky, G., Pickens, J., & Back, M. (2008). A Taxonomy of Collaboration in Online Information Seeking. In *JCDL*. Pittsburgh, PA.

Golovchinsky, G., Qvarfordt, P., & Pickens, J. (2009). Collaborative information seeking. *IEEE Computer*, *42*(3).

González-Ibáñez, R., Haseki, M., & Shah, C. (2013). Let's search together, but not too close! An analysis of communication and performance in collaborative information seeking. *Information Processing & Management*, *49*(5), 1165–1179.

Halvey, M., Vallet, D., Hannah, D., Feng, Y., & Jose, J. M. (2010). An asynchronous collaborative search system for online video search. *Information Processing & Management*, *46*(6), 733–748.

Hansen, P., & Järvelin, K. (2005). Collaborative Information Retrieval in an information-intensive domain. *Information Processing & Management*, *41*(5), 1101–1119.

Harman, D. (1992). Relevance feedback revisited. In *Proceedings of the 15th annual international ACM SIGIR conference on Research and development in information retrieval,* 1–10. New York, New York, USA: ACM Press.

Harrison, D. A. (2006). Ties, leaders, and time in teams: Strong inference about network structure's effects on team viability and performance. *Academy of Management Journal*, *49*(1), 49–68.

Hart, S. G., & Staveland, L. E. (1988). *Human Mental Workload*. *Advances in Psychology*, 52, 139–183. Elsevier.

He, D., Göker, A., & Harper, D. J. (2002). Combining evidence for automatic Web session identification. *Information Processing & Management*, *38*(5), 727–742.

Hearst, M. (2009). *Search User Interfaces*. Cambridge University Press.

Hearst, M. A. (2014). What 's missing from the Collaborative search. *IEEE Computer,* (3), 58–61.

Hertzum, M. (2008). Collaborative information seeking: The combined activity of information seeking and collaborative grounding. *Information Processing & Management*, *44*(2), 957–962.

Holscher, C., & Strube, G. (2000). Web search behavior of Internet experts and newbies, *33*, 337–346.

Hong Xie. (2002). Patterns between interactive intentions and information-seeking strategies. *Information Processing & Management*, *38*(1), 55–77.

Hsieh-Yee, I. (1993). Effects of search experience and subject knowledge on the search tactics of novice and experienced searchers. *Journal of the American Society for Information Science, 44*(3), 161–174.

Hsieh-Yee, I. (2001). Research on Web search behavior. *Library & Information Science Research*, *23*(2), 167–185.

Hust, A. (2004). Introducing query expansion methods for collaborative information retrieval. In M. J. Dengel & A. Weisbecker (Eds.), (pp. 252–280). London: Springer.

Hyldegard, J. (2006). Collaborative Information Behavior - Exploring Kuhlthau's Information Search Process Model in a Group-based Educational setting. *Information Processing & Management*, *42*(1), 276–298.

Jansen, B. J., Booth, D. L., & Spink, A. (2009). Patterns of Query Reformulation During Web Searching. *Journal of the American Society for Information Science and Technology*, *60*(7), 1358–1371.

Jansen, B. J., & Pooch, U. (2000). A review of web searching studies and a framework for future research. *Journal of the American Society for Information Science and Technology*, *53*(3), 235–246.

Joho, H., Coverson, C., Sanderson, M., & Beaulieu, M. (2002). Hierarchical presentation of expansion terms. In *Proceedings of the 2002 ACM symposium on Applied computing - SAC '02* (p. 645). New York, New York, USA: ACM Press.

Joho, H., Hannah, D., & Jose, J. M. (2008). Comparing collaborative and independent search in a recall-oriented task. *Proceedings of the Second International Symposium on Information Interaction in Context - IIiX '08*, 89.

Kato, M. P., Sakai, T., & Tanaka, K. (2012). Structured query suggestion for specialization and parallel movement. In *Proceedings of the 21st international conference on World Wide Web - WWW '12* (p. 389). New York, New York, USA: ACM Press.

Kelly, D. (2009). Query Suggestions as Idea Tactics for Information Search. In *HCIR*, 43, 83-87.

Kelly, D., Cushing, A., Dostert, M., Niu, X., & Gyllstrom, K. (2010). Effects of popularity and quality on the usage of query suggestions during information search. In *Proceedings of the 28th international conference on Human factors in computing systems - CHI '10* (p. 45). New York, New York, USA: ACM Press.

Kelly, D., Gyllstrom, K., & Bailey, E. W. (2009). A comparison of query and term suggestion features for interactive searching. In *Proceedings of the 32nd international ACM SIGIR conference on Research and development in information retrieval - SIGIR '09* (p. 371). New York, New York, USA: ACM Press.

Kelly, R., Kingdom, U., & Payne, S. J. (2013). Division of Labour in Collaborative Information Seeking : Current Approaches and Future Directions. In *CSCW Workshop on Collaborative Information Seeking* (pp. 2–5).

Kim, J. (2009). Describing and Predicting Information-Seeking Behavior on the Web. *Journal of the American Society for Information Science and Technology*, *60*(4), 679–693.

Kromer, P., Snasel, V., & Platos, J. (2008). Investigating Query Similarity Masures for Collaborative Web Search. In *Proceedings of the 7th Computer Information Systems and Industrial Management Applications.*

Kuhlthau, C. C. (1991). Inside the search process: Information seeking from the user's perspective, *42*(5), 361–371.

L.E.Baum, G.Soules, & Weiss, N. (1970). A maximization technique occuring in the statistical analysis of probabilistic functions of Markov chains. *Ann. Math. Statist*, *41*(1).

Lau, T., & Horvitz, E. (1999). Patterns of search: analyzing and modeling Web query refinement. *Courses and Lectures-International Centre for Mechanical Sciences*, 119–128.

Lazonder, A. W. (2005). collaboration on web search behaviour and search outcomes. *British Journal of Educational Technology*, *36*(3).

Liu, C., Gwizdka, J., Liu, J., Xu, T., & Belkin, N. J. (2010). Analysis and evaluation of query reformulations in different task types. In *Proceedings of the American Society for Information Science and Technology* (Vol. 47, pp. 1–9).

Mahony, O., Michael, P., Smyth, B., Briggs, P., Coyle, M., & Mahony, M. O. (2009). Google shared. A case study in social search. In *User Modeling, Adaptation, and Personalization* (pp. 283–294). Springer Berlin Heidelberg.

Marchionini, G. (1995). *Information seeking in electronic environments* (p. 240). Cambridge University Press.

Marchionini, G. (2006). From finding to understanding. *Communications of the ACM*, *49*(4), 41–46.

McGrath, J. E., & Hollingshead, A. B. (1993). Putting the group back in group support systems: Some theoretical issues about dynamic processes in groups with technological enhancements. In L. M. Jessup & J. S. Valacich (Eds.), *Group Support Systems: New Perspectives* (pp. 78–96). New York: Macmillan.

McKenzie, P. J. (2003). A model of information practices in accounts of everyday-life information seeking. *Journal of Documentation*, *59*(1), 19–40.

McQuarrie, A., & Tsai, C. (1998). *Regression and Time Series Model Selection*. Singapore: World Scientific.

Mei, Q., Zhou, D., & Church, K. (2008). Query suggestion using hitting time. In *Proceeding of the 17th ACM conference on Information and knowledge mining - CIKM '08* (p. 469). New York, New York, USA: ACM Press.

Mennecke, B. E., Wheeler, B. C., & Iubacs, B. (1993). Tasks matter: Modeling group task processes in experimental CSCW research. In *Proceeding of the Twenty-Sixth Hawaii International Conference on System Sciences* (pp. 71–80).

Mishra, D., & Mishra, A. (2009). Effective Communication , Collaboration , and Coordination in eXtreme Programming : Human-Centric Perspective in a Small Organization. *Human Factors*, *19*(5), 438–456.

Morris, M. (2008). A survey of collaborative web search practices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1657–1660). Florence, Italy: ACM.

Morris, M. R. (2013). Collaborative search revisited. In *Proceedings of the 2013 conference on Computer supported cooperative work - CSCW '13* (p. 1181). New York, New York, USA: ACM Press.

Morris, M. R., & Horvitz, E. (2007). *SearchTogether: An interface for collaborative web search*. *Proceedings of the 20th annual ACM symposium on User interface software and technology - UIST '07* (p. 3). New York, New York, USA, NY, USA: ACM Press.

Morris, M. R., & Teevan, J. (2010). *Collaborative Search: Who, What, Where, When, Why, and How*. Morgan & Claypool Publishers.

Paul, S. A., & Morris, M. R. (2010). Sensemaking in Collaborative Web Search. *Social Cognition*, 1–66.

Pickens, J., Golovchinsky, G., Shah, C., Qvarfordt, P., & Back, M. (2008). Algorithmic mediation for collaborative exploratory search. *Proceedings of the 31st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval - SIGIR '08*, 315.

Pickens, J., Golovchinsky, G., Shah, C., Qvarfordt, P., & Back, M. (2008). Algorithmic Mediation for Collaborative Exploratory Search. In *Proceedings of the 31st annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 315–322).

Poltrock, S., Grudin, J., Dumais, S., Fidel, R., Bruce, H., & Pejtersen, A. M. (2003). Information seeking and sharing in design teams. *Proceedings of the 2003 International ACM SIGGROUP Conference on Supporting Group Work - GROUP '03*, 239.

Qu, Y., & Furnas, G. (2007). Model-driven formative evaluation of exploratory search: A study under a sensemaking framework. *Information Processing & Management*, *44*, 534–555.

Reddy, M. C., & Jansen, B. J. (2008). A model for understanding collaborative information behavior in context : A study of two healthcare teams. *Information Sciences, 44*, 256–273.

Reddy, M. C., Jansen, B. J., & Krishnappa, R. (2009). The role of communication in collaborative information searching. *Proceedings of the American Society for Information Science and Technology*, *45*(1), 1–10.

Reddy, M., & Spence, P. (2008). Collaborative information seeking: A field study of a multidisciplinary patient care team. *Information Processing & Management*, *44*(1), 242–255.

Russell, D. M., Stefik, M. J., Pirolli, P., & Card, S. K. (1993). The cost structure of sensemaking. In *Proceedings of the SIGCHI conference on Human factors in computing systems CHI 93* (Vol. 93, pp. 269–276).

Saracevic, T. (2007). Relevance : A Review of the Literature and a Framework for Thinking on the Notion in Information Science . Part II : Nature and Manifestations of Relevance. *Journal of the American Society for Information Science and Technology*, *30*, 1915–1933.

Shah, C. (2010). *A Framework for Supporting User-Centric Collaborative Information Seeking*. *Dissertation,* University of North Carolina - Chapel Hill.

Shah, C. (2013). Effects of Awareness on Coordination in Collaborative. *Journal of the American Society for Information Science and Technology*, *64*(6), 1122–1143.

Shah, C., & González-ibáñez, R. (2010). Exploring Information Seeking Processes in Collaborative Search Tasks. In *Proceedings of ASIS&T*.

Shah, C., & González-Ibáñez, R. (2011). Evaluating the synergic effect of collaboration in information seeking. *Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information - SIGIR '11*, 913.

Shah, C., & Marchionini, G. (2010). Awareness in Collaborative Information Seeking. *Journal of the American Society for Information Science and Technology*, *61*(10), 1970–1986.

Smyth, B., Balfe, E., Freyne, J., Briggs, P., Coyle, M., & Boydell, O. (2005). Exploiting Query Repetition and Regularity in an Adaptive Community-Based Web Search Engine. *User Modeling and User-Adapted Interaction*, *14*(5), 383–423.

Sonnenwald, D. H., Maglaughlin, K. L., & Whitton, M. C. (2004). Designing to support situation awareness across distances: an example from a scientific collaboratory. *Information Processing & Management*, *40*(6), 989–1011.

Spink, a. (2002). A user-centered approach to evaluating human interaction with Web search engines: an exploratory study. *Information Processing & Management*, *38*(3), 401–426.

Spink, A. (1997). Study of interactive feedback during mediated information retrieval. *Journal of the American Society for Information Science*, *48*(5), 382–394.

Stone, N. J., & Posey, M. (2008). Understanding coordination in computer-mediated versus face-to-face groups. *Computers in Human Behavior*, *24*(3), 827–851.

Strijbos, J.-W., Martens, R. L., Jochems, W. M. G., & Broers, N. J. (2004). The Effect of Functional Roles on Group Efficiency: Using Multilevel Modeling and Content Analysis to Investigate Computer-Supported Collaboration in Small Groups. *Small Group Research*, *35*(2), 195–229.

Talja, S. (2002). Information sharing in academic communities: Types and levels of collaboration in information seeking and use. *New Review of Information Behavior Research*, *3*, 143–159.

Talja, S. (2003). Supporting scholars' collaboration in document seeking, retrieval and filtering. In *Proceedings of the Workshop on Computer Supported Scientific Collaboration* (pp. 49-55).

Talja, S., & Hansen, P. (2006). Information Sharing. In A. Spink (Ed.), *New directions in human information behavior* (pp. 113–134). Netherlands: Springer.

Teevan, J., & Alvarado, C. (2004). The perfect search engine is not enough: a study of orienteering behavior in directed search. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 415–422.

Toms, E. G., Brien, H. O., Mackenzie, T., Jordan, C., Freund, L., Toze, S., Macnutt, A. (2008). Task Effects on Interactive Search : The Query Factor. In *6th International Workshop of the Initiative for the Evaluation of XML retrieval.* (pp. 359–372).

Twidale, M. (1997). Browsing is a collaborative process. *Information Processing & Management*, *33*(6), 761–783.

Walkerdine, J., & Rodden, T. (2001). Sharing searches: Developing open support for collab orative searching.

White, R. W., & Drucker, S. M. (2007). *Investigating behavioral variability in web search*. *Proceedings of the 16th international conference on World Wide Web - WWW '07* (p. 21). New York, New York, USA, NY, USA: ACM Press.

White, R. W., & Marchionini, G. (2006). A study of real-time query expansion effectiveness. *Proceedings of the 29th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval - SIGIR '06*, 715.

White, R. W., Muresan, G., & Marchionini, G. (2006). Evaluating Exploratory Search Systems: Introduction to special topic issue of information processing and management. *Information Processing & Management*, 433–436.

White, R. W., & Roth, R. a. (2009). Exploratory Search: Beyond the Query-Response Paradigm. *Synthesis Lectures on Information Concepts, Retrieval, and Services*, *1*(1), 1–98.

Wikipedia Internet Movie Database - Wikipedia, the free encyclopedia. (2014). Retrieved from http://en.wikipedia.org/wiki/Internet_Movie

Wilson, M. L., & Schraefel, M. C. (2008). Evaluating collaborative search interfaces with information seeking theory. In *Workshop on collaborative information retrieval*.

Wilson, M., & schraefel, m. c. (2008). Improving Exploratory Search Interfaces: Adding Value or Information Overload? Retrieved from http://eprints.ecs.soton.ac.uk/16604

Wilson, T. (1999). Models in information behaviour research. *Journal of Documentation, 55*(3), 249–270.

Xie, I., & Joo, S. (2010). Transitions in Search Tactics During the Web-Based Search Process. *Journal of the American Society for Information Science*, *61*(11), 2188–2205.