ONLINE HELP SEEKING IN COMPUTER SCIENCE EDUCATION

by

QIANG HAO

(Under the Direction of Robert Maribe Branch)

ABSTRACT

Help seeking, as an important self-regulated learning strategy, has been found an important contributor to student resilience and efficacy at overcoming barriers. Computer Science education in United States is facing the challenges of exponentially growing number of enrollments and high student to instructor ratio. Directing question & answer activities online could give students more opportunities to learn from each other and interact with the instructors beyond the limits of time and locations in such a situation. This dissertation is dedicated to explore the questions such as how computer science students seek help online, what factors are important to their online help-seeking behaviors, and what strategies could improve computer science students' help-seeking skills.

INDEX WORDS: Computer Science Education, Online Help Seeking, Factor Analysis, Machine Learning

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DEDICATION

To my wife Yanran,

Thank you for your support in the past eight years.

You are my soulmate.

To my parents,

Thank you for your support,

I did it.

ACKNOWLEDGEMENTS

My journey at The University of Georgia could not be possible without love, help, support I received from mentors and friends.

I wouldn’t be where I am today without the guidance from Dr. Janette Hill, Dr. April Galyardt, Dr. Khaled Rasheed and Dr. Brad Barnes. Your advice and mentorship means everything to me.

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CHAPTER 1

INTRODUCTION

As we move into the 21st century, computer science education at the college level faces many unprecedented changes, such as fast growth of student size and faster interdisciplinarity between computer science and other fields. Computer science students, in such environments, are faced with more challenging learning demands and less individual attention from teachers (Kearney, Hershbein, & Boddy, 2015). As a result, computer science students need to adjust their focuses on competing attentions from different sources, and adapt their behaviors to overcome problems and challenges (Kearney, Hershbein, & Boddy, 2015). Help seeking, as an important self-regulated learning strategy, has been found an important contributor to student resilience and efficacy at overcoming barriers (Karabenick & Newman, 2006; Schunk, & Zimmerman, 2008). Help seeking can be an essential skill for computer science students to succeed in such environments.

Although there is a long history of research on help seeking, help-seeking behaviors in the new learning environments powered by technology and various forms of social interaction may have gone beyond the scope of traditional research. Many efforts have been made in the most recent decade on help seeking in intelligent tutor systems, but help seeking in open online environments still does not draw enough attentions as expected (Karabenick, 2011). It is not clearly known how computer science students seek help in open online environments, and what assistance is in need to improve their online help-seeking skills.

1.1 Organizing Framework

This dissertation is composed of several individual studies that serve the ultimate goal of facilitating help-seeking skills of computer science students on a large scale. The understanding of how computer science students seek help online, and what factors influence their online help seeking is essential for proposing an effective facilitation strategy that helps better their help-seeking skills. Therefore, two studies were conducted to gain insights towards such an understanding. Based on the findings of the two studies, automatic question classification is proposed and investigated as a potential solution to facilitating computer science students with online help seeking.

There are four major contributions throughout this dissertation:

1. A systematic classification of help seeking
2. Evidence of how computer science students seek help online in terms of frequency and efficacy
3. Understanding of the extent to which factors important to face-to-face help seeking influence online help seeking.
4. Exploration of automatic question classification by learning-relevance and efficacy

1.2 Outline

Figure 1.1 provides a road map for the flow of ideas and information in this dissertation to facilitate the reader.

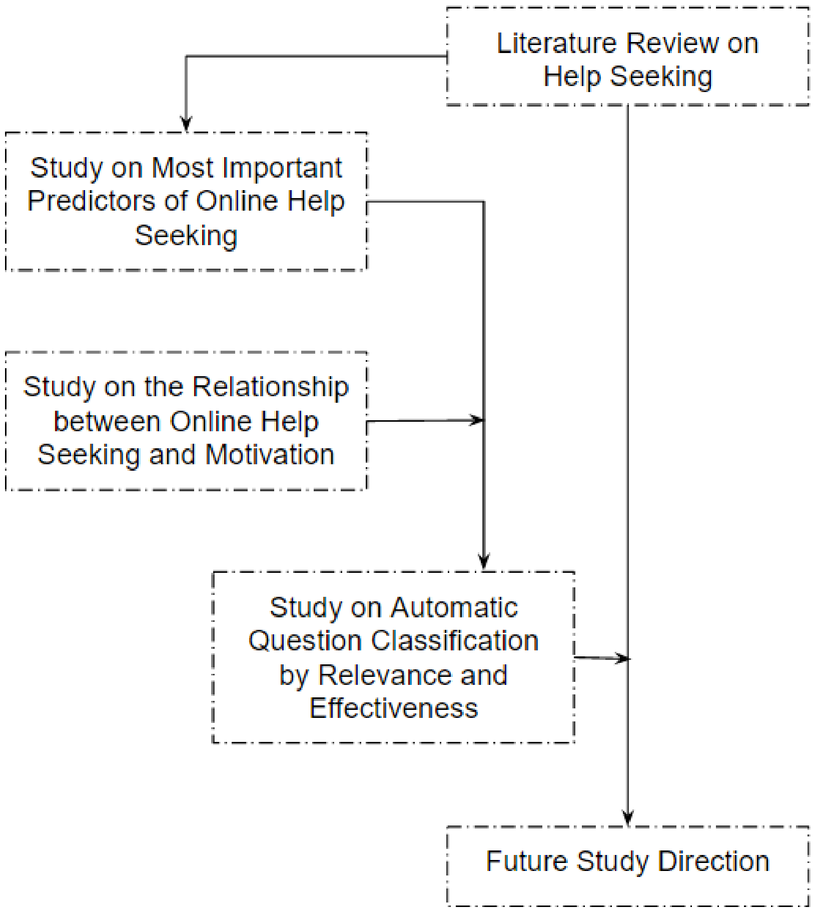

Figure 1.1. A Road Map of Idea Flow in this Dissertation.

This document is composed of three major parts: Chapter 2 provides a classification on help seeking and discusses the relationship between learning and online help seeking based on previous related studies. Chapter 3 and Chapter 4 explore how computer science students seek help online, and what factors influence their online help-seeking behaviors. Chapter 5 proposes a solution to helping students enrolled in large-scale classes improve their online help-seeking efficacy, and examines the viability of such a solution through analyzing students’ questions on online question and answer platforms. Chapter 6 discusses the future research directions of online help seeking.

The research design of Chapter 3 to Chapter 5 are briefly summarized in the following:

- *Chapter 3*: What are the most important predictors of computer science students' online help-seeking behaviors?
    - *Participants*: 203 computer science students from a large university in southeastern United States
    - *Context*: Large-scale computer science classes
    - *Primary Data Collection Tools*: Self-developed survey
    - *Data Analysis*: Exploratory factor analysis, predictor selection, and permutation test
- *Chapter 4*: The Influence of Achievement Goals on Online Help Seeking of Computer Science Students Authors
    - *Participants*: 165 computer science students from a large university in southeastern United States
    - *Context*: Large-scale computer science classes
    - *Data Collection Tools*: Achievement Goal Questionnaire-Revised Survey developed by Elliot and Murayama (2008)
    - *Data Analysis*: Correlational analysis and Confirmatory Factor Analysis
- *Chapter 5*: Automatic Learning Question Classification by Relevance and Efficacy within the Context of Large-Scale Classes
    - *Participants*: 759 computer science students from a large university in southeastern United States
    - *Context*: Large-scale computer science classes

- *Target Data*: 983 questions asked by the participants on an online question and answer platform
- *Data Analysis*: Naive Bayes Multinomial, Logistic Regression, Support Vector Machines, and Boosted Decision Tree

CHAPTER 2

LITERATURE REVIEW

This Chapter has two foci. The first focus is to propose a classification of help seeking based on literature review. The second focus is to examine the relationship between learning and online help seeking.

Before reviewing online help seeking and learning, we look at the classification of help seeking. Firstly, we review the prior efforts on help-seeking classifications, and put forward a new classification of help seeking. Secondly, we review models of seeking social assistance and information-seeking processes, discuss their relationships with online help seeking, and put forward a new model of general online help-seeking processes. Thirdly, we look at the relationship between learning and online help seeking.

2.1 Classification of Help Seeking

A comprehensive classification of help-seeking is important to guide researchers' questions, hypotheses and systematic research development on this topic, and also the key to direct research focus to less studied but important subtopics. However, the classification of help seeking has received less attention than expected. Without a commonly-accepted classification, many studies name the same type of help seeking differently, which hinders communication and confuses readers. Therefore, we discuss prior efforts in classifying help seeking first, and then propose a new comprehensive classification of help seeking from the perspective of challenges for learners.

The earliest efforts in classifying help seeking were made by Zimmerman and Pons (1986), who distinguished seeking social assistance from seeking information. Social assistance refers to help from peers, teachers or other people, while the sources of information seeking are usually machines. According to Zimmerman and Pons (1986), only seeking social assistance can be counted as help seeking, while seeking information is the topic that should be addressed by other academic fields, like information search. However, education literatures in the last two decades have suggested the convergence of seeking social assistance and information (Karabenick, 2011; Kitsantas & Chow, 2007; Puustinen & Rouet, 2009). More help-seeking activities involve the supports from machines, such as question & answer platforms, search engines or tutor systems, while more information-seeking activities serve the purpose of help seeking (Aleven, et. al., 2003; Puustinen & Rouet, 2009).

Karabenick and Knapp (1991) proposed five categories of help seeking: (a) seeking help from teachers or teacher assistants, (b) seeking help from peers or friends, (c) studying more, (d) lowering performance requirement, and (e) altering learning goals. This classification was limited in the context of classroom learning environment. In addition, three proposed types of help seeking, including studying more, lowering performance requirement and altering learning goals, do not align with the commonly accepted definition of help seeking.

As technology is increasingly integrated into learning and teaching activities, different and more comprehensive classifications emerged. Puustinen and Rouet (2009) proposed three categories of help seeking based on types of helpers and locations of help seeking: (a) seeking help face-to-face from a human (b) seeking help online from a human, and (c) seeking help from a helping system. Cheng and Tsai (2011) further suggested that help seeking behaviors might differ by the relationship between helpers and help seekers in online communication, such as teachers and students, or students and peers. However, little evidences were found to support such a claim.

Although all the proposed classifications contributed to our theoretical understanding of help seeking, they did not address the critical question how various types of help seeking, as important cognitive skills, pose different challenges and require different competencies. Answers to such a question is the key that can direct research to less studied and more challenging types of help seeking. To address this question, we propose a new classification of help seeking based on particular challenges and required competencies:

1. Face-to-face seeking help
2. Interactive help seeking
3. Online seeking help

Face-to-face help seeking has been researched extensively in the last 30 years. The special challenges posed by this type of help seeking come mostly from interaction with humans, including self-esteem threat and demands for appropriate communication (Kitsantas & Chow, 2007). A successful help seeker needs to disconnect help seeking behavior with incompetency, and understand how to use appropriate communication to solicit answers (Nelson-LeGall, 1981; Newman, 2000).

Interactive help seeking refers to seeking help from the helper functions of a tutor system. Typical helper functions usually include on-demand hints and glossaries (Roll, et. al, 2007). The last fifteen years witnessed a growing research attention on this type of help seeking (e.g., Roll, et. al, 2007; Roll, et. al, 2011; Stahl & Bromme, 2009). A tutor-system environment, despite of being set up locally or online, is very different from authentic classroom or online environment. A tutor system sets a closed environment where help seeking involves much fewer cognitive activities. Seeking help in such an environment does not necessarily require organized thinking and language, formation of a clear question, or conversion between questions and search queries (Hao, 2016b). The distance between learners and helps is only a mouse-click away. Therefore, it is observed that many students tend to game the system by overusing helps (e.g., Aleven & Koedinger 2000; Aleven, et. al, 2006; Bartholomé, Stahl, Pieschl, & Bromme, 2006). Learners need to understand the affordances, limits and working mechanism of a tutor system, in order to use its helper functions effectively (Aleven, et. al, 2003).

Online help seeking refers to help seeking behavior supported by general tools, such as question & answer platforms, search engines, emails or online messengers in open online environments. Online help seeking is less much threatening to self-esteem than face-to-face help seeking (Cheng & Tsai, 2011; Kumrow, 2007; Karabenick, 2003). If used properly, help seekers can take advantage of the abundant online resources and help from experts around the globe. There have been a significant improvement of search engines in terms of both usability and functionality over the last two decades. Only accurate keywords would lead to satisfactory searching results 15 to 20 years ago, but major search engines, such as Google and Bing, have no problems parsing a clear question nowadays (Büttcher, et al., 2016). It is worth noting that a major gap exists between “help systems” provided by most tutor systems and major search engines in terms of usability and functionality, although literatures use the term “help systems” in general to stand for all machines that learners interact with when seeking help. However, no matter interacting with a search engine or engaging in an asynchronous communication with a helper, online help seeking is less adaptive than face-to-face communication (Puustinen & Rouet, 2009; Hao, et. al, 2016b). Such an inadaptiveness requires skills from help seekers in terms of forming logical and decontextualized questions and queries.

In summary, face-to-face help seeking has higher requirements for social competencies, like self-confidence and communication skills. Online help seeking has a lower demand for social skills, but higher requirements for cognitive competencies, like forming clear and logical questions, or converting questions to searchable queries. Interactive help seeking is intrinsically differently from help seeking in open environments. The controlled environments of tutor systems make help seeking less socially and cognitively demanding, yet their common designs create the new problem of help overuse.

2.2 Processes of Online Help Seeking

Two models were found partially aligning with online help seeking processes from the literature. One model was put forward by Nelson-LeGall (1981), and the other model was proposed by Eisenberg and Berkowitz (1992). We review the two models and their partial alignment with online-help seeking processes, and then put forward a new online help seeking process through synthesizing the two models.

The model proposed by Nelson-LeGall (1981) and elaborated by Newman and Schunk (1994) focused on the essential process of help seeking in social contexts. The model is composed of five steps:

1. *Become aware of needs for help*: Students must become aware help is in need by assessing task difficulties, monitoring task progress, or evaluating their own capability.
2. *Decide to seek help*: Students must take into consideration of all factors besides those mentioned in first step, such as threats to self-esteem and fear of embarrassment, and decide whether to seek help accordingly.
3. *Identify potential helpers*: Students must find a suitable and accessible helper.
4. *Elicit help*: Students must decide how to request help, based on the knowledge of the problem and the potential helpers.
5. *Evaluate help*: Students need to reflect upon the received help to decide if it is helpful and whether further help is required.

Online help seeking includes both seeking help from distant people and from machines, depending on the tools help seekers decide to use. Seeking help from distant people and machines interweave with each other in authentic environments. If we limit the scope of online help seeking only to seeking help from distant people, the model of Nelson-LeGall's (1981) is applicable. However, two major differences are noticeable:

- Certain factors key to face-to-face help seeking, such as self-esteem threats and fear of embarrassment, may play less significant roles in asking people online for help. Communication with people online, especially anonymously, poses fewer self-esteem threats to most people.
- Identifying a specific potential helper is very unusual for online help seeking. Instead, students may need to determine which online communities would be most knowledgeable of their questions.

Online searching, as an approach of online help seeking, was mainly studied in the field of information seeking. The “Big Six Skill” put forward by Eisenberg and Berkowitz (1992) is the model that most accurately summarizes the processes of online searching from the perspective of information searching. The model comprises 6 steps:

1. *Task definition*: Students must become aware that if help is in need, and define the problem and information in need
2. *Information Seeking Strategies*: Students need to determine possible sources of the information by forming possible queries for online searching.
3. *Location and Access*: Students must try different possible queries or forming new queries in online searching, until they find most relevant information that can help with problem solving.
4. *Use of Information*: Students need to engage with the collected information and extract most relevant information.
5. *Synthesis*: Students need to apply the information to problem solving
6. *Evaluation*: Students need to evaluate the effectiveness of the information to determine if it is helpful and whether further online searching is required.

The processes of asking people online for help and online searching share many similarities, such as assessments of the needs of help or evaluation of received help. Therefore, we propose a new model synthesizing the models of Nelson-LeGall (1981) and Eisenberg and Berkowitz (1992) to depict a more general online help seeking process. Our model has 4 steps:

1. *Assess the needs of help*: This step is the same as in Nelson-LeGall's (1981) model. Students must decide whether to seek help by assessing task difficulties, their self-capabilities, and whether they are stuck.
2. *Determine help-seeking strategies*: Students need to determine which strategy is the best fit given the nature of the problem, from choices of online searching and seeking help from distant experts.
3. *Seek help*: Students need to form a question or a query depending on the chosen help-seeking strategy, and proceed to post the question to selected online professional communities or search with the query. In reality, students may need to repeat this step with different choices, questions or queries.
4. *Evaluate help*: Students need to evaluate the effectiveness of the gathered answers and information to determine
    a. If the gathered answers and information are helpful
    b. Whether further help seeking is in need
    c. If further help seeking is in need, whether to change the help-seeking strategy
    d. If further help seeking is in need, whether to revise the formed question or query

In an authentic environment, students may search online with different queries recursively for multiple rounds first, and use the gathered information to further determine if it is necessary to seek help from an online professional community. The reason is that online searching returns immediate results, but the communication with distant experts is usually asynchronous, and may take a long time to get replies. Online help seeking is more open and "messy" than other types of help seeking (Karabenick, 2011). As an interesting field on its own, online help seeking deserving more attention. Whether the model we put forward accurately depicts the general process of online help seeking also needs verification from empirical studies.

2.3 Online Help Seeking and Learning

Having discussed help seeking from a theoretical perspective, we turn to empirical studies examining help seeking and learning now. There have been surprisingly little empirical evidences on the connections between help seeking and learning, especially between online help seeking and learning. Therefore, we discuss learning and help seeking in face-to-face and tutor system environments firstly, and then turn to studies examining the relationships between online help seeking and learning.

In comparison with help seeking in other contexts, more empirical studies were conducted to examine help seeking in face-to-face contexts, and most of the studies found a positive relationship between the use of help seeking and academic performance in such a context. Students who have better academic performance tend to have better metacognitive skills, and tend to seek help more frequently (Karlsson et al., 2012). Middle and high school students who sought help in classroom environment were found to have better self-regulated learning capabilities, and more advanced metacognitive skills. All these advantages were found linked to their better academic performance (Corno, 1989; Newman, 2000; Skinner & Wellborn, 1994). These findings were not only limited to young learners. Lee (2007) and Karabenick (2004) found similar connections between face-to-face help seeking and learning in college students.

A growing number of studies on help seeking in tutor system were witnessed in the last two decades. However, conflicting evidence on the relationship between learning results and use of help seeking in tutor systems were found. Bartholomè, et al. (2006) showed that the frequency of using contextualized help in tutor systems was positively related to better academic performance. Renkl (2002), and Schworm and Renkl (2002) found that a causal relation existed between the availability of help functions in tutor systems and better learning results. On the other hand, Aleven et al. (2006) found a negative correlation between help seeking and learning in tutor systems, despite that students used the help functions at appropriate frequency. According to the analysis of the authors, the issue was due to the ineffective design of the tutor systems that gave students chances to game the systems. In other words, students could abuse the help functions to quickly get direct answers.

The connection between online help seeking and learning is much less studied among the three types of help seeking. To our best knowledge, the studies of Zhu et al. (2011) and Hao et al. (2016a) were the only two studies exploring the relationships between learning and online help seeking. Zhu et al. (2011) investigated the connection of online searching for academic purposes and academic self-efficacy among 295 high school students in Taiwan using surveys, and found that online searching is positively related to academic self-efficacy. Hao, et al. (2016a) explored the frequency of online help seeking and academic performance among 165 college students majoring in computer science, and found that students who sought help more frequently tended to have significantly better academic performance. Additional studies are needed to establish more firmly correlations between online help seeking and learning, and determine what causal relationship exists between the two.

CHAPTER 3

WHAT ARE THE MOST IMPORTANT PREDICTORS OF COMPUTER SCIENCE STUDENTS' ONLINE HELP-SEEKING BEHAVIORS?[1]

[1] Hao, Q., Wright, E., Barnes, B., & Branch, R. M. (2016). What are the most important predictors of computer science students' online help-seeking behaviors?. Computers in Human Behavior, 62, 467-474.
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Abstract

This study investigates the most important predictors of computer science students' online help-seeking behaviors. 203 computer science students from a large university in southeastern United States participated in the study. Online help-seeking behaviors explored in this study include online searching, asking teachers online for help, and asking peers online for help. Ten-fold cross validation was used to select the most significant predictors from eight potential factors, including prior knowledge of the learning subject, learning proficiency level, academic performance, epistemological belief, interests, problem difficulty, age and gender. Problem difficulty was selected as the most important predictor for all three types of online help seeking, while learning proficiency level, academic performance, and epistemological belief were selected as the most important predictors for both online searching and asking teachers online for help. Based on the selected factors and their relationships with online help seeking, the study provides guidance on targeted training for online help seeking in an era of mass higher education.

3.1 Introduction

Since the late 20th century there has been a mass expansion of higher education on a global scale. In the United States, 41.0% of 18 to 24 years old were enrolled in degree granting institutions in 2012, compared to 35.5% in 2000, 32.0% in 1990, and 25.7% in 1980 (National Center for Education Statistics, 2015). A further expansion in higher education is crucial to ensure that youth are equipped with skills to find gainful employment and to support the long-term economic competitiveness of the country (Brynjolfsson & McAfee, 2014; Goldin & Katz, 2009; Kearney, Hershbein & Boddy, 2015). Nevertheless, this expansion has inevitably accompanied a range of stressors to the infrastructure of higher education, especially in terms of resources and supports per-student that institutions can provide. This trend has hastened a transition to new forms of teaching and learning, which rely heavily on the Internet and other forms of technologies (Allen & Seaman, 2013; Bernard et al., 2009; Yang & Cao, 2013).

In such environments, pro-active online help seeking is likely to become increasingly important to academic success of college students (McInnerney & Roberts, 2004; Newman, 2008; Rakes & Dunn, 2010). Help seeking has been identified as an effective learning strategy and is associated with a capacity for self-regulated learning (Lee, 2007; Roll, Aleven, McLaren & Koedinger, 2011). Online help seeking, more specifically, refers to help seeking facilitated by online tools, including search engines and communication platforms. Online help seeking offers a range of potential advantages compared with help seeking in traditional classroom contexts. For instance, students often hesitate to approach potential helpers due to lack of self-confidence in classroom contexts, while these problems are less prevalent in either searching or asking questions anonymously online (Karabenick, 2003; Kozanitis, Desbiens, & Chouinard, 2007; Ryan & Shin, 2011). However, online help seeking also poses new challenges to students. As an example, search engines remain rather limited in their capacity to respond to students' problems if students fail to input accurate keywords.

It is crucial, therefore, to have guidelines that can inform educators about teaching students to seek help online effectively, given its potentials and challenges. To ensure the effectiveness of such guidelines, there is a need for a better understanding of what factors influence student's online help-seeking behavior. In response, this study investigated the most significant predictors for students' online help seeking.

This paper starts with reviewing the existing literature on online help seeking and potential factors associated with online help seeking, then follows with methodology and results, and finally discusses the main findings with references to the existing literature. The results of this study will contribute to the development of guidelines informing educators about how to best guide students to seek help online.

3.2 Literature Review

3.2.1 Online Help Seeking

Help seeking is a cognitive skill involving a set of actions including realizing the need of help, identifying problems, and forming questions to solicit help (Aleven, et al., 2006; Newman, 2008). Online help seeking specifically refers to help seeking supported by online tools, such as search engine, emails or question & answer forums.

Two classification standards were proposed for online help seeking, including the nature of helpers, such as human beings or machines, and the relationship between helpers and help seekers, such as peers or teachers (Cheng & Tsai, 2011; Le Bigot, Jamet,

& Rouet, 2004; Puustinen & Rouet, 2009). Three types of online help seeking emerged based on the above two classification (Cheng & Tsai, 2011):

1. Online searching
2. Asking teachers for help online
3. Asking peers online for help

Online help seeking has different characteristics compared with help seeking in other contexts. Firstly, online help seeking is more open and "messy" than help seeking in tutor-system environments (Karabenick, 2011). Increasingly ubiquitous, regardless of locations and devices, online environments offer abundant access to information and help from experts around the world. In contrast, tutor systems typically provide limited on-demand hints and glossaries in a closed environment. Secondly, many factors important to face-to-face help seeking are much less important for online help seeking. Both searching and asking questions anonymously online are much less threatening to students' self-esteem than face-to-face help seeking in classroom contexts (Kumrow, 2007). Thirdly, online help seeking poses new and significant challenges to learners. Search engines are limited in adapting to students' questions if students fail to provide accurate queries. In addition, asynchronous communication on question & answer forums with other people can be prone to misunderstandings and thus may not yield the desired information.

3.2.2 Potential Factors influencing Online Help Seeking

This section of the paper reviews the literature on the potentially influential factors on online help-seeking behavior, including prior knowledge of the learning subject, learning proficiency level, academic performance, epistemological belief, interests, problem difficulty, age and gender.

Prior knowledge of the learning subject refers to learners' prior knowledge of the current learning content. Aleven, et al. (2003) and Li and Belkin (2010) found that middle school students with less prior knowledge are less likely to know when to seek help, how to organize information and how to form questions. Therefore, they are expected to seek help online less frequently. Different from prior knowledge of the learning subject, learning proficiency level refers to the general learning aptitude and experience of a student, which can be used to differentiate novice and expert learners. Novice learners are often more dependent on authorities, less able at finding answers themselves (Kitsantas & Zimmerman, 2002; Yang & Taylor, 2013). Conversely, expert learners are associated with better self-regulation and help-seeking strategies. Notably, Karlsson et al. (2012) found that expert learners have superior skills at online searching.

Academic performance has been found to be an important factor related to face-to-face help seeking in classroom contexts. Studies conducted by Karabenick and Knapp (1991), Karabenick (1998), and Kitsantas and Chow (2007) indicated that students with better academic achievements generally had higher levels of confidence. As a result, students tended to seek help more frequently, and help seeking in turn consolidated strong academic performance. Nevertheless, different from face-to-face help seeking, it is possible to remain anonymous when seeking help online. Therefore, confidence may be a less important factor for online help seeking.

Epistemological beliefs refer to the personal beliefs of knowledge and knowing. Belief about the source of knowledge, as a component of epistemological belief, is the focus of this study. For instance, Cheng and Tsai (2011), Muis and Franco (2009), and Strømsø and Bråten (2010) noted that beliefs about the source of knowledge are likely to be related to students' choices of online help seeking approaches. They also found that students with a perception that knowledge is transmitted from expert external authorities tended to ask teachers online for help rather than search or ask peers for help online.

Relationships between interests in the learning topic and help seeking have been mainly studied in classroom contexts. Though most studies to date indicated that students with higher levels of interests engaged in more face-to-face help-seeking activities (e.g., Beal, Qu, & Lee, 2008; Boscolo & Mason, 2003), Bartholomè et al. (2006) found that interests had little effect of help seeking in tutor-system contexts. Given the difference between online help seeking and help seeking in other contexts, different results may emerge on the relationship between interests and online help seeking.

Difficulty of problems being tackled may also influence the extent to which students engage in online help seeking activities (Jonassen & Hung, 2008; Li & Belkin, 2010). A study by Li and Belkin (2010) found that students facing problems perceived as difficult tended to increase their dependence on experts rather than finding helpful information on their own. Reflecting this, it is likely that students will rely more on asking help online from teachers when problem difficulty increases.

Age and gender have been found influential factors on help seeking in face-to-face classroom contexts. Though help-seeking abilities have been consistently found to be positively related to age (e.g., Newman & Schwager, 1995; Ryan & Pintrich, 1998), to what extent age influences online help seeking has not been explored. Comparatively, the relationship between gender and help seeking is less clear. A growing body of literature has, however, noted that a positive femininity can be more conducive to face-to-face help seeking (Eccles & Blumenfeld, 1985; Kessels & Steinmayr, 2013; Marchand & Skinner, 2007). To what extent gender influences online help seeking has not been investigated either.

3.3 Research Questions

The research question that guided this study is:

- What are the most important predictors of college students' online help seeking behavior (online searching, asking teachers online for help, and asking peers online for help) among the proposed factors (prior knowledge of the learning subject, learning proficiency level, academic performance, Epistemological belief, interests, problem difficulty, age and gender)?

3.4 Research Method

3.4.1 Participants

Two groups of 203 undergraduate students from a large research university in southeastern United States participated in this study. One group included 162 students enrolled in an entry-level course of computer science. This group of students were identified as novice learners. The other group included 41 students enrolled in an advanced course of computer science. This group of students have taken 5 different prerequisite courses in computer science before enrolling in the current course, so they were identified as expert learners in comparison to the first group.

3.4.2 Research Design

A survey developed by the authors was used to measure participants' frequency of different online help seeking behavior and six of the proposed factors (age, gender, epistemological belief, interest, prior knowledge of the learning subject, and problem difficulty). The seventh factor, learning proficiency level, identified which group participants belong to. The eighth factor was academic performance. All students' grades were collected by the end of the semester and standardized to represent their academic performance.

There were 15 questions divided into 3 sections in the survey. The first section had questions on participants' basic personal information, including gender and age. The second section had questions measuring the frequency of students' online help seeking activities. The third section had questions measuring the four potential factors influencing online help seeking, and each factor was measured by two or three questions. All questions adopted the design of a four point Likert-scale format (see Appendix A).

3.5 Results

3.5.1 Factor Analysis of Survey on Online Help Seeking

Data from 203 participants were collected, while 4 participants were excluded from analysis due to missing major information in their survey. Descriptive summaries of how students seek help online are presented in Table 3.1.

Table 3.1

Descriptive analysis of online help seeking (Means and Standard Deviation of the response levels from Likert-Scale survey questions; response levels coded from 1 to 4).

	Novice students		Expert students		Total	
	Mean	SD	Mean	SD	Mean	SD
Online searching	2.87	0.83	3.45	0.78	2.99	.85
Asking teachers online for help	2.03	0.80	2.28	0.82	2.08	.81
Asking peers online for help	2.55	0.90	2.88	0.76	2.62	.88

Exploratory factor analysis was conducted on 10 questions in section 3 of the survey measuring the proposed four factors with oblique rotation (varimax). The Kaiser-Meyer-Olkin (KMO) measure verified the sampling adequacy for the analysis (KMO = .60). Overall reliability α is .61. Four factors with eigenvalues over Kaiser's criterion 1 emerged, and explained 54.13% of the variance in total (see Table 3.2).

Table 3.2

Exploratory factor analysis on 10 questions on online help seeking.

	Pattern matrix			
Item	Interest	Prior Knowledge	Epistemological belief	Problem difficulty
1. LearnLike	.84			
2. LearnWill	.75			
3. CourseWill	.66			
4. PriorKnow		.98		
5. PriorExp		.67		
6. DifIncAsk				.87
7. DifIncSearch				.46
8. SelfLearnPerc			.51	
9. SelfLearnLike			.90	
10. ClassLearnDis			.23	
Reliability Coefficient (α)	.78	.80	.54	.57

Overall α= .61, total variance explained=54.13%.
LearnLike Interests in course content, LearnWill Willingness to master course content, CourseWill Willingness to take such an elective course, PriorKnow Prior knowledge, PriorExp Prior learning experience, DifIncAsk Willingness to ask for help online when difficulty increases, DifIncSearch Willingness to search online when difficulty increases, SelfLearnPerc Perception of self-learning, SelfLearnLike Preference of self-learning, ClassLearnDis Dislike of classroom learning.

3.5.2 Most Important Predictors of Online Help Seeking

Backward stepwise selection on linear regression and cross-validation were used for predictor selection from the proposed eight factors (prior knowledge of the learning subject, learning proficiency level, academic performance, Epistemological belief, interests, problem difficulty, age and gender). Multicollinearity diagnostics were conducted on each regression model presented in the following sections. The Variance Inflation Factor of all the predictors was smaller than 2.5 in each model.

3.5.2.1 Online Searching

The 10-fold cross-validation scheme for predictor selection did not involve training or testing as in prediction or classification. Instead, the data was randomly split into 10 folds, and only 9 folds were used for predictor selection. Backward stepwise regression was applied for the predictor selection purposes. 1,000 trials were conducted to stabilize the selection result. 64.2 % of the cross-validation selected 4-factor models as the ones with lowest test error rate (see Figure 3.1).

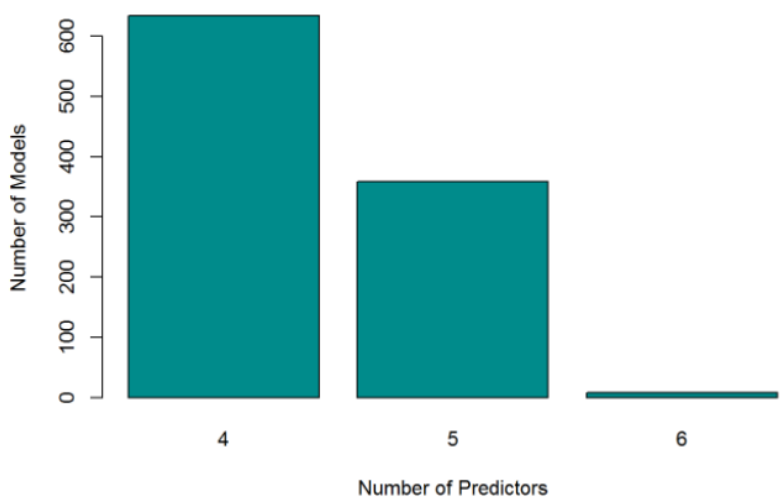

Figure 3.1. Number of Selected Predictors of 1,000 Selection Trials for Online Searching.

The selection of the 4 predictors was performed on the full data set to ensure the accuracy of predictor coefficient estimates. The selected predictors include learning proficiency level, academic performance, epistemological belief and problem difficulty. The four factors explained 29.8% variance of online searching (R^2 = .298, p < .00) (see Table 3.3). In contrast, all eight proposed factors explained 30.9% variance of online searching (R^2 = .309, p < .00). All predictors were significant in the four-factor regression model.

Table 3.3

Multiple regression analysis on best subset model of online searching.

	R^2	R^2_{adj}	ΔF	ß	t
Online searching	.298	.283	20.54		
Academic Performance				0.15**	2.89
Learning proficiency level				0.53***	4.20
Epistemological belief				0.33***	5.86
Problem difficulty				0.20***	3.45

** p < .05; ** p < 0.01; *** p < .001*

3.5.2.2 Asking Teachers Online for Help

The same procedures of predictor selection for online searching were applied for asking teachers online for help. 70.9% of the 1,000 cross-validation results had 5-factor models as the ones with lowest test error rate. The selected predictors include learning proficiency, academic performance, gender, epistemological belief and problem difficulty (see Figure 3.2).

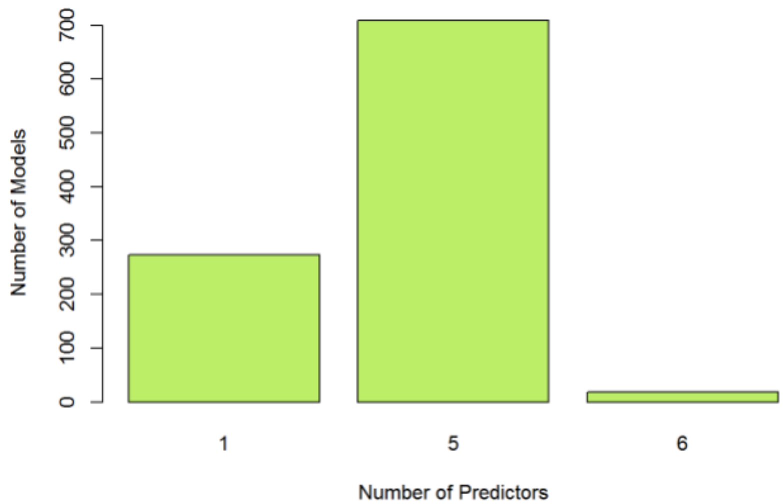

Figure 3.2. Number of Selected Predictors of 1,000 Selection Trials for Asking Teachers Online for Help.

The five selected predictors explained 7.9% of variance of asking teachers online for help (R^2 = .079, p < .01) (see Table 3.4). In contrast, all eight proposed factors explained 8.1% variance of online searching (R^2 = .081, p < .01). Three predictors, including academic performance, learning proficiency level, and problem difficulty, were significant in the five-factor regression model.

Table 3.4

Multiple regression analysis on best subset model of asking teachers online for help.

	R^2	R^2_{adj}	ΔF	ß	t
Asking peers online for help	.079	.055	3.29		
Gender				0.21	1.53
Academic Performance				0.10*	1.74
Learning proficiency level				0.26*	1.85
Epistemological belief				-0.10	-1.23
Problem difficulty				0.14*	2.20

* *p < .05; ** p < 0.01; *** p < .001*

3.5.2.3 Asking Peers Online for Help

The same predictor selection procedures were applied for asking peers online for help. 80.4% of 1,000 cross-validation results had 2-factor models as the ones with lowest test error rate. The selected predictors include epistemological belief and problem difficulty (see Figure 3.3).

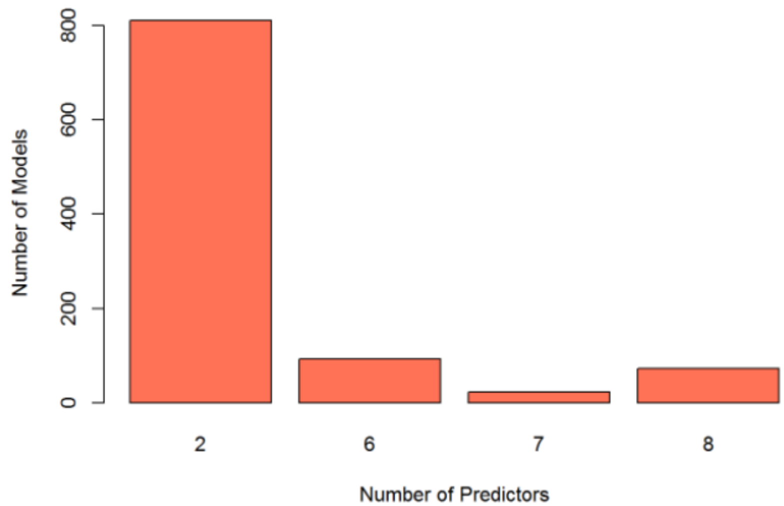

Figure 3.3. Number of Selected Predictors of 1,000 Selection Trials for Asking Peers Online for Help.

The two factors, including epistemological belief and problem difficulty, explained 21.4% of variance of asking peers online for help (R^2 = .192, p < .01) (see Table 3.5). In contrast, all eight proposed factors explained 23.8% variance of online searching (R^2 = .238, p < .01). Both of the two predictors were significant in the model.

Table 3.5

Multiple regression analysis on best subset model of asking peers online for help.

	R^2	R^2_{adj}	ΔF	ß	t
Asking peers online for help	.192	.184	23.32		
Interest				-0.26***	-4.19
Problem difficulty				0.35***	5.38

** p < .05; ** p < 0.01; *** p < .001*

3.6 Discussion

Problem difficulty was selected as an important predictor for all three types of online help-seeking behaviors. Three factors, including epistemological belief, learning proficiency level, and academic performance, were selected as important predictors for two types of online help-seeking behaviors, including online searching and asking teachers online for help. The below section will discuss the findings with reference to the existing literature on these four factors and online help seeking.

Firstly, problem difficulty is positively related to all types of online help-seeking behaviors. While the students sought help online more frequently as problem difficulty increased, their preferences among the three approaches of online help seeking varied. Notably, students preferred to ask peers online for help more than search online. This finding may indicate that online searching poses more cognitive challenges for students than asking other people for help. In other words, as problems become difficult, it could be more effective to communicate with human beings than machines. It important, therefore, for trainings of online searching to avoid highly complex problems, in order to lessen students' cognitive loads. Although students tended to seek more help online from human beings as the problem difficulty increased, participants in this study did not demonstrate a strong dependence on teachers compared to the study of Li and Belkin (2010). Given that students' strong preference for asking peers online for help, online help-seeking training may need to give priority to the guidance of asking peers online for help.

Secondly, epistemological belief is an important predictor for two types of online help-seeking behaviors. Students who preferred independent learning tended to search online rather than ask teachers for help, while students who preferred classroom learning tended to ask teachers online for help more frequently. This finding shows the strong effect of epistemological belief on students' online help-seeking behavior, and indicates that instructional designs involving online help seeking should take students' acceptance of independent learning into consideration for their designs. Moreover, effective online help-seeking training should incorporate efforts to increase students' acceptance of independent learning.

Thirdly, academic performance was also an important predictor for two types of online help-seeking behaviors. This result was consistent with the findings of Karabenick and Knapp (1991) and Karabenick (1998) that students with better academic achievements tended to seek help more frequently. Nevertheless, more frequent online searching, in this study, was more likely to reflect better online searching skills rather than self-confidence. This is because online searching poses limited self-esteem threats, given that students can remain anonymous in online environments. This finding necessitates deliberate training for students' to enhance online help-seeking skills, especially for academically challenged students.

Lastly, learning proficiency level is the other important predictor for two types of online help-seeking behaviors. Expert learners tended to use all types of online help-seeking approaches more frequently than novice learners, especially online searching. This finding confirms that there is a discrepancy between expert and novice learners in online help seeking skills (see Karlsson et al., 2012), and further necessitates deliberate training of such skills. Moreover, this finding also provides practical guidance for instructional design that decisions on whether to incorporate online help seeking need to take learners' proficiency level into consideration.

3.7 Conclusion

Higher education in the United States has long since transitioned into the upper end of what Martin Trow (1976), the prominent writer on the global expansion of higher education, defined as a "mass system" (i.e., enrollments of 15 to 50 percent of the age cohort). As previously noted, further growth in enrollments is arguably required to ensure that young people are equipped with the requisite skills to participate in the labour market and to drive economic growth. It seems inevitable, however, that teaching and learning in colleges need to adjust as enrollments increase and resources on a per-student basis come increasingly under strain. Notably, Trow (2007) foresaw a progressive decline in personal relationships between students and lecturers alongside a heavier reliance on distant learning and other forms of technological aids to instruction.

Reflecting this, there has been mounting interests in the role of online learning for college students in recent years, including the much discussed emergence of Massive Open Online Courses (MOOCs) and on e-learning at "bricks and mortar" colleges across the country (Allen & Seaman, 2013; Bernard et al., 2009; Yang & Cao, 2013). In this emerging context, pro-active online help seeking will continue to play an increasingly important role in the academic success of college students (Aleven et al., 2003; McInnerney & Roberts, 2004; Newman, 2008; Rakes & Dunn, 2010). It is, therefore, crucial to better understand what factors influence students' engagement with online help seeking. This paper responded to this under-researched area of enquiry by illuminating that problem difficulty, epistemological belief, academic performance, and learning proficiency were the most important factors associated with online-help seeking.

Among our findings, we wish to highlight that academically high-performing students (in terms of both academic performance and learning proficiency) in our study were more likely to engage in online help seeking. This finding indicates that there exists a discrepancy in online help-seeking skills between academically high-performing students and their counterparts. An implication is that deliberate training for online help seeking is necessary, especially for low academic performers. This will be crucial to facilitating an overall increase in academic standards as well as avoiding a growing disparity in academic outcomes between students who are better able to take advantage of online help seeking and those who may be reluctant to engage in such behavior.

CHAPTER 4

THE INFLUENCE OF ACHIEVEMENT GOALS ON ONLINE HELP SEEKING OF COMPUTER SCIENCE STUDENTS[2]

[2] Hao, Q., Barnes, B., Wright, E., & Branch, R. M. (2016). The influence of achievement goals on online help seeking of computer science students. British Journal of Educational Technology. doi:10.1111/bjet.12499

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Abstract

This study investigated the online help-seeking behaviors of computer science students with a focus on the effect of achievement goals. Online help-seeking behaviors examined in this study included online searching, asking teachers online for help, and asking peers or unknown people online for help. 165 students studying computer science from a large university in the south-eastern United States participated in the study. It was found that students searched online significantly more frequently than they asked people online for help. Contrary to prior findings on face-to-face help seeking, no achievement goals were found significant in predicting students' tendency of online help seeking in this study. These findings provide evidence to support the role of online searching as an integral part of online help seeking and demonstrate that research findings on face-to-face help seeking should not be assumed extendable to online help seeking.

4.1 Introduction

Higher education enrollments have grown substantially in the United States in the last decade. The enrollment of students under age 25 has increased by more than 35 percent since 2000, and is expected to further increase 12 percent by 2023 (U.S. Department of Education, 2015). Such an expansion has put stress on the infrastructure of higher education regarding resources and support provided per-student and also calls for new forms of learning and teaching which rely heavily on Internet Technology (Allen & Seaman, 2013; Yang & Cao, 2013).

In the context of such changes to teaching and learning in higher education, college students have to increasingly self-regulate their learning in either large classroom or online learning environments, given the growing ratio of students to teachers (Newman, 2008). Being able to seek help online is becoming increasingly important for effective self-regulated learning in such environments (McInnerney & Roberts, 2004; Rakes & Dunn, 2010). Moreover, online help seeking has a range of particular advantages compared with face-to-face help seeking, such as immediate answers, low self-esteem threats, and the potential of reaching bigger professional communities (Kozanitis, Desbiens, & Chouinard, 2007; Ryan & Shin, 2011). It is, therefore, crucial for educators and researchers to better understand how to facilitate students' online help seeking, which necessitates the exploration of the potential factors influencing online help seeking.

This study aimed to explore how college students majoring in computer science seek help online and the effect of achievement goals on their online help-seeking behavior. Although prior studies have established a strong link between achievement goals and face-to-face help seeking in classroom contexts (e.g., Butler & Neuman, 1995;

Cheong, Pajares, & Oberman, 2004; Roussel, Elliot, & Feltman, 2011), research on the relationship between achievement goals and online help seeking is still lacking. Therefore, there is a gap in the existing literature examining whether findings in classroom contexts can be extended to online contexts.

4.2 Literature Review

4.2.1 Online Help Seeking

As a cognitive skill that manifests self-regulated learning, help seeking involves a set of actions, such as being aware the need of help, identifying problems and potential helpers, and forming questions to solicit help (Aleven, McLaren, Roll, & Koedinger, 2006; Karabenick, 2003; Newman, 2008). Online help seeking, as a subcategory of help seeking, refers to help seeking that is aided by online tools, such as emails or question & answer forums.

Seeking social assistance from other people was traditionally understood as the only form of help-seeking behavior (Zimmerman & Pons, 1986; Ryan, & Pintrich, 1997). As a result, information seeking, such as online searching, was not classified as a type of help seeking. Nevertheless, the boundary between seeking information and social assistance has been blurred with the development of Internet technology. Interaction with machines, such as search engines, for help-seeking purposes has become ubiquitous in teaching and learning. Although Puustinen and Rouet (2009) and Cheng and Tsai (2011) suggested that online searching should be classified as a type of online help seeking, evidence supporting such a claim is still lacking.

4.2.2 Achievement Goals

Achievement goals refer to goals or aims set by students, which guide their competence-relevant behaviors (Karabenick, 2004; Roussel, et. al, 2011). The features of competence and valence have been highlighted as significant in distinguishing achievement goals (Elliot & McGregor, 2001; Yang & Cao, 2013). On the one hand, competence distinguishes mastery-goals from performance-goals. Mastery-goals guide learners to emphasize the mastery of learning contents, while performance-goals orient learners to focus on self-competence relative to others (Dweck, 1986; Elliot & Church, 1997). On the other hand, valence differentiates achievement goals from the aspect of approach and avoidance. Learners with approach-goals focus more on achieving positive results, such as good academic performance, whereas learners with avoidance-goals usually try to avoid negative results (Cury, Elliot, Da Fonseca, & Moller, 2006; Huet, Escribe, Dupeyrat, & Sakdavong, 2011). The features of competence and valence classify achievement goals into four categories: mastery-approach, performance-approach, mastery-avoidance and performance-avoidance goals (see Figure 4.1). This classification is also referred as 2*2 achievement goal framework (Elliot & McGregor, 2001; Huet, et. al, 2011).

Figure 4.1. 2*2 Achievement Goal Framework.

The relationship between achievement goals and help seeking has been studied extensively in classroom learning contexts (e.g., Butler & Neuman, 1995; Cheong, et. al., 2004; Huet, et. al, 2011; Roussel, et. al, 2011; Skaalvik & Skaalvik, 2005; Yang, & Cao, 2013). It was found that students with higher mastery-approach goals tend to seek help more frequently in mathematics, computer science, and experimental problem-solving environments (e.g., Butler & Neuman, 1995; Cheong, et. al., 2004; Skaalvik & Skaalvik, 2005). Conversely, students with higher performance-avoidance goals were found more likely to actively avoid help seeking (e.g., Roussel, et. al, 2011; Skaalvik & Skaalvik, 2005). However, contradictory results were found regarding the effect of other two types of achievement goals on students' tendency of help seeking. For example, Ryan and Pintrich (1997) found that performance-approach and mastery-avoidance goals were negatively related to students' tendency of help seeking, while Tanaka, Murakami, Okuno and Yamauchi (2001) found the opposite results. Cheong and his colleagues

(2004) also found that performance-approach goals were unrelated to students' tendency of help seeking.

Nevertheless, research is still lacking in testing the relationship between achievement goals and help seeking in *online* contexts. This is a notable omission given that online help seeking is intrinsically different from face-to-face help seeking in classroom contexts. Firstly, many factors key to face-to-face help seeking are less important for online help seeking, such as the ability to identify potential helpers, and self-esteem threats (Karabenick, 2003; Kumrow, 2007). Secondly, new and significant challenges are posed by online help seeking. Search engines are more limited in adapting to students' questions than human helpers, so students who have difficulties in devising accurate queries may fail to solicit relevant information from search engines (Tabatabai & Shore, 2005). In addition, asynchronous communication on question & answer forums with other online users can be prone to misunderstandings and thus may not yield the desired information (Rovai & Jordan, 2004). Reflecting on these issues, more studies are needed to explore whether prior research findings in classroom contexts can be extended to online contexts.

4.3 Research Questions

The research questions that guided this study were:

1. How do computer science students seek help online?
2. How do achievement goals influence computer science students' online help-seeking tendency in terms of online searching, asking teachers online for help, and asking peers or unknown people online for help?

4.4 Research Design

4.4.1 Participants

Data were collected from four different computer science courses in a large research university in the south-eastern United States. 165 undergraduate students agreed to participate in this study. Participants were predominantly male (88.5%) and lower-level undergraduates (84.8%). All four courses implemented Piazza (https://piazza.com/) for students to ask questions to other peers, teachers, or teaching assistants. Teachers and teaching assistants were also accessible for questions through email. Each course evaluates students by their performances on a) Individual tasks, b) Individual projects, c) Group projects, and d) midterm and final exams.

4.4.2 Instrument

A survey was used to measure participants' achievement goals and the frequency of online help seeking. The survey was distributed to all participants and it was required that all questions were answered. The survey is composed of two parts: Achievement Goal Questionnaire-Revised (AGQ-R) and Online-Help-Seeking Measures. The AGQ-R developed by Elliot and Murayama (2008) measures four aspects of achievement goals, including mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance goal commitment. Online Help-Seeking Measures (see Appendix B) developed by the authors included three questions measuring online help seeking. Based on the studies of Puustinen and Rouet (2009) and Cheng and Tsai (2011), three aspects of online help seeking were measured, including searching, asking teachers, and asking peers or unknown experts online for help. A four-point Likert scale was used for all survey questions.

4.4.3 Data Analysis

Descriptive data analysis and permutation tests were applied to answer the first research question "*How do computer science students seek help online?*". Confirmatory Factor Analysis (CFA) was conducted to validate the measurements of achievement goals survey, and covariance-based Structural Equation Modeling (SEM) was further applied to explore the relationships among achievement goals and online help seeking behaviors, aiming at answering the second question "*How do achievement goals influence computer science students' online help-seeking tendency in terms of online searching, asking teachers online for help, and asking peers or unknown people online for help*?".

4.5 Results

4.5.1 Online Help Seeking of Computer Science Students

Data from all 165 participants were collected. Table 4.1 presents the descriptive summaries of students' online-help seeking behaviors. Permutation tests were used to examine differences among three online help seeking behaviors of all students. The result indicated that the students searched online [Mean (total) = 3.39] more frequently than they asked peers or unknown experts online for help [Mean (total) = 2.82] (Difference between Means = .57, $p < .01$). In addition, the students asked peers or unknown experts online for help significantly more frequently than they asked teachers for help online [Mean (total) = 2.20] (Difference between Means = .62, $p < .01$).

Table 4.1

Descriptive analysis of online help seeking (Means and Standard Deviation of the response levels from Likert-Scale survey questions; response levels coded from 1 to 4).

	Lower-level undergraduates		Higher-level undergraduates		Total	
	Mean	SD	Mean	SD	Mean	SD
Online searching	3.36	0.71	3.56	0.57	3.39	0.69
Asking teachers online for help	2.16	0.88	2.44	0.87	2.20	0.88
Asking peers or unknown experts online for help	2.84	0.95	2.72	1.02	2.82	0.96

4.5.2 Influence of Achievement Goals on Online Help Seeking

CFA was applied to the twelve items of achievement goals, using maximum likelihood estimations on the covariance matrix. Four indexes were used to evaluate the model fit to the data, including chi-square degree of freedom ratio (χ^2/df), comparative fit index (CFI), incremental fit index (IFI), and root-mean-square error of approximation (RMSEA). The results of the four indexes (χ^2/df = 1.68, CFI = .95, IFI = .95, RMSEA = .06) indicated that the model fit was acceptable. Cronbach's alpha of the four achievement goal factors and correlational coefficients of all variables are presented in Table 4.2. A Cronbach alpha coefficient as low as 0.55 can be deemed as accepted for social science research (Hatcher & Stepanski, 1994). Therefore, the measurement of achievement goals in this study is deemed to be sufficiently reliable.

Table 4.2

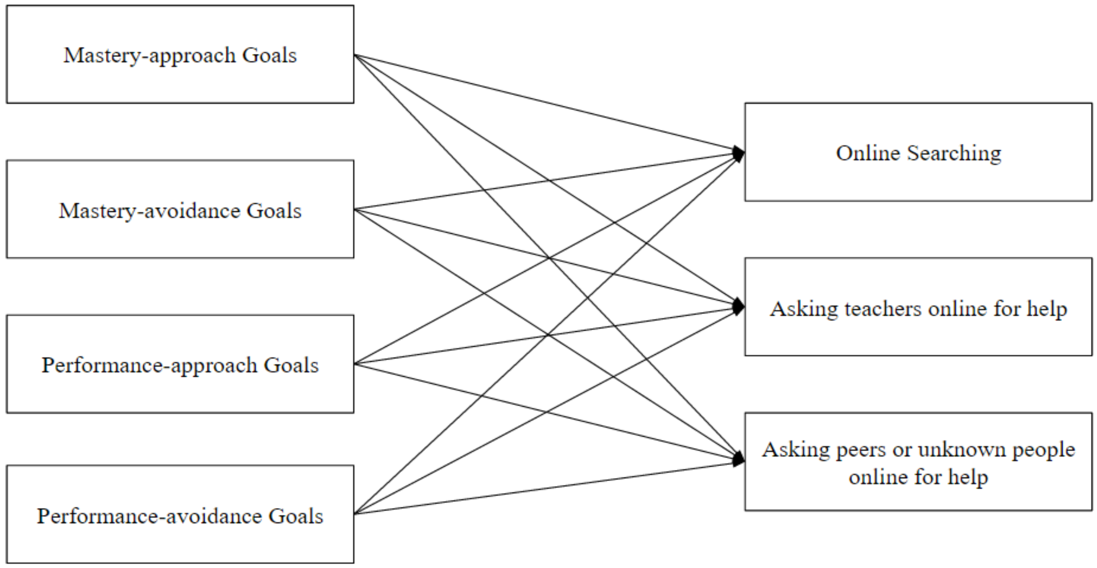
Cronbach's a and Correlational Coefficients of main variables (N = 165).

	Cronbach's a	1	2	3	4	5	6
OnlineSearch							
OnlineTeacher		-0.04					
OnlinePeer		.217**	.282**				
PAP	0.87	-0.08	0.01	0.07			
PAV	0.54	0.10	.173*	.262**	.302**		
MAV	0.80	0.13	0.15	.213**	0.00	.804**	
MAP	0.67	-0.10	-0.03	-0.01	.305**	0.13	0.08

OnlineSearch – online searching for help seeking; OnlineTeacher – Asking teachers online for help; OnlinePeer – Asking peers or unknown people online for help; PAP – Performance-approach goals; PAV – Performance-avoidance goals; MAV – Mastery-avoidance goals; MAP – Mastery-approach goals.
*p < .05, **p < .01.

Correlational analysis showed that there were positive associations between performance-avoidance goals and asking teachers online for help ($r = .17$, $p < .05$), performance-avoidance goals and asking peers online or unknown experts for help ($r = .26$, $p < .01$), and mastery-avoidance goals and asking teachers online for help ($r < .21$, $p < .01$). However, all the significant correlation coefficients were below .30, which indicated little or no correlation between the associated variables (Calkins, 2005).

Covariance-based SEM was applied to further explore the relationship between the four types of achievement goals and the three types of online help seeking. The hypothesized model of achievement goals on online help seeking is presented in Figure 4.2. The testing results (χ^2/df = .76, CFI = 1.00, IFI = 1.00, RMSEA = .00) indicated a high model fit of the hypothesized model to the data.



(a)

Figure 4.2. Proposed model of achievement goals on online help seeking.

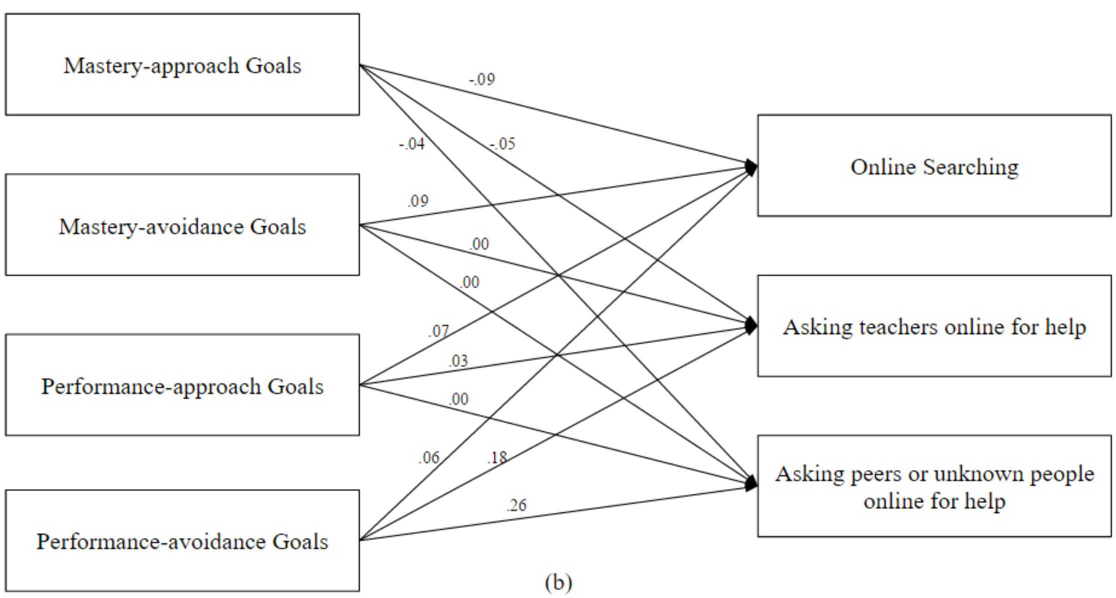


Figure 4.3. Standardized coefficients of achievement goals on online help seeking from the regression analysis.

Contrary to the findings of previous studies (e.g., Cheong, et. al., 2004; Roussel, et. al, 2011; Yang, & Cao, 2013), no factors of achievement goals were found to be significant in predicting any type of online help seeking (see Figure 4.3). The four factors, including mastery-approach, performance-approach, mastery-avoidance, and performance-avoidance goals, explained 5.00 % variance ($R^2 = .07$, $R^2_{adj} = .05$, $p < .05$) of asking peers or unknown experts online for help in total, but were not found to be significant in predicting online searching ($R^2 = .03$, $R^2_{adj} = .01$, $p > .05$) or asking teachers online for help ($R^2 = .03$, $R^2_{adj} = .01$, $p > .05$).

4.6 Discussion

4.6.1 Online Help Seeking of Computer Science Students

A core finding of this study was that computer science students searched online for help-seeking purposes significantly more frequently than they asked teachers, peers or unknown experts online. This finding contributes to the existing research literature on help seeking by a) demonstrating that online searching plays a major role in computer science students' online help seeking, and b) providing direct evidence supporting the notion that online searching should be considered as a type of help-seeking behaviors (Puustinen & Rouet, 2009).

Online searching was traditionally understood as a topic that should be addressed by other academic fields, like information search (Zimmerman & Pons, 1986). Yet, the findings of this study demonstrate that the boundary between seeking social assistance and information searching has become blurred at least for computer science students, which calls for more research from educational perspectives on online searching in learning and teaching of more fields.

4.6.2 Influence of Achievement Goals on Online Help Seeking

The need to encourage students to seek help online for learning problems is becoming increasingly urgent as student-to-teacher ratios and online-course enrollment rates continue to escalate (Allen & Seaman, 2013; Yang & Cao, 2013). Notably, the findings of this study indicate that achievement goals may not be the right starting point to approach this problem, at least not for computer science students, although the connection between achievement goals and face-to-face help seeking is well established.

In contrast to the findings of most studies on face-to-face help seeking (e.g., Cheong, et. al., 2004; Roussel, et. al, 2011; Skaalvik & Skaalvik, 2005), this study found limited correlation between achievement goals and online help seeking. None of the four types of achievement goals were found to be significant in predicting any online help-seeking behaviors of computer science students. A possible explanation is that there are significantly fewer barriers for students to seek help online than to seek face-to-face help, so motivations do not play an important roles in online help seeking. The results of this study indicated that findings on face-to-face help seeking should not be assumed naturally extendable to help seeking in online environments (Aleven, et. al., 2003; Puustinen & Rouet, 2009). Therefore, future studies may need to consider careful examination of the effect of predictors deemed as important to face-to-face help seeking on online help seeking. Furthermore, to better answer questions about how to encourage students to effectively seek help online, more explorative research on online help seeking is essential.

4.7 Limitations

The present study is not without limitations. Firstly, all participants of this study were studying computer science. Whether the findings of this study can be generalized to a bigger population, such as college students across a wider range of disciplines, needs further examination. Secondly, all participants of this study came from the same school. The cultural norm of individual schools may promote different foci in terms of achievement goals, and limit the generalization of the results. Thirdly, this study focused exclusively on students' tendency to seek help online. Future research may consider studying the differences between instrumental and executive online help-seeking behaviors, which will serve as guidance for effective online-help seeking facilitation (Cheong, et. al., 2004; Huet, et. al, 2011). Lastly, Online Help-Seeking Measures used three single questions to measure students' three types of online help seeking behaviors, which may not be individually reliable. Future studies may consider using multiple questions to measure each type of students' online help seeking.

4.8 Conclusion

Online help seeking is becoming an increasingly important help-seeking approach for college students to succeed in their academic studies. This research adds to the emerging literature on online help seeking by a) providing direct evidence to support the role of online searching as an integral part of online help seeking and b) demonstrating that findings on the relationship between achievement goals and face-to-face help seeking are not extendable to online help seeking. The findings of this study necessitate further investigation of potential predictors of online help seeking.

CHAPTER 5

AUTOMATIC LEARNING QUESTION CLASSIFICATION BY RELEVANCE AND EFFICACY WITHIN THE CONTEXT OF LARGE-SCALE CLASSES[3]

[3] Hao, Q., Galyardt, A., Barnes, B., Lu, J., Branch, M. R., Wright, E. & Wong, M. (2016) Automatic Learning Question Classification by Relevance and Efficacy within the Context of Large-Scale Classes. Submitted to Computers & Education, 11/15/2016.

Abstract

This study explored the automatic learning question classification in the context of a large-scale computer science class. To achieve this, 983 questions were collected from a question & answer platform implemented by an introductory programming course over four semesters in a large research university in the Southeastern United States. Questions were firstly manually classified into three hierarchical categories: 1) learning-irrelevant questions, 2) effective learning-relevant questions, 3) ineffective learning-relevant questions. The inter-rater reliability of the manual classification (Cohen's Kappa) was .88. Four different machine learning algorithms were then used to automatically classify the questions, including Naive Bayes Multinomial, Logistic Regression, Support Vector Machines, and Boosted Decision Tree. Both flat and single path strategies were explored, and the most effective algorithms under both strategies were identified and discussed. This study brings new insights to old educational problems, by being the first to explore learning question classification by relevance and effectiveness.

5.1 Introduction

Help seeking is essential for college students to achieve academic success. As an important cognitive skill, help seeking has been associated with a capacity for self-regulated learning (Lee, 2007; Roll, Aleven, McLaren & Koedinger, 2011). However, students often encounter significant barriers when seeking help in classroom contexts, such as difficulties in finding helpers, self-esteem threats or a lack of self-confidence (Kozanitis, Desbiens, & Chouinard, 2007; Ryan & Shin, 2011).

As web technologies, such as online question & answer (Q & A) platforms and search engines, are integrated in learning and teaching, students can now easily seek help online. Online help seeking offers some distinct advantages over help seeking in classroom contexts, such as low self-esteem threats, instant answers from search engines, and help from significantly larger professional communities (Karabenick, 2003; Kozanitis, Desbiens, & Chouinard, 2007). Despite this, distant experts reading questions on a Q & A platform or search engines are unlikely to be as adaptable as face-to-face interactions in solving problems. Notably, if learners fail to provide effective questions, they are not likely to receive helpful answers. Therefore, it is especially important for learners to ask effective and relevant questions when seeking help online.

Online Q & A platforms have been implemented in many universities for answering questions in large-scale courses. While this should be a great opportunity to help college students ask better questions, this job can easily go beyond the capacity of course instructors. For instance, if every student asks only one question on a large project from a class with 200 students, it may take more than a week for the instructor and teaching assistants to reply to each of them. For many large-scale classes, instructors could barely find time answering students' questions on Q & A platforms, let alone giving guidance on improving students' help seeking skills (e.g., Maderer, 2016 May). However, previous studies have shown that students do need help in terms question asking (Cheng & Tsai, 2011; Hao, et al., 2016 April).

If Q & A platforms can automatically detect if questions are relevant to learning and effective, and provide adaptive suggestions for ineffective learning questions accordingly, they may have great potential to improve the efficacy of students' questions. The key challenge to this, however, is the automatic detection of learning relevance and efficacy of a question. Responding to this challenge, this study explores automatic question classification by standards of learning relevance and efficacy.

5.2 Literature Review

The traditional thinking on improving students' help seeking skills focused on what factors are most important to help seeking, and investigating proposed intervention strategies on the most significant factors (Bartholome, et al., 2006; Karabenick, 2003; Newman, 2008). However, such studies (e.g., Bartholome, et al., 2006; Kessels & Steinmayr, 2013; Kitsantas & Chow, 2007) were mostly limited to face-to-face help seeking. Besides, such a strategy may not scale up very well to large-scale classes or learners of massive open online course, given the heavy teaching loadings of instructors and other constraints. Hao et al. (2016a) and Hao et al. (2017) explored major factors important to face-to-face help seeking on online help seeking, and found that major factors important to face-to-face help seeking, such as achievement goals and interests, were not equally significant to online help seeking, which indicated that either new factors need to be examined or different thinking and solutions are in need to improve students' online help seeking skills.

A series of studies on improving help seeking skills within intelligent tutor systems have been conducted in the last decade (e.g., Aleven, et al., 2006; Roll, et al., 2011; Vaessen & Jeuring, 2014; Walker, Rummel, & Koedinger, 2014). Despite of their significant findings on how to better students' interaction between students and tutor systems, help seeking in tutor systems is essentially different from that in open environment. For most tutor systems examined in prior studies (e.g., Aleven, et al., 2006; Roll, et al., 2011), helper functions, including on-demands hints and glossaries, were provided side by side of the given learning problems. Students' help seeking in such a closed environment is much simplified. To seek help online in open environments, students need to diagnose problems, organize thinking and languages, and form questions. In contrast, answers or help are just mouse-click away in tutor systems, and all the cognitive labors demanded by open environments are usually not in need when seeking help in tutor systems. Although the studies on help seeking in tutor systems did not directly respond to the challenges of improving students' online help seeking skills, they shed some lights on different thinking of tackling this challenge scalably, which is using the interaction between machines and human beings.

Investigating automatic question classification by relevance and efficacy makes question classification the core of this study. Although question classification has been studied intensively, most studies focused on classifications by topics (e.g., Blunsom, Kocik, & Curran, 2006; Qu, et. al., 2012; Zhang & Lee, 2003), semantic functions (e.g., Bu, Zhu, Hao, & Zhu, 2010; Mohler & Mihalcea, 2009) and facts & opinions (e.g., Aikawa, Sakai, & Yamana, 2011; Yu, & Hatzivassiloglou, 2003). Few studies have examined automatic question classification from educational perspectives. Yahya and Osman (2011, December) explored question classification by Bloomberg taxonomy using support vector machine. Kumar, et al. (2005) investigated learning question classification by semantic functions. To our best knowledge, this study is the first to explore automatic question classification from the perspective of relevance and effectiveness.

5.3 Research Purposes

This study serves the ultimate goal of helping improve the efficacy of students' questions on Q & A platforms automatically by investigating the automatic question classification by relevance and effectiveness in the context of large-scale classes. The two specific questions that guided this study are as followings:

1. How do students perform on asking questions on Question & Answer platforms in terms of 1) learning relevance, 2) question efficacy?
2. To what degree of accuracy can we identify computer science students' ineffective learning-relevant questions using hierarchical text classification?

Most importantly, if ineffective learning questions can be detected automatically, Q & A platforms can be modified to give adaptive suggestions to students who ask the ineffective questions, so students can revise their questions accordingly and solicit better answers. This process will help students learn how to ask better learning questions. Besides, students taking the same course in different semesters tend to ask same or similar learning questions. If good learning questions asked previously can be identified, they can be fixed in the Q & A platform for all current and future students to view.

Therefore, students can learn from good questions and their answers directly. In addition, they do not need to ask the same questions again and again.

5.4 Research Design

5.4.1 Data Collection

Longitudinal data was collected from an entry-level programming course in a large research university in the southeastern United States. The course typically has more than 150 enrolled students every semester. An online Q & A platform, Piazza (see Figure 5.1), was implemented by this course for students to ask questions to and answer questions from each other. The data collected in this study are text data, including students' questions asked on Piazza in four different semesters from fall in 2013 to spring in 2015. Although the course was taught by different instructors in each semester, the syllabus, course requirements, and contents of the course remained unchanged during this period.

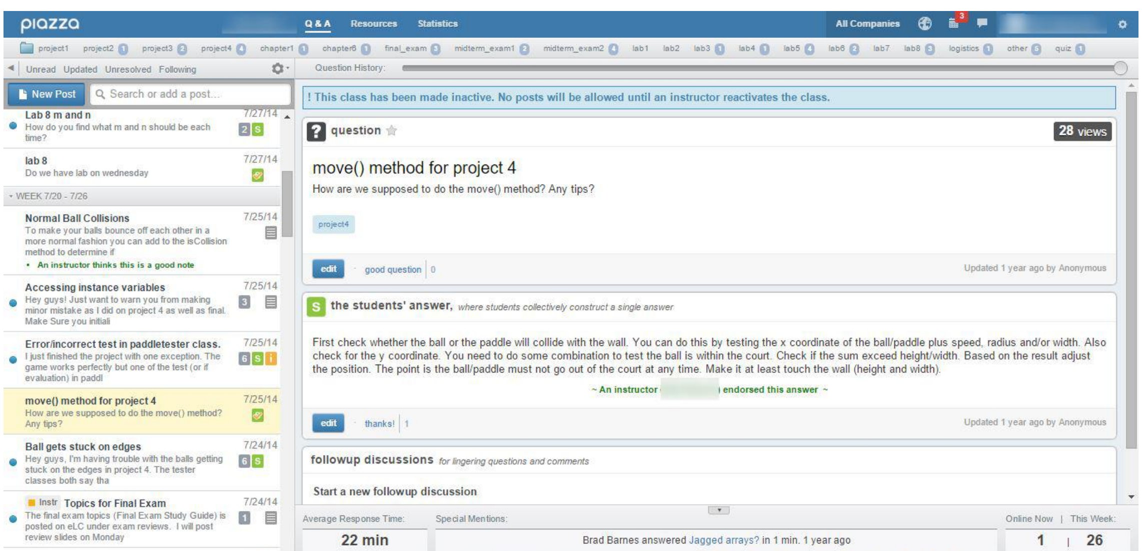


Figure 5.1. Interface of Q & A Platform Piazza (https://piazza.com).

5.4.2 Manual Classification by Human Experts

In total, 983 questions were collected. The question data come without class information. In order to explore the performance of automatic classification using machine learning algorithms, the collected questions were manually classified firstly. The manual classifications were used as the target values for machine learning algorithms.

The questions were classified hierarchically by trained graduate students majoring in computer science by two standards: 1) learning-relevance, 2) question efficacy (see Figure 5.2).

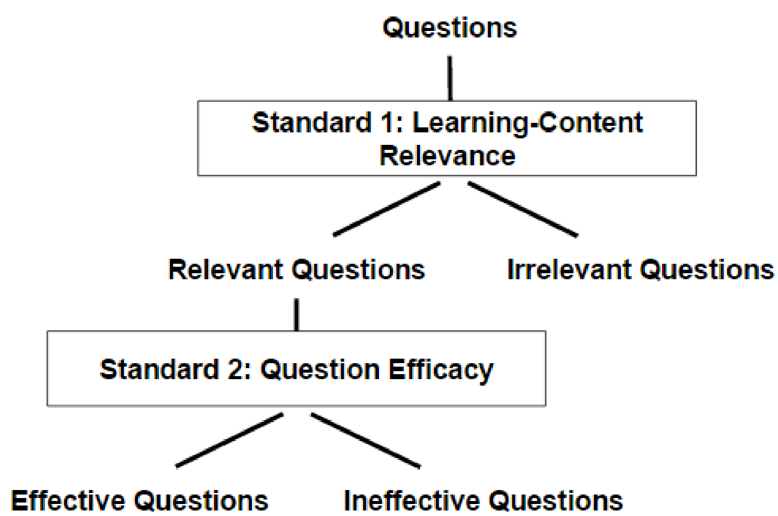


Figure 5.2. The Structure of Manual Hierarchical Classification.

The idea of learning-relevance is self-explanatory. Students may ask questions relevant to learning, but may also ask about due dates of homework or teaching assistants' email addresses. Learning-relevant questions asked in one semester will still be of value to students enrolled in the same course in future semesters. In contrast, learning-irrelevant questions have much less value. As for all learning-relevant questions, we further classified them into effective and ineffective questions. The classification rubrics for question efficacy are presented in Table 5.1. The coding and classification of a sample question is presented in Table 5.2.

Table 5.1

Classification Rubrics of Students' Questions.

Rubrics	Rationales
Whether the question is easily searchable	Answers to questions on definitions, terms, or usage of default functions can be immediately retrieved using either search engines or textbooks. Asking similar questions and waiting for answers are not good for just-in-time learning (Schmidt-Jones, 2012). Therefore, if a question is easily searchable, it is considered ineffective.
Whether there is evidence of prior efforts	Prior efforts in problem solving before asking questions are strongly associated with strong capability in self-regulated learning (Puustinen, Bernicot, Volckaert-Legrier, & Baker, 2015). Questions emerging after problem-solving efforts are more likely to benefit learners and others. Therefore, if there is evidence of prior efforts in a question, it is considered effective.
Whether the question is asking for direct answers	Asking for a direct answer is usually deemed as executive help seeking, which indicates a lack of learning desire and wish for expedient task completion (Newman, 2008). Therefore, a question asking for direct answers is considered ineffective.
Whether the question is specific	If a question does not provide sufficient information for others to understand, it is unlikely to solicit helpful answers. Therefore, a question that is not specific enough is considered ineffective.

Each question was classified by at least two trained students independently. If a question was classified differently, the classification of that question would be further rated by a third person. The inter-rater reliability (Cohen's Kappa) is .88.

Table 5.2

A Sample of Coding and Classification for One Question.

Rubrics	Question
	"I am having *a stupid amount of trouble trying* [2] to get the code to produce a random word. I'm not really sure *what I'm doing wrong* [2], but I'm probably not putting the RandomWord.java file into eclipse the right way or something. Can anyone give me *some more specific, streamlined instructions* [3] for where to download the file and how to call upon the RandomWord.newWord() method? For reference, what I tried to do was simply download the .java file into the src folder of *my Goomba java project* [1], and then I tried to retrieve a word with the line: String secretWord = RandomWord.newWord(); Eclipse red underlines RandomWord and suggests that I create class 'RandomWord'. I've tried a few different things but haven't figured anything out, so I decided that I should ask for help here." [4]
Is easily searchable (1)	Yes
Has evidence of prior efforts (2)	Yes
Is asking for direct answers (3)	No.
Is specific (4)	Yes

** This question was classified as effective learning-relevant.*

5.4.3 Automatic Classification using Machine Learning Algorithms

Both flat strategy and single path strategy were used for hierarchical classification in this study. Flat strategy builds a classifier for the all the leaf nodes without considering hierarchical structure (Yang & Pedersen, 1997). In contrast, single path strategy builds different classifiers hierarchically at different levels, and allows only one path from the root to a leaf node when testing the classifiers on a question (Qu, et. al., 2012).

Four machine learning algorithms were applied as the classifiers on both levels in this study, including Naive Bayes Multinomial (NBM), Decision Tree (DT), Logistic Regression (LG), and Support Vector Machines (SVM). Ensemble learning using the boosting method was used to stabilize the classification results of Decision Tree, given the inherent instability in its schema. The process of automatic classification using the four machine learning algorithms is presented in Figure 5.3.

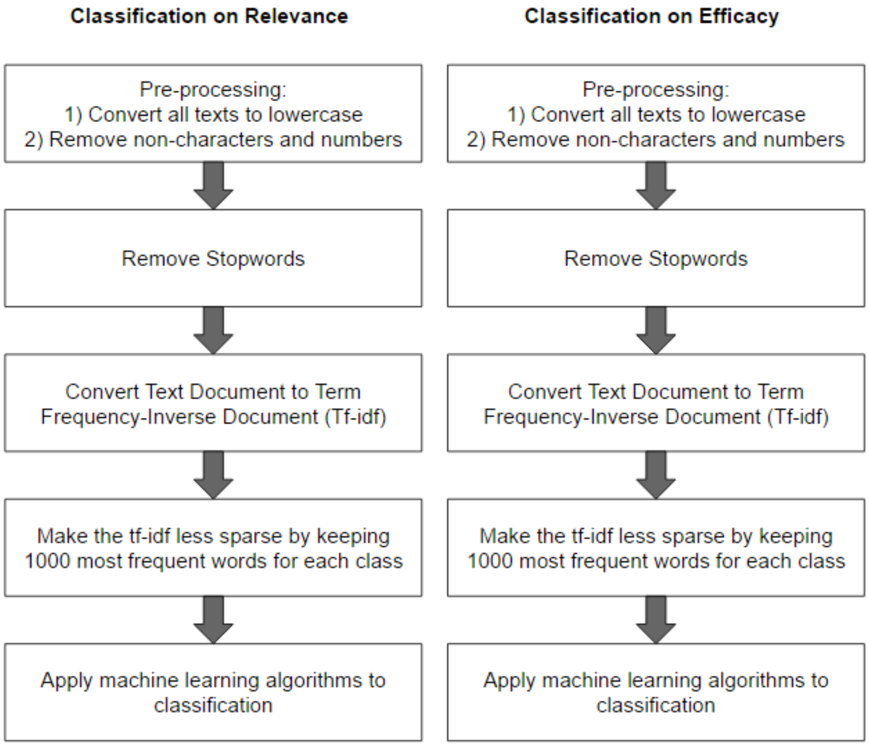


Figure 5.3. Process of Automatic Classification.

5.5 Results

5.5.1 Students' Performance on Question Asking in Terms of Relevance and Efficacy

The performance of the students on question asking in terms of relevance and efficacy was determined through manual classification. 983 questions in total were classified hierarchically into the following three categories:

1. Learning-irrelevant questions
2. Effective learning-relevant questions
3. Ineffective learning-relevant questions

240 out of 983 questions were classified as learning-irrelevant, while 743 questions classified as learning-relevant. Among the 743 learning-relevant questions, 366 were classified as effective, and 377 ineffective (see Figure 5.4).

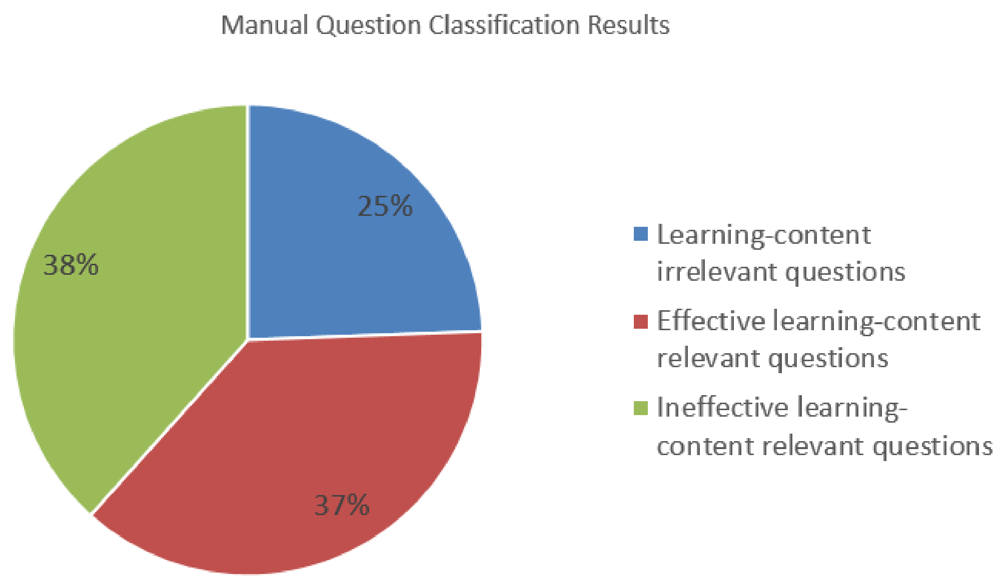


Figure 5.4. Manual Question Classification Results.

5.5.2 Automatic Classification using Machine Learning Algorithms

Recall of the questions classified as both ineffective and learning-relevant was selected as the primary evaluation criteria, and F1-score was selected as the secondary evaluation criteria in this study. The rationale of the evaluation criteria selection are the followings:

1. The primary research goal of this study is to explore whether ineffective learning-relevant questions can be identified, so Q & A platforms can give automatic adaptive suggestions. Therefore, selecting as many ineffective and learning-

relevant questions as possible is more of our interest than achieving an overall high accuracy.

2. Imbalance existed in different classes in our results, and F1 score can provide a more comprehensive and combinatory evaluation in such cases.

5.5.2.1 Application of Flat Strategy in Hierarchical Classification

Flat strategy builds a classifier for the all leaf nodes without considering hierarchical structure. The application of this strategy in our study is presented in Figure 5.5. We applied the four machine learning algorithms to the classification of question relevance on 968 questions directly. Following this, ten-fold cross validation was used in all classifications to derive the classification measurements.

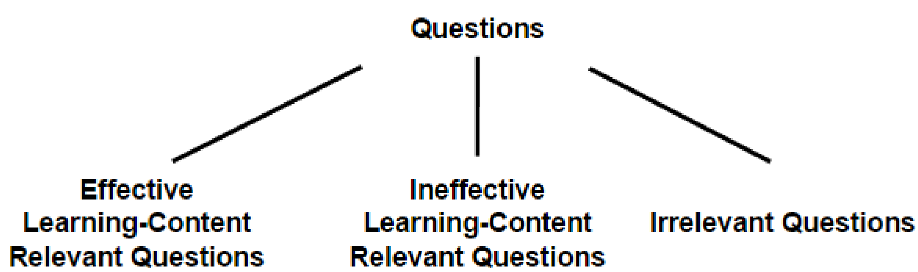


Figure 5.5. Application of Flat Strategy in Question Classification.

The classification comparisons of the four machine learning algorithms are presented in Table 5.3. SVM is identified as the most effective algorithm by evaluating F1-score. The recall and F1-score of SVM for identifying ineffective learning-relevant questions are .864 and .601 separately.

Table 5.3

Measurements of Question Classification Using Flat Strategy.

Algorithm	Base-rate Accuracy	Identification of Ineffective Learning- Irrelevant Questions		
		Recall	Precision	F-Measure
Support Vector Machine	.536	.864	.460	.601
Boosted Decision Tree	.532	.527	.483	.504
Naive Bayes Multinomial	.590	.436	.526	.477
Logistic Regression	.517	.447	.459	.453

Number of all questions: 968, Number of learning-irrelevant questions: 228, Number of effective learning-relevant questions: 364, Number of ineffective learning-relevant questions: 376.

5.5.2.2 Application of Single Path Strategy in Hierarchical Classification

Single path strategy builds different classifiers hierarchically at different levels, and allows only one path from the root to a leaf node when testing the classifiers on a question. The application of this strategy in our study is presented in Figure 5.6. Four machine learning algorithms were applied to classification at both relevance and efficacy levels. Ten-fold cross validation was used in all classifications to derive the classification measurements.

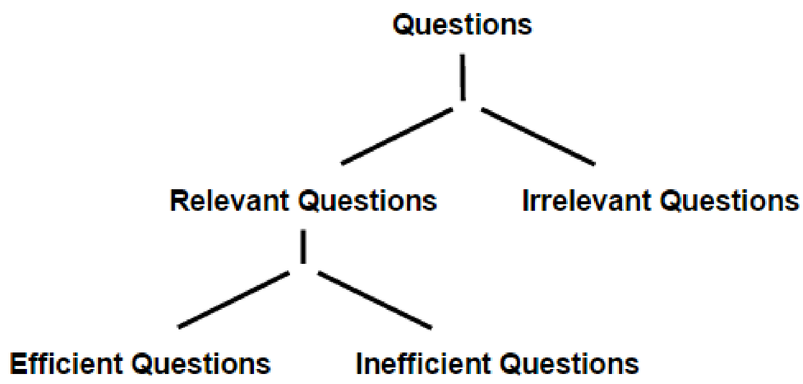


Figure 5.6. Application of Single Path Strategy in Question Classification.

The classification comparisons on the first level, learning-relevance, are presented in Table 5.4. NBM is identified as the most effective algorithm. The recall and F1-score of NBM for identifying learning-relevant questions are .950 and .936 separately.

Table 5.4

Measurements of Classification on Question Relevance Using Single Path Strategy.

Algorithm	Identification of Learning-Relevant Questions			
	Accuracy	Recall	Precision	F-Measure
Naive Bayes Multinomial	.901	.950	.923	.936
Support Vector Machine	.860	.932	.889	.910
Boosted Decision Tree	.840	.931	.869	.899
Logistic Regression	.789	.872	.855	.863

Number of all questions: 968, Number of learning-irrelevant questions: 228, Number of learning-relevant questions: 740.

737 questions were classified as learning-relevant using the model derived from NBM algorithm, including 17 actually irrelevant questions and 720 true relevant questions. The 720 true relevant questions are composed of 360 effective questions and

360 ineffective questions (see Figure 5.6). We further applied the four machine learning algorithms to the 737 questions for efficacy classification. The classification comparisons on question efficacy are presented in Table 5.5. SVM is identified as the most effective algorithm. The recall and F1-score of SVM are .847 and .664 separately.

Table 5.5

Measurements of Classification on Question Efficacy Using Single Path Strategy.

Algorithm	Identification of Ineffective Learning-Irrelevant Questions			
	Accuracy	Recall	Precision	F-Measure
Support Vector Machine	.578	.847	.547	.664
Logistic Regression	.556	.547	.593	.569
Boosted Decision Tree	.531	.564	.527	.545
Naive Bayes Multinomial	.493	.350	.563	.432

Number of questions classified as learning-irrelevant : 737. Among the 737 questions: Number of learning-irrelevant questions: 17, Number of effective learning-relevant questions: 360, Number of ineffective learning-relevant questions: 360.

5.6 Discussion

The manual classification results showed that 38% of the asked questions were ineffective, while 37% of the questions were effective. This result concurred with literatures that novice learners of computer science do indeed need guidance and help to improve their help-seeking skills (Cheng & Tsai, 2011; Hao, et al., 2016 April). Particularly, there is a pressing need to better understand how to support students in improving their capacity for asking effective questions on online Q & A platforms.

Both flat and single path strategies were explored in this study. The most effective algorithm under the flat strategy was identified as SVM. In comparison, the most effective algorithm combination under the single path strategy was identified as NBM and SVM. In summary, both strategies were able to identify around 85% of all ineffective learning-relevant questions. This is the key step that allows a Q & A platforms to provide further adaptive suggestions on question revisions, and the results of this study justified further implementation of adaptive suggestion revision function in Q & A platforms and investigation of its empirical efficacy.

The identification of ineffective questions (Recall: 84.7%; Accuracy Rate: 57.8%) was far from satisfactory. The low accuracy might be due to the definition of effective questions as an umbrella concept composing multiple rubrics. Future studies may consider using the rubrics individually instead of the umbrella efficacy concept to further improve the accuracy.

5.7 Limitations

The present study is not without limitations. Firstly, this study was within one large-scale computer science class. Whether similar results can be found in other large-scale classes and other contexts using the same methods need further investigation. Secondly, how to further improve the overall accuracy of the automatic classification need to be investigated. Future studies may consider experimenting with a wider range of classification methods, such as ensemble approaches and neural networks. In addition, N-gram features and special stopwords for questions (e.g., Zhang & Lee, 2003) may be explored.

5.8 Conclusions

Online help seeking is becoming an increasingly critical skills for college students to succeed academically as massification continues to transform higher education. This study contributes to the emerging literature on online help seeking by (1) proposing and exploring helping students ask better questions using machine learning techniques, and (2) demonstrating that results on the automatic question classification using two strategies and four machine learning algorithms. To build on the findings of this study, we call for more research to further investigate the potential of automatic learning question classification.

CHAPTER 6

CONCLUSION AND FUTURE STUDY DIRECTIONS

Overall, the major contributions of this dissertations include:

1. A systematic classification of help seeking
2. Evidence of how computer science students seek help online in terms of frequency and efficacy
3. Understanding of the extent to which factors important to face-to-face help seeking influence online help seeking.
4. Exploration of automatic question classification by learning-relevance and efficacy

Beyond the contributions, there are a number of future work items in both learning theories and practice, such as implementing rule-based chat bot that can be plugged into a question & answer platform, and constructing question & answer platforms that can respond to the scenarios when a questions is classified as learning-relevant and ineffective. This section focuses on issues and problems that require more research.

6.1 Generalization

Although the survey results from the studies described in Chapter Three and Chapter Four were found statistically reliable, the samples of the surveys all came from a single university in southeastern United States. To fully confirm the findings in these studies, it is necessary to replicate these studies on computer science students from different universities in different regions.

6.2 Classification Strategy

The classification on question efficacy is a challenging task for machine learning algorithms to perform well. The study described in Chapter Five managed to reach a very good accuracy in terms of the classification between learning and routine questions, but the result on the question efficacy classification was less than satisfying. Although more machine learning algorithms could be applied to this problem, alternative strategies should also be considered in the future.

One thing that needs to be noted is that the general concept of question efficacy is easy for human beings to understand and communicate, but not necessarily for machines. Question efficacy is a compound concept consisting of four individual standards (see Chapter Five), including:

1. Whether the question is easily searchable
2. Whether there is evidence of prior efforts
3. Whether the question is asking for direct answers
4. Whether the question is specific

In comparison with the general question efficacy, each individual standard might be possibly much easier for machine learning algorithms to perform well. Focusing on the classification in terms of each individual standard has the potential of boosting the classification accuracy, and could also make it easier for machines to provide adaptive suggestions accordingly.

6.3 Time-Efficient Manual Question Classification Scheme

We foresee a major challenge of designing an effective course-based intelligent question & answer platform that need more research in the future, which is in terms of manual question classification. To fully automate the platform, a more time-efficient manual question classification scheme is in need. A possible solution would be a democratic voting system, which requires each student to classify several questions every time when he or she logs into the platform (Cheng, et al., 2014; Draper & Brown, 2004). More research are in need to investigate how to ensure that students would not game the system by rushing through the required manual classification.

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APPENDICES

Appendix A

Survey: What factors influencing online help seeking

Section 1

1. What is your gender?

A. male B. female

2. What is your age?

Section 2

1. When you find difficulties in solving problems (e.g., algorithmic problems - find the mode from an array of integers) in assignments, how often do you search online to learn about it?

A. never B. occasionally C. sometimes D. always

2. When you find difficulties in solving problems (e.g., algorithmic problems - find the mode from an array of integers) in assignments, how often do you email the teacher or teaching assistant for help?

A. never B. occasionally C. sometimes D. always

3. When you find difficulties in solving problems (e.g., algorithmic problems - find the mode from an array of integers) in assignments, how often do you ask your peers or some unknown experts online for help?

A. never B. occasionally C. sometimes D. always

Section 3

1. I am interested in the learning content of the class.

A. strongly disagree B. disagree C. agree D. strongly agree

2. I would like to master the learning content of the course I am taking.

A. strongly disagree B. disagree C. agree D. strongly agree

3. I would still like to take the course if it is elective.

A. strongly disagree B. disagree C. agree D. strongly agree

4. I have prior knowledge of the learning content of the course.

A. strongly disagree B. disagree C. agree D. strongly agree

5. I have related learning experience before taking the course.

A. strongly disagree B. disagree C. agree D. strongly agree

6. I will become more willingly to seek help from others online if the learning task I have problems with is very complex.

A. strongly disagree B. disagree C. agree D. strongly agree

7. I will become less willingly to search online if the learning task I have problems with is very complex.

A. strongly disagree B. disagree C. agree D. strongly agree

8. I believe that one can master knowledge and skills of certain subjects (e.g., coding) by learning independently with the open online resources and search engines.

A. strongly disagree B. disagree C. agree D. strongly agree

9. I think self-paced learning with search engines, online open resources, and helps from others online is a very important way to learn.

A. strongly disagree B. disagree C. agree D. strongly agree

10. I think learning with an expert (physically present) through lecture or class is the best way to learn.

A. strongly disagree B. disagree C. agree D. strongly agree

Appendix B

Survey: The Influence of Achievement Goals on Online Help Seeking

Section 1. Online Help-Seeking Measures

1. When you find difficulties in solving problems (e.g., algorithmic problems - find the mode from an array of integers) in assignments, how often do you search online to learn about it?

A. Never B. Seldom C. Sometimes D. Often

2. When you find difficulties in solving problems (e.g., algorithmic problems - find the mode from an array of integers) in assignments, how often do you email the teacher or teaching assistant for help?

A. Never B. Seldom C. Sometimes D. Often

3. When you find difficulties in solving problems (e.g., algorithmic problems - find the mode from an array of integers) in assignments, how often do you ask your peers or some unknown experts online for help?

A. Never B. Seldom C. Sometimes D. Often

Section 2. Achievement Goal Questionnaire-Revised

Mastery-Approach Goal Items

1. My aim is completely master the material presented in this class.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

7. I am striving to do well compared to other students.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

3. My goal is to learn as much as possible.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

Mastery-Avoidance Goal Items

5. My aim is to perform well relative to other students.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

11. My aim is to avoid learning less than I possibly could.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

9. My goal is to avoid performing poorly compared to others.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

Performance-Approach Goal Items

4. I am striving to understand the content as thoroughly as possible.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

2. My goal is to perform better than the other students.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

8. My goal is to avoid learning less than it is possible to learn.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

Performance-Avoidance Goal Items

12. I am striving to avoid performing worse than others.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

6. My aim is to avoid doing worse than other students.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

10. I am striving to avoid an incomplete understanding of the course material.

A. Strongly disagree B. Disagree C. Agree D. Strongly agree

Appendix C

Institutional Review Board Human Subjects Research Approvals

(See the next page)

The University of Georgia

Phone 706-542-3199

Fax 706-542-3660

Office of the Vice President for Research
Institutional Review Board

APPROVAL OF PROTOCOL

July 23, 2015

Dear ROBERT Branch:

On 7/23/2015, the IRB reviewed the following submission:

Type of Review:	Initial Study
Title of Study:	How do College Students Seek Help Online in Problem Solving: A Study of Individual Difference
Investigator:	ROBERT Branch
IRB ID:	STUDY00002307
Funding:	None
Grant ID:	None

The IRB approved the protocol from 7/23/2015.

In conducting this study, you are required to follow the requirements listed in the Investigator Manual (HRP-103).

Sincerely,

Larry Nackerud, Ph.D.
University of Georgia
Institutional Review Board Chairperson

629 Boyd Graduate Studies Research Center ◆ Athens, Georgia 30602-7411
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The University of Georgia

Phone 706-542-3199

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Office of the Vice President for Research
Institutional Review Board

APPROVAL OF PROTOCOL

September 24, 2014

Dear ROBERT Branch:

On 9/24/2014, the IRB reviewed the following submission:

Type of Review:	Initial Study
Title of Study:	What Factors Influence Learners' Online Help Seeking in Technology-Rich Learning Environments
Investigator:	ROBERT Branch
IRB ID:	STUDY00001392
Funding:	None
Grant ID:	None

The IRB approved the protocol from 9/24/2014.

To document consent, use the consent documents that were approved and stamped by the IRB. Go to the Documents tab to download them.

In conducting this study, you are required to follow the requirements listed in the Investigator Manual (HRP-103).

Sincerely,

Larry Nackerud, Ph.D.
University of Georgia
Institutional Review Board Chairperson

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