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A New Model of Information Seeking Stopping Behavior

APPROVED BY
SUPERVISING COMMITTEE:

Supervisor: ______________________________

Jacek Gwizdka

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Yan Zhang

A New Model of Information Seeking Stopping Behavior

by

Yinglong Zhang, B.E.

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Abstract

A New Model of Information Seeking Stopping Behavior

Yinglong Zhang, MSInfoStds
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Supervisor: Jacek Gwizdka

Web search engines play an important role in peoples daily life. Widespread usage of search engine poses continuous challenges for designing information search systems that can bring people best user experience. To address this challenges, it is particularly important to understand how people seek information. In spite of a large number of studies on human information seeking, the reasons of when and why users terminate information seeking are uncertain and many proposed theories have a limited capability for predicting this type of behavior. In our study, we conducted lab-based experiments, where participants performed assigned information search tasks on Wikipedia pages. Inspired by theories and methods from cognitive science, we captured participants information search behavior such as query usage, search engine result page visits, Wikipedia page visits, and task duration. Additionally, we used eye-tracking techniques to examine the number of people's eye fixations. Using exploratory factor analysis (EFA), we have confirmed exploratory and validation processes can be distinguished based on different types of costs associated with each of them. Based on the findings of the regression tree model, evaluating the cost and gain in the validation process provide important feedback to people for controlling and monitoring their information search.

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Chapter 1: Introduction

Interaction with information is central to peoples lives. Search engines have become the main channel for people to get access to information. In terms of Statistas report[1], there were approximate 2,710 millions Internet users in 2013; among these Internet users, 74% used search engines and 64% utilized social networking sites. Concerning the wide spread usage of search engines, a number of people have been realizing the importance of designing technology that can best support information search. In order to inform the technology design, research has been conducted to investigate human information seeking in the fields of Information Retrieval as well as Human-Computer Interaction.

The extensive examinations of the prior research on information seeking have been made into how people define information need, generate queries, examine documents, refine queries, and make sense of the information they find [23]. Aiming to understanding user experiences in information searches, most of the prior studies kept their focus on examinations of why and how people seek information, but fewer efforts have attempted to explain when and why people want to stop their information seeking [6, 5, 10].

Several studies have actually demonstrated the importance of investigating stopping behavior of information seeking. Based on their results, terminating information searching process too early or too late can bring about specific harmful effects on peoples outcomes of information seeking [6, 25]. Specifically, too early termination of information search can result in reduced effectiveness, for example insufficiency for answering the questions accurately; on the other hand, stopping information search too late is likely to reduce efficiency due to the amount of time and effort required to be invested [14]. In a context of Human-Computer Interaction, investigation of stopping behavior can facilitate the design of systems for supporting human decision-making in the process of terminating their information seeking.

[1] http://www.statista.com.ezproxy.lib.utexas.edu/statistics/273018/number-of-internet-users-

To put it together, studies on information seeking should not limit their topics in information need as well as the process of information searches. The research on stopping behavior can benefit our understanding of human information seeking as well as design of information technology. In this paper, we attempt to investigate what factors can contribute to the stopping behavior of information seeking and whether the stopping behavior can be predicted based on these factors.

The rest of this paper is organized as follows: we first describe the concept of the stopping behavior of information seeking and review the perspectives and the models of the stopping behavior. After the literature review, we propose a new model of the stopping behavior of information seeking. In the experiment and result sections, the lab-based experiment is described and its findings are shown and explained. In the discussion and conclusion parts, we discuss our results and potential future work on information stopping.

Chapter 2: Background and Related Work

2.1 Stopping behavior of information seeking

The information stopping behavior is defined as the last step in information acquisition activities before the information seeker proceeds to make use of the obtained information [14]. People stop their information searches mainly because of their limited information capacity. In other words, the stopping behavior can be regarded as an adaptive mechanism for human to address information explosion and prevent cognitive overload in Web information searches. Although this mechanism is pervasive in our daily life, it is not clear how humans make their decisions in terminating information searches.

2.1.1 Cost and Gain of Information Seeking

A number of previous studies investigated stopping behavior based on how humans balance the cost (time, money, mental efforts, etc.) and the gain (learning relevant, helpful information or knowledge) in information searches [2]. According to this perspective, the value of the gain in information seeking is not accumulative. People rarely calculate weighted gain and losses but tend to estimate the profits in a holistic fashion. Additionally, not all of the cost will hinder information searches. Some cost can be seen as sunk cost, which will not reduce the overall profits but can motivate people to seek for more information before they achieve their goals of information seeking [4].

An issue relating this model is whether the model can explain the stopping behavior of information seeking in a real situation. Some research found people will rarely follow the economic principle, especially when they are exposed to a large amount of information [26, 31]. It is believed that other factors can influence human decision making in the process of terminating information seeking.

2.1.2 Choice Problems

A choice problem is another aspect that has been widely examined in the studies on stopping behavior. Different from the investigation on the cost and gain of information seeking, the research on choice problems concentrates on the cognitive aspects of stopping behavior. In particular, the research attempt to explain how people use their cognitive rules to choose the information that can best meet the needs of their information seeking. To describe how people deal with choice problems, Gigerenzer [11] developed three stopping rules: The Minimalist, Take the last, and Take the best.

In The Minimalist rule, people will randomly search for information cues that describe a certain number of choices respectively. If one cue can be found that is superior to others, people will stop searching; otherwise, they will repeat this process.

The Take the last rule is based on peoples prior experiences. People attempt to find information cues for judging whether an ongoing searching process is similar to the ones they conducted before. If they can ensure the ongoing process is repetitive, they will terminate it.

In the Take the best rule, people collect information cues as well as additional information relating to the validity of the information cues. By ranking these cues based on the additional information, people will select the most superior one among them.

Understanding choice problem is useful to explain how people choose and gain information, but some specific knowledge regarding to information cues is incomplete and unclear. Specifically, we do not understand how people find and make sense of these information cues.

2.1.3 Sufficiency of Information

Sufficiency of information is an important factor behind the stopping behavior of information seeking. People will stop searching information as they collect enough information to accomplish their goals. In terms of Brownes cognitive stopping theory [6], shown in **table 2.1**, people judge the sufficiency of the information that they have collected based on one or some of the following criteria: mental list, representational stability, difference threshold, magnitude threshold, and single criterion.

Rule	Description
Mental List	People must satisfy a mental list of items before they stop collecting information
Representational Stability	People will stop their information searches when their mental model (representation) stabilizes.
Difference Threshold	People adopt a priori threshold to determine when they cannot learn something new before information searches. If this criterion is stratified, information seeking behavior will be terminated.
Magnitude Threshold	When a cumulative amount of information (enough information) meets a criterion established by people before information searches, people will stop information seeking behavior.
Single Criterion	People adopt a single criterion for stopping information searches. When they have enough information about the criterion, information seeking behavior will be ended.

Table 2.1: Cognitive stopping rules [6]

The selection of these stopping rules is largely contingent on the complexity of tasks. In complex tasks, people are prone to use the mental list and the single criterion rules because they know the specific cues that can determine whether to terminate their information searches. In simple tasks, people are more likely to use the magnitude thresholds and the representational stability stopping rules and they may stop searching information when a pre-defined amount of information has been acquired or when their mental representations of the tasks shifts [14].

Regarding these cognitive rules, one point that can be criticized is the difficulty of specifying and quantifying the threshold of sufficiency. Sufficiency is subjective perception and can be altered by several factors, such as motivation, personal experiences, domain knowledge, and personality. This uncertainty becomes a problem for using these rules to describe and predict the stopping behavior.

2.1.4 Motivation

Motivational perspective addresses some external and internal factors behind information seeking stopping behavior [14]. As a external factor, time-pressures are closely related to early termination of information searches [6, 19, 35, 13]. A lack of time can influence the performance as well as the current mood during information seeking and may lead to the subsequent stopping behavior. Under extreme time-pressures, people are likely to skip words during reading. When useful information is neglected in the fast reading, the outcomes of information seeking can be affected negatively and people may feel frustrated. This negative emotion can result in earlier stopping behavior of information seeking.

Need for cognition and need for cognitive closure are two internal factors influencing the stopping behavior. Need for cognition influences how people search for information systematically and how they consider a higher amount of information before terminating information searches [14, 34].

Need for cognitive closure is defined as an individuals desire for a firm answer to a question and a aversion to ambiguity [15]. People with high need for cognitive closure will terminate information seeking behavior earlier if they can find relevant, convincing information that they do not know before.

The motivational perspectives stay focus on the individual characteristics and make a significant contribution to broadening our understanding of information seeking. In the previous studies, the need for cognition and the need for cognitive closure were measured in terms of the psychological scales developed for education psychology research [22, 7]. An issue relating to these studies on the stopping behavior is whether these scales can be used in the investigation of information seeking without modifications. Few studies have tested the reliability and validity of these scales in the context of Information Science.

2.2 THEORIES OF INFORMATION SEEKING STOPPING BEHAVIOR

In the previous research, two kinds of models have been proposed to model human information seeking stopping behavior: economical models and cognitive models. In the following part, we will review these models and their findings.

2.2.1 Economic Models of Search

As Varian pointed out in his keynotes at 1999 SIGIR conference, economics can provide useful tools for modeling how people make decision, deal with risk, and handle uncertainty [32]. In a recent study, Azzopardi proposed to use production theory to examine human information seeking [2]. Specifically, production theory models how corporations take their inputs (such as capital and labor) and convert them to output (such as products or services). In terms of this theory, Azzopardi considers users with search engines can be considered as the corporations; gain received from relevant documents found during information searches can be regarded as the output [2].

In the economical model developed by [2], the cost of information searches can be evaluated based on a number of queries (Q), examining a number of search result page per query (V), inspecting a number of snippets per query (S), and assessing a number of documents per query (A). The cost function was modeled as follows:

$$c(Q, V, S, A) = c_q.Q + c_v.V.Q + c_s.A/P_a.Q + c_a.A.Q \quad (2.1)$$

In the Eq. 2.1, c_q is the cost of a query; c_v is the cost of viewing a page; c_s is the cost of inspecting a snippet; and c_a is the cost of assessing a document.p_a is the probability of assessing a document given the snippet and defined in terms of:

$$A = S.P_a \quad (2.2)$$

The gain function in this model is defined in terms of posing a number of queries and assessing a number of documents per query (A):

$$g(Q, A) = k.Q^{\alpha}.A^{\beta} \tag{2.3}$$

where α represents the relative efficiency of querying and assessing. An assumption underlying this model is : α = β =1.

A discussion of this model is whether it can reflect the actual search process. In terms of the gain function (**Eq.2.3**), it seems that all of the relevant documents are of the same value regarding their contribution to the gain of information seeking. However, it has been found that some relevant documents add less value to the gain of information seeking when they are similar to the relevant document found earlier [32]. That is to say, this gain function may inflate the gain of information seeking.

2.2.2 Task, Technology, and Individual Characteristics Model

Task, Technology, and Individual Characteristics Model is a cognitive model developed by [14]. In this model, it is assumed that information processing behavior is influenced by task, technology, and individual characteristics, shown in **Figure 2.1**.

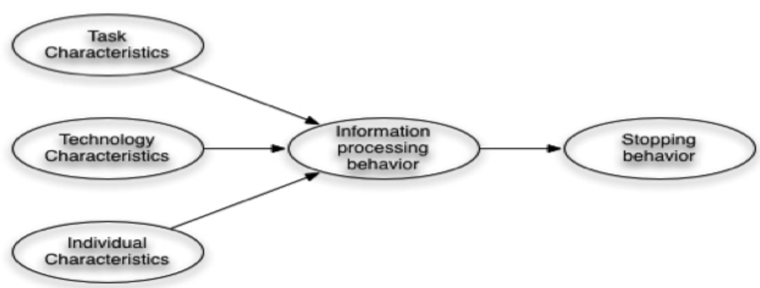


Figure 2.1: Task, technology, and individual characteristic model

Impact of Task Characteristics

The complexity of tasks can influence the stopping behavior of information seeking. The subjective perception of tasks complexity can affect how the tasks are interpreted and how the problem-relevant information of the tasks is transmitted to people. In complex tasks, people need more efforts to perform their cognitive processing, such as evaluating more contradicting pieces of information in complex task scenarios [27, 30].

In addition to complexity, the importance of a task can alter peoples stopping behavior to some degree. In information seeking, people have to balance the trade-off between minimizing their cognitive effort and maximizing the accuracy of task outcomes [14]. The criteria used to balance this trade-off can be partially modified by a given tasks importance. Specifically, if tasks are closely related to reward and punishment mechanisms (high importance), people are very likely to get actively involved in these tasks [28].

Impact of Technology Characteristics

The technology characteristics refer to how users will influence each other through technology. According to Hemmers model, human information processing is more likely to be changed when web sites incorporate more social presence [14]. Cry found similar results determining that the photos of the people who post information online will alter readers information processing[9].

Individual Characteristics

In this cognitive model, individual characteristics include task motivation, task experience, and need for cognition [14]. High task motivation can increase peoples involvement and therefore expand their effort in information processing. Task experiences are closely related to human information processing. It has been found that the activities of specific brain areas working on information processing will increase significantly when people read the words that they are familiar with [17].

Need for cognition is thought of as a predictor of the use of systematic information processing strategies [8]. Higher score of need for cognition will result in a more thorough evaluation of peoples own thoughts. This feedback enables people to control the whole process of information seeking (goal setting and management, query generation, query revision, decision making, etc.)

Compared to the economical model, Hemmers model examines the stopping behavior based on different perspectives, but some problems still need to be addressed in future research. Firstly, the impacts of technology, task, and individual are assumed to be independent, but actually, there are some interaction effects among these impacts. For instance, people with low need for cognition may be more likely to be affected by the complexity of tasks, compared to those with high need for cognition. Secondly, regarding the impact of technology, Hemmer failed to consider the usability of technology and its impact on stopping behavior. A number of studies in Human Computer Interaction have demonstrated bad usability can affect users affective states negatively and decrease their involvement in the technology [21].

Chapter 3: Proposed model of the stopping behavior of information seeking

Based on the aforementioned economic model and cognitive model, we propose a new economic-cognitive model to explain the stopping behavior of information seeking. The stopping behavior is defined as the moment when people exit a Web search task. It is assumed that given a sufficient time for performing a task, participants can actively decide when to stop searching for information. In this model, to examine the stopping behavior from a multifaceted perspective, we incorporate the impacts, such as the gain and the cost of information seeking, design of technology, design of tasks, and psychological characteristics.

3.1 Cost and gain of information seeking

In the proposed model, the cost and the gain in information seeking results from two aspects: an exploratory and a validation process. In the exploratory process, people first try to set their task goals (defining the characteristics of the relevant documents that they anticipate finding) in tasks and then attempt to generate useful queries to locate these relevant documents. In this process, people will try to explore different queries and examine the search engine result page (SERP) per each query. The definitions of useless, partially useful, and useful queries are independent of document examinations and defined as follows:

- **Useless query**: the query is used only once and cannot locate relevant documents.
- **Partially useful query**: the query cannot locate relevant documents but is used more once. We hypothesized these queries can be still somewhat useful because they can provide useful information for modifying queries as well as creating new queries. Additionally, if users repeat the queries, they are likely to learn more information from the documents they examined.

- **Useful query**: the query can locate relevant documents.

The validation process is about how people attempt to confirm whether the information they already found matches the information they anticipate gaining. If the examined documents can meet the requirements people set in their initial goals completely or partially, these documents will be judged as relevant or usefully and can be seen as a gain in the validation process. However, if the documents are useless, the examinations of these documents become a cost in the validation process. The definitions of relevant, useful, and useless documents are as follows:

- **Useless document**: the examined document is irrelevant and located through a useless query;
- **Useful document**: the examined document is either located by a partially useful query or located by a useful query but not judged as relevant.
- **Relevant document**: the examined document is judged as relevant by participants.

Additionally, a task description is designed for people to check the questions they need to address in each task scenario. When people revisit the task description, it is assumed that they were not confident about the matching process and need additional efforts to confirm it. In our study, revisiting tasks descriptions is regarded as a cost in validation process.

Different from the aforementioned studies [2, 3, 1], our research is not limited to behavioral data. We also include eye fixations in this study. In previous research, it has been found that the number of fixations is related to internal cognitive activity [18]. In the proposed model, we assume the number of fixation is related to information gained while reading documents. Particularly, the more eye fixations that are on a document, the more information is likely to be processed by human brain.

3.2 TASK FACTORS

Complexity is one of the task factors that can influence human information seeking stopping behavior. The findings of the aforementioned studies [27, 30] have indicated people are likely to make more efforts to perform their cognitive processing in complex tasks.

It is noteworthy that the high complexity of tasks will not necessarily result in long time for information searches. In extremely complex tasks, people may terminate their information searching earlier. The extreme complexity can make them feel frustrated and give up the tasks before they accomplish them.

Additionally, the subjective perception of complexity can be influenced by several individual factors. For instance, people with greater domain knowledge of tasks may consider these tasks less complex, compared to those with less domain knowledge.

3.3 TECHNOLOGY FACTORS

As a medium, technologies convey information (knowledge) to users. Well-designed technologies can decrease extraneous cognitive load. In instructional technology designs, extraneous cognitive load is assumed to be caused by the format of the instruction [24]. Such cognitive load results from unnecessarily high use of working memory due to the poor design of technologies. Extraneous cognitive load not only slows down human information processing but also makes people discontent and frustrated. Both the cognitive and the affective consequences are likely to cause earlier termination of information seeking. Moreover, given limited working memory capacity, the greater extraneous cognitive load, the less working memory capability is available for queries generation, queries revision, and sense-making process in information seeking.

3.4 COGNITIVE FACTORS

Working memory is an important cognitive factor behind the stopping behavior, which will influence peoples perception of complexity as well as the outcomes of their information seeking. It has been found that people with high working memory capability accomplished search tasks faster than those with low working memory capability [12]. In addition to working memory, need for cognition is also the possible factor that may influence stopping behavior. People with great need for cognition are expected to invest more efforts and spend more time to perform tasks.

Chapter 4: Method

We conducted a controlled, lab-based experiment to investigate Web searches on Wikipedia. Each experiment session was held in the Information experience lab in the School of Information at the University of Texas at Austin.

4.1 Participants

There were 32 subjects participating in this experiment. Their ages range from 18 to 37; there were 15 female participants and 17 male participants. To control the influence of language on human reading as well as the impact of human vision on eye-tracking techniques, we recruited native English speakers who had normal, or corrected-to normal, vision [1]. After accomplishing the experiment session, each participant received $30 compensation for their participation.

4.2 Experiment Design

Each experiment session was completed within 1.5 hours, where the participants were asked to complete four search tasks, shown in **Appendix A**. These tasks were designed to be at two complexity levels: simple and complex.

Based on a commercial test search test engine developed by Search Technologies Corp, we created two kinds of user Interface (UI) : one interface with a list of Wikipedia categories and one without these categories, shown in **Figure 4.1** and **Figure 4.2**.

To control the order effect, we created 32 different rotations in terms of the combinations of task complexity levels and user interface types as well as a constraint that UI is switched only after two tasks. The 32 rotations are assigned to each participant in a random order.

[1]Normal vision is 20/20 in terms of a Snellen chart.

Figure 4.1: UI with categories

A within subject design was used in our search. In each search task, participants were required to read task description, complete pre- and post questionnaires, and search information on Wikipedia using either of the two user interfaces. Participants can save any pages that they thought were useful to answer the question in the search scenario. During information searches, they also needed to respond to a secondary task. There were no time limits set for each search task. They were able to exit the experiment session whenever they wanted to. Before exiting each experiment session, participants were asked to fill out exit questionnaires.

4.3 Independent and Dependent Variables

In our study, the independent variable was the time participant spent completing a task (task duration). The beginning time for each participant was the first time they visited the home search page and the ending time was when participants clicked the exit button. The task duration was recorded in terms of milliseconds.

The dependent variables include the cost and the gain of information seeking, task

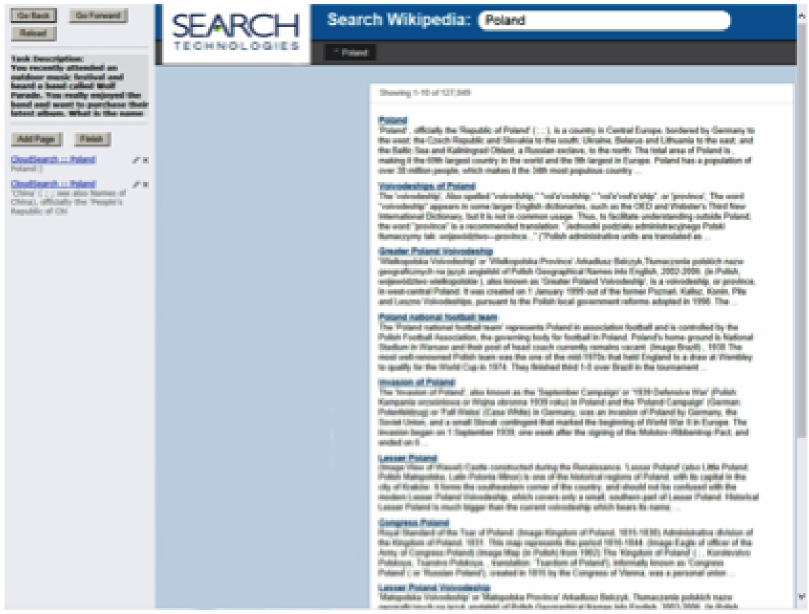


Figure 4.2: UI without categories

complexity (easy and complex task), and user interface (with categories and without categories).

As mentioned above, the cost of information seeking results from an exploratory process and a validation process. In the exploratory process, we assume the cost could be reflected by three different aspects:

- The number of word used to generate all of the useless queries in each task $W_{useless}$
- The time spent to generate all of the useless queries in each task $T_{useless}$
- The number of fixations on all of the visited SERP F_{SERP}

In the validation process, the cost can be shown in the following three aspects:

- The number of fixations on all of the visited useless documents $D_{useless}$
- The number of fixations on all of the visited task descriptions $F_{taskDescription}$
- The time of visiting all of the task descriptions $T_{taskDescription}$

The gain of information seeking mainly results from the validation process:

- The number of fixations on all of the visited useful documents D_{useful}
- The number of fixations on all of the visited relevant documents $D_{relevant}$

Chapter 5: Research Questions and Hypotheses

In our study, we attempt to examine how the cost and the gain of information, task complexity, and user interfaces can influence the time participants spent in completing the tasks in the experiment. Specifically, we formulated the following hypothesis:

H1: Exploratory and validation processes can be distinguished based on different types of costs associated with each of them.

H2: The task complexity can influence the time participants spent in completing the tasks in the experiment

H3 The interface types can influence the time participants spent in completing the tasks in the experiment.

H4: The cost and the gain of information seeking, the task complexity, and the user interface types can be used to predict the time participant spent performing tasks.

Chapter 6: Data Analysis and Results

Our data analysis consisted in three parts: in the first part, we used exploratory factor analysis (EFA) to confirm our first hypothesis that the cost of information can be estimated in terms of the exploratory and validation process. The second part attempted to examine the impacts of task complexity as well as user interface types on the cost and the gain in information seeking and the time spent in completing tasks. In the third part, we used linear regression and regression tree model to explore whether the cost and the gain of information seeking, task complexity, and UI types can predict the task duration.

6.1 Data Preprocessing

Before performing data analysis, we did transformations of all predictors to make sure that they had a common scale. Specifically, each value of the predictor variable is divided by its standard deviation. Through scaling the data, the numerical stability of calculations will be improved [16].

6.2 Exploratory Factor Analysis (EFA)

Exploratory factor analysis (EFA) can be used to identity the underlying relationship between latent factors and manifest variables [20]. Specifically, latent factors are the variables that cannot be observed directly, and manifest variables are the variables that can be measured or observed directly. Although latent factors cannot be observed directly, they can be inferred from other manifest variables. In this part, we attempted to use a statistical method to uncover a relationship between the latent factor, the cost of information seeking, and the manifest variables ($W_{useless}$, $T_{useless}$, F_{SERP} , $D_{useless}$, $F_{taskDescription}$, $T_{taskDescription}$, $D_{useless}$, $D_{useless}$, etc.). If these dimensions and questions in **H1** can be matched, then we should observe expected correlations between these manifest variables in EFA.

Prior to EFA, we performed Kaiser- Mayer-Olkin (KMO) Measure of Sampling Adequacy and Bartletts Test of Sphericity to ensure our sample supports valid EFA [33]. KMO indicates the extent to which a correlation matrix actually contains factors or simply chance correlations between a small subset of variables. Tabachnick and Fidell [29] suggest that values of 0.60 and higher are required. Bartletts (1950) test of Sphericity is used to estimate the zero correlation probabilities in the matrix. The result of KMO was 0.64, with Bartletts Test yielding 600.46 ($p < 0.001$). Both values indicate that our own sample used satisfies the requisite assumptions for proceeding with EFA.

The initial EFA was conduced using R, assuming no correlations between 8 manifest variables. After applying principal component analysis (PCA), the resulting Scree plot for the initial EFA was shown in **Figure 6.1**. The six eigenvalues (marked by crosses) are computed from the correlation matrix and ordered by decreasing value along the x-axis. To determine the number of the factors to keep, we use parallel analysis. A random dataset is generated in terms of the same number of responses and variables as in our sample. The parallel analysis line was marked as red dashed line in **Figure 6.1** and the factors above it should be kept in EFA [36]. In our study, two factors were kept.

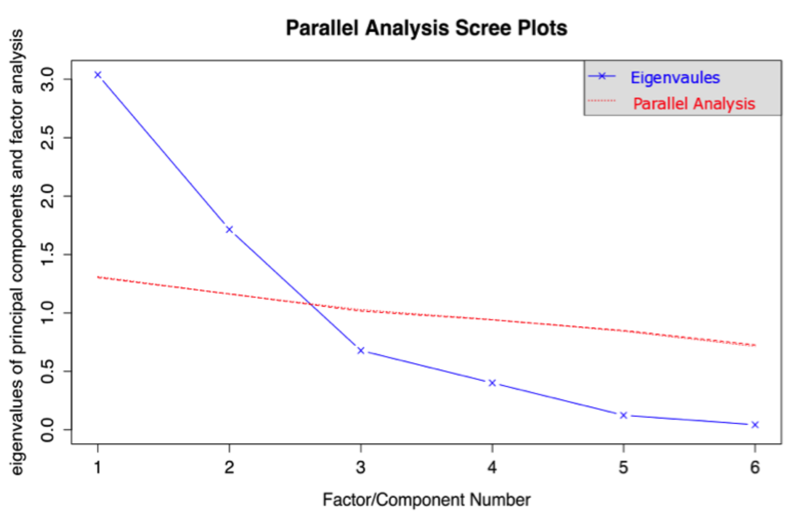


Figure 6.1: Revised scree plot showing parallel analysis results

Given the number of the factors determined in the initial EFA, we run EFA again using PCA with oblique (Promax) rotation and the number of factors fixed to 2. We adopted oblique rotation because it allowed the factors to be correlated with others. The Pearson correlation between the two factors was 0.31. The factor loadings for manifest variables were shown in **Table 6.1**. In terms of the results, the six factors cluster as we expected in the H1. The unstandardized loadings of these manifest variables (highlighted in grey color in **Table 6.1**) ranged from 0.70 to 0.98. The value of h^2 indicates the final communality estimate: the proportion of variance accounted for by retained factors. A value of h^2 <0.40 indicates that an item is less strongly correlated with its corresponding factor [33]. Based on this criterion, the manifest variables in our research were correlated with its corresponding factor.

	Exploratory Process	**Validation process**	h^2
$T_{useless}$	0.98	-0.09	0.91
$W_{useless}$	0.94	-0.07	0.85
F_{SERP}	0.75	0.17	0.68
$F_{taskDescription}$	-0.08	0.98	0.92
$T_{taskDescription}$	0	0.94	0.88
$D_{useless}$	0.04	0.7	0.51

Table 6.1: Factor loadings for each manifest variable

Having confirming that exploratory and validation processes can be distinguished based on different costs associated with each of them, we calculated the cost of the exploratory process and the cost of the validation process as follows:

$$C_{exploratory} = T_{useless} + W_{useless} + F_{SERP} \tag{6.1}$$

$$C_{validation} = F_{taskDescription} + T_{taskDescription} + D_{useless} \tag{6.2}$$

Similar to calculating cost, we estimated the gain as follows:

$$C_{gain} = D_{useful} + D_{relevant} \tag{6.3}$$

Regarding the estimation of the cost and the gain, one points should be mentioned.

First, all of these manifest variables had been scaled in the data preprocessing part. That is to say this calculation would not been influenced by the different scales of these variables.

6.3 ANALYSIS OF VARIANCE

The results of ANOVA indicated that there were no significant impacts between UI types (with categories vs. without categories) on the gain of information seeking ($p = .852$), the cost in exploratory process ($p = .639$), the cost in validation process ($p = .628$), and the time spent in completing tasks ($p = .834$). That is to say the categories cannot decrease the cost and the gain in information seeking and are not likely to influence task durations.

In terms of ANOVA, task complexity had a significant impact on the cost and the gain of information seeking ($p < .001$) as well as the task duration ($p < .001$). Specifically, according to the Post-hoc analysis (seen in **Table 6.2**), it was found participants needed more time to accomplish complex tasks than to accomplish simple tasks. Regarding the gain and the cost, participants got more gain in complex tasks; on the other hand they had more cost in the exploratory and validation processes.

	Difference(complex - simple)	**p value (adjusted)**
Task duration	545535.6	P = 0.000
Gain	1.404748	P <0.001
Cost in exploratory process	3.32131	P = 0.000
Cost in validation process	2.501666	P = 0.000

Table 6.2: Post-hoc analysis for task complexity

6.4 LINEAR REGRESSION ANALYSIS AND REGRESSION MODEL TREE

6.4.1 Linear Regression Analysis

In order to examine how the cost-gain factor, technology factor, and task factor can predict the task duration, we performed linear regression and the results were show in **Table 6.3**. In terms of the findings, except for the UI types, all of other predictors had significant effects on the task duration. The R^2 of the linear regression model is 0.683, which indicated there was 68.3% of the variability of the task duration that could be explained by this model.

	Estimate	**Std. Error**	**p value**
(Intercept)	584786	44468	p = 0.000
Task complexity	-174564	61374	p <0.001
UI types	-2488	43474	p = .95
Gain	91778	16429	p = 0.000
Cost in exploratory process	30823	10461	p = 0.000
Cost in validation process	55840	9898	p <0.001

Table 6.3: Coefficients of regression model

Given that the UI types had no significant effect on the change of the task duration in this regression model, we proposed and tested a modified model that excluded the predictor of UI types. The comparison between the initial model (M0) and the modified model (M1) is shown in **Table 6.4**. The Akaike information criterion (AIC) of the modified model was decreased by 1.847, which means that the modified model was of relatively better quality than the initial model.

	Df	**Deviance**	**AIC**
Initial model (M0)			3156.5
Modified model (M1)	1	194872118	3154.653

Table 6.4: Model comparison: Initial Model and Modified Model

6.4.2 Regression Tree Model

In order to investigate how these predictor (dependent) variables could be used to predict the task duration, after linear regression analysis we performed regression model tree analysis using R with the rpart package [1]. As a predictive model, regression tree model can be used to visually and explicitly demonstrate the process of decision-making. Specifically, in our research, we tried to examine how these predictors could be employed by humans to decide when to stop searching for information and exiting the tasks.

[1] http://cran.r-project.org/web/packages/rpart/index.html

Beginning with the entire sample dataset, S, regression tree model searches every distinct value of every predictor to find a predictor and its split value that partitions the data into two groups (S_1 and S_2) such that the overall sums of squares error are minimized [16]:

$$SSE = \sum_{i \in s_i} (y_i - \bar{y_1})^2 + \sum_{i \in s_i} (y_i - \bar{y_2})^2 \tag{6.4}$$

Where $\bar{y_1}$and $bary_2$ are the average of the dataset outcomes with groups S_1 and S_2. Using the same method, within each of group S_1 and S_2, another predictor and spit value will be found, which can best reduce SSE.

Considering that the outcome (Task duration) is a continuous variable, in research, we adopted ANOVA method as the splitting criteria to decide which variable gives the best split. Specifically, the splitting criteria is:

$$SSE = SS_T - \sum_{i \in s_i} (y_i - \bar{y_1})^2 + \sum_{i \in s_i} (y_i - \bar{y_2})^2 \tag{6.5}$$

where $SS_T = \sum (y_i - \bar{y_1})^2$ is the sum of the squares for the node. This criterion attempts to choose the split to maximize the between-groups sum of squares

In order to control the size of the tree and find an optimal tree size that has the smallest error rate. Error rate is penalized as follows:

$$SSE_{C_p} = SSE + c_p * (terminalnode) \tag{6.6}$$

Where c_p is the complexity parameter and $N_{terminalnode}$ is the number of the terminal nodes. In our model, the complexity parameter was selected as 0.01.

The resulting tree was selected based on the relative error. The relative error is equivalent to $1 - R^2$. Similar to linear regression, the smaller relative error is, the more variability of the outcome can be explained in terms of the model. Based on the results show in **Table 6.5**, the model with seven splits had lowest relative error (0.2660). The xerror in **Table 6.5** is related to the predicted residual sum of squares (PRESS) statistic, which is used to measure the structures of a number of candidate models for the same sample. The lowest value of PRESS means the best structures. The xerror of our final model indicated it had the best structure.

CP	**Number of splits**	**Relative Error**	**xerror**
0.4265	0	1	1.0051
0.1324	1	0.5735	0.769
0.1216	2	0.441	0.6346
0.02	3	0.3194	0.5141
0.0116	4	0.2994	0.4634
0.0114	5	0.2878	0.4595
0.0104	6	0.2764	0.4595
0.01	7	0.266	0.4595

Table 6.5: The relative error and xerror of each split

In the final model, the four variables had been used in tree construction: the cost in validation process, the cost in exploratory process, the gain of information seeking, and task complexity. The regression tree was visually displayed in **Appendix B**.

According the results of the regression tree model, the importance of the variables is as follows (from most important to less important): cost in validation process, gain, cost in exploratory process, task complexity, and UI types. Specifically, based on **Appendix B**. The cost in validation process and the gain had been used several times for deciding when to stopping and exiting search tasks.

Chapter 7: Discussion

In this study, we examined the factors that might influence the stopping behavior on information seeking. The findings of all research first demonstrate that the cost of information seeking can be divided into two distinct aspects: exploratory process and validation process. Although in our study, we could not directly compare the two kinds of costs in terms of their absolute value, the result of the regression tree model has indicated the cost in the validation process was more important to predict how participants decided when to stop searching for information. As mentioned before, the validation process can enable people to confirm whether the information they find satisfies their expectation (information need). This process involves high-level cognitive activities, in which people need to be aware of what information they have gained from information seeking, whether the information meets their information needs, and how much additional information (what additional information) they have to collect so that their information need can be satisfied. That is to say, the evaluation of the cost and gain in validation process can enable people to monitor and control when to modify or change queries and when to stop information seeking so that they can generating less useless queries and examining more useless documents. To this point, it is not surprising to see the cost in the validation process played such important role in the regression tree model.

In fact, the findings of the regression tree model can partially support our claim that validation process is important when providing feedback about tasks to users. Recall the assumption that all of the gain in information seeking derives from the validation process. In **Appendix B**, only the cost and the gain in the validation process had been used more than once in deciding when to stop tasks. It seems that the participants needed the feedback (the cost and the gain in the validation process) to assist their decision-making process.

Regarding the impact of task complexity, our results have showed that participants had more cost and more gain in complex tasks than in simple tasks. Additionally, the time of completing complex tasks was longer than that in simple tasks. As to why people had more gain of complex tasks, one possible explanation is that complex tasks in our experiment included more controversial questions and required participants to answer the proposed questions based on different angles. Therefore, participants had to save and read more relevant documents in complex tasks and the number of fixations on relevant documents increased. Concerning the difference in scales of the cost and the gain, one limitation in our research is that we cannot compare the cost and the gain within a task. We cannot tell when the cost of information seeking is larger than the gain. In future research, we will revise the cost and the gain functions to address this issue.

Surprisingly, UI types did not have significant impacts on task duration and the cost and gain in information seeking. One possible explanation is that categories not only assist people in narrowing down the search scope, but also provide support for sensemaking. The categories in our experiment came from Wikipedia ontology and taxonomy of terms assigned to articles by their authors or editors. These terms can help participants modify their conceptual maps of search tasks, refine their queries, and make sense of what they read. Actually, everything comes at a price. Although the information contained in categories can be helpful in search, people may use more time and need to invest more mental effort to learn and understand these resources. This may explain it well why no significant difference exists in the cost and the gain and task duration between using UI with or without categories.

Chapter 8: Conclusion

In this research, we have showed that exploratory and validation processes can be distinguished based on different types of costs associated with each of them. The cost and gain of information seeking and task complexity can influence the time needed to complete tasks. However, we could not detect any significant impact of UI types on the gain and the cost of information searches nor the task duration. Using the linear regression model and regression tree model, our findings indicated that the cost in the exploratory process, the cost in the validation process, the gain in validation process, and the task complexity can be used to predict the participants stopping behavior (task duration). Particularly, the cost and the gain in the validation process both play important roles in the process of deciding when to exit tasks.

Regarding the implication of our research, we used EFA to investigate that the cost of information seeking can be reflected in the exploratory and validation processes. This point has been rarely mentioned before in the previous studies. Additionally, we found that the information about the cost and the gain in the validation process can provide feedback for people to control and monitor their information seeking. This finding actually expands our knowledge about the roles of cost and the gain in information seeking.

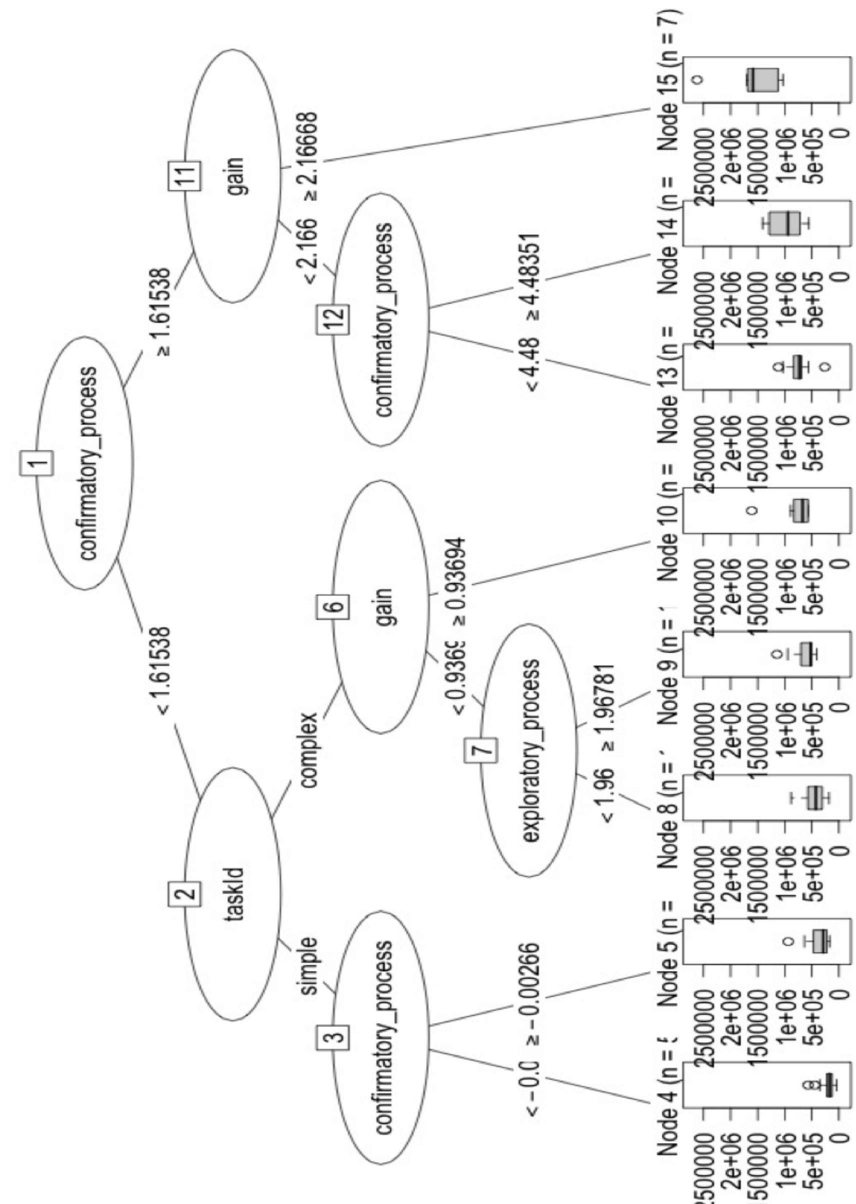
With regard to future research, we will first enlarge our data sample. Owing to the limitation of the data sample we used in this study, we had no additional dataset to test our regression tree model. In addition, we will modify the cost and the gain functions to allow them to be comparable within a task. Moreover, in future study, we will test the cognitive impact on the stopping behavior. Specifically, we plan to examine whether working memory and need for cognition can influence the task duration and the cost and gain in information seeking.

Appendix A: Search Task Scenarios

Complexity Level	Task Scenario
Simple 1	You love history and, in particular, you are interested in the Teutonic Order (Teutonic Knights). You have read about their period of power, and now you want to learn more about their decline. You want to find out: What year was the Order defeated in a famous battle? And you also want to find out which army (or armies) defeated the Order?
Simple 2	You recently attended an outdoor music festival and heard a band called Wolf Parade. You really enjoyed the band and want to purchase their latest album. What is the name of their latest (full- length) album? And you also want to know when this band resumed their work together?
Complex 1	A local water conservation group requests ideas to expand their efforts. Currently, they pick up debris from local waterways and try to raise awareness about water pollution. In an effort to help out, you volunteer for the group but also, you want to expand their efforts. What other forms of land use are impacting waterways? Which forms of land use have are the highest impact on the environment?
Complex 2	A debate is underway after an international logging and mining corporation submitted a bid to buy a local nature reserve. The city needs more jobs but many residents are upset because they find selling a nature reserve as short sighted. And many people actively use the nature reserve for recreation and educational field trips. In an effort to be balanced with support for the community and to be fair to economic development, you decide to investigate both sides further. What are the small and large scale impacts of logging and mining? What are some economic considerations for land preservation? What are your recommendations to the city if the corporation's bid is successful?

Appendix B: Final Regression Tree Model

The numbers at the bottom of each terminal node represent the number of samples and percent coverage of the node.



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