Information acquisition and reduction in problem solving

by

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A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

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2007

UMI Number: 3259506

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ACKNOWLEDGMENTS

Looking back in time, about six years ago, I came to United States with a very strong willing to pursue my graduate studies. But I was in a new country, speaking new language, meeting new people with a different cultural background, and actually starting a new life. My success seemed so far away at that time.

I often compare my life in States to a story of a little bird that was raised in the warmth of a family in a golden cage. The family always took care of every need of this bird and never let this bird be alone. However, one day the little bird decided to fly away from its cage to make its own career. As expected, the road for new life and success was not smooth. There were many times that this bird wanted to give up and wanted to fly back to its cage, but the strong desire to succeed kept it going. Eventually the bird could accomplish its goal. My life is similar to this bird. Several times, I missed my golden cage and my beloved family in Thailand, but I always told myself I cannot go back without succeeding

Time passed, finally, this is the end of walk for my academic path. It has been a long journey and completing this work is definitely a high point in my academic career. This dissertation would show that I have completed the Ph.D. degree, but it does not reflect what I have found along this journey. I have found love from family and friends who were my inspiration and my driving force through out this path. Also, I have found the generosity and support of people. Without the assistance of many individuals, my success would not be possible. Therefore, I would like to express my deepest appreciation to people who have helped me along this journey

First of all, my deepest appreciation and gratitude goes to my major advisor, Dr.John Jackman who was a source of inspiration and provided motivation throughout this research. His kindness, enthusiasm, and support made all the difference in my academic career. He has given me his shoulder to stand on to reach my academic dream, a dream I could have never reached without his help. Moreover, Dr. Jackman is not only being my major advisor but also had been an exceptional supporter and I considered him as my USA dad. He is the one who helped me the most for the past six years. He gave me an opportunity to work with him and taught me many things both in academic and life in general.

Some people are lucky enough to have one good supporter in their research, I was so lucky to have support from all my committee members. I am especially grateful to Dr. Veronica Dark Dr. Dark has always assisted and supported me in this work. She guided me to a foreign world, psychology. Her suggestion and recommendation were very valuable and helpful for conducting this experiment as well as analyzing the results.

I would also like to express my deepest thanks to the rest of my committee members, Dr. Sigurdur Olafsson, Dr. Sarah Ryan and Dr. Craig Ogilvie. They deserve a special note of praise, for they have watched over me since my first days as their graduate student. Without their contribution, this work would not have been possible.

The faculty and staff of Industrial Engineering department at Iowa State University are the most dedicated and generous people that I have ever met and I feel honored to have them in a part of my life. Their assistance and guidance has served me well and I owe them my heartfelt appreciation.

Several people whom I have met while in graduate school have become my closest and dearest friends, and counselors, and to all of you I give my love and thanks. Special thanks go to Pravina Kitikoon (Jae Kaew), Nipattra Debavalya (Jae Pook), Duangrut Julthongpiput (P.Mai), Karthik Viswanathan (my best Indian friend), and Zoila Yadira Guerra de Castillo (my best research mate from Panama). Thank you so much for your unconditional love and support.

Outside the Iowa State community, I shared my tears and laughter through this journey with my beloved friends in Thailand. Special thanks to Vararat Kongsmai and Chonlatorn Chunhaviksit for helping my family and me with computer related stuff while I was in the States. On a more personal note, my high school friends are still cheering and supporting me even in my lowest moments over a decade.

Best things are saved for last; similarly I left the most important people to the end. I would like to express my appreciation and my deepest love to my family in Thailand, especially my dear mother (Varaporn Kumsaikaew) and my beloved sisters (N.Aea and N.Pai) whose love is so great that it crosses the ocean. Even though, initially no one in my family agreed with me to continue for my Ph.D. since they really wanted me to be with them, but once I made the decision they supported me in all aspects. The result of my achievements has been based on the fact that my family respected my decision and gave me the freedom to fulfill my dreams. At the same time, they also provide me a place where the door is always open. It is hard to put in words my love and gratitude to my family and of course they don’t expect this, but I feel really happy to have this chance to acknowledge them. Finally, I would like to dedicate this work to my special person who is no longer here, my father. He always is my academic inspiration. Although, he passed away when I was eight, I could remember that he was seriously paying attention to our studies and I hope that this work makes him proud.

I end this long list of acknowledgments not with a "thank you" but with my love and soul to you, my special people. Nothing in a simple paragraph can express the love I have for the all of you. However, I promise I will take you and the memory of you with me for the rest of my life.

ABSTRACT

Identifying task relevant information is a critical step in the problem solving process. It can be considered as an information reduction process. Acquiring information is a related process that can either precede information reduction or occur in conjunction with information reduction. In this study, we examine how the expertise level, problem representation and problem solving process affect information acquisition and reduction behavior. An experiment was conducted in which engineering students identified task relevant information in engineering problems that differ in terms of the level of concept similarity between relevant and irrelevant information and the level of domain knowledge similarity in irrelevant information. Signal detection theory, Markov model and Clustering analysis were used to analyze the results.

CHAPTER1. INTRODUCTION

Cognitive activities related to searching, gathering, deducing, and using information are critical elements of work tasks in problem solving. A problem solver must be able to reason effectively about information, whether that information is readily available or it must be gathered from multiple sources. In this study we examined the effects of changing the contents of the information set on certain aspects of problem solving process. A problem consists of a perceived goal and an information set containing related and unrelated content. For example, the problem description for an inventory control problem shown below contains statements which may be relevant to solving the problem (Askin et al 2002). The goal is to "*Determine the optimal order quality and reorder point.*"

> "*An automotive repair shop stocks many sizes of tires. One particular size and model is purchased for $30 and sold for $45. The manager estimates the cost to order at $75, including the delivery charge and the paperwork. Using the cost of rent, interest, and utilities, the manager estimates the cost of carrying inventory at approximately 50% per year based on average inventory value. The shop sells approximately 2,000 of these tires per year. Determine the optimal order quality and reorder point. Orders are received two week after placement.*"

The large volume and variety of information in real world problem solving situations make it difficult to acquire relevant information (i.e., information used directly to solve a problem) because it is mixed with irrelevant information. The process of scanning information is called *information acquisition* (Choo 1995) while the process of selecting relevant information is described as *information reduction* (Haider and Frensch 1996; Green and Wright 2003).

Based on Problem Space Theory, the problem solving process can be characterized by the initial state of a problem, the traversal through some space of possible intermediate states, and the arrival at a goal state (Newell and Simon 1972). Newell and Simon suggested that problem descriptions contain chunks of information that are used by a problem solver to define, analyze, formulate, and solve a problem. Typically, some chunks correspond to a goal state (what one is attempting to achieve) and other chunks correspond to information that is used directly to solve the problem. Relating chunks of information is based on making connections with some underlying knowledge of principles and models. This process has been described in the context of concept maps (Novak 2002). These connections associate additional chunks of relevant knowledge to an existing cognitive structure.

1.1 INFORMATION REDUCTION AND INFORMATION ACQUISITION

Information reduction research focuses on strategies used to identify task-relevant elements. Cognitive activities in information reduction involve evaluating and selecting chunks based on one or more knowledge schemas. The cognitive processes associated with identifying task relevant information are not well understood. Shanteau (1992) found that the amount of information used in making decisions is independent of the degree of expertise. This study found that experts do not always use all or a greater amount of relevant information to make a decision. However, the information used by experts was more relevant than information used by novices. Experts and novices differed in their ability to evaluate what information is relevant in a given context, that is, they differed in terms of information reduction skill. Experts have learned to distinguish relevant and irrelevant information and process only relevant information. Novices find it difficult to separate irrelevant from relevant information in the process of completing their tasks.

Information acquisition involves scanning and identifying information from an information source. Information acquisition is related to information reduction. Information acquisition can be performed as a prior step or possibly in conjunction with information reduction. Eye movement patterns can be used to determine how people acquire information and execute decisions or solutions.

A number of studies have examined information reduction in acquiring specific skills. Haider and Frensch (1996) conducted an experiment to study information reduction in cognitive skill acquisition. Participants were asked to verify the correctness of an alphanumeric string that contained a varying number of task-irrelevant characters. As participants became more skillful, they were increasingly unaffected by the varying amount of task-irrelevant characters. Results indicated that practice affects which information is processed and that with practice on multiple cases, subjects learned to separate task relevant information from task irrelevant information and to limit their processing to the relevant information. Task instruction has an effect on the degree of information reduction (Haider and Frensch 1999a). In an eye-tracking experiment, Haider and Frensch (1999b) studied changes in subjects' attention strategies by considering eye movements as the main dependent variable. Their results supported the information reduction hypothesis that people learn to distinguish between task-relevant and task-redundant information and to limit their processing to task-relevant information with increased practice.

The Mouselab System

Mouselab has been used to track the information acquisition stages (Payne et al.1993). A mouse and a computer display are the key components of this system. First, all information items are hidden behind boxes. Users can reveal an item by moving the mouse cursor over the box. The item will be hidden when the mouse cursor moves out of the box (see Figure 1). Only one box can be opened at a time. The Mouselab system records the sequence and number of opened boxes and the time spent in each box

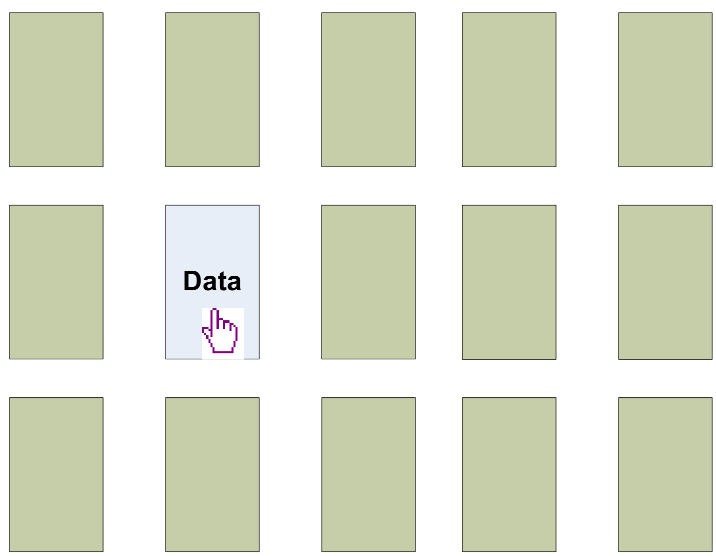


Figure 1: An example of Mouselab system

1.2 EVALUATING PERFORMANCE

In this section we briefly describe performance measures for information reduction (using signal detection theory) and information acquisition (using time per item).

1.2.1 Information reduction measures based on Signal Detection Theory

Signal detection theory (SDT) was developed to measure decision making performance (Green and Swets 1966). SDT is used in decision making contexts where there is some degree of uncertainty about the identification of some signal or target present in the context (Heeger 1997; Heeger 2003). A subject makes an assessment of the strength of evidence in support of some hypothesis, compares that assessment to some decision criterion, and then decides for or against the hypothesis. The threshold for a decision criterion will depend on a subject's skill level and ability to discriminate between instances when the hypothesis is true (i.e., the target is present) and when it is not (i.e., no target is present, only distractors). The response of a subject can be characterized by a distribution (typically assumed to be a normal distribution). Two distributions are considered, namely, the noise (distractors) distribution, $f_N(x)$ and the signal distribution, $f_S(x)$. The noise distribution characterizes the strength of evidence when there are no targets present and represents background noise as shown in Figure 2. The signal distribution represents the strength of evidence when a target is present. The higher the ability of a subject to identify the presence of the signal (target), the less overlap there is between the two distributions. That is, as the ability of a subject improves or the strength of the signal increases, then we would expect the signal distribution to shift to the right and/or decrease its spread.

SDT experiments consist of asking subjects to make a decision based on a presentation of information. In our experiment, the information consisted of statements in a problem and a set of decisions as to which statements were relevant. In the terminology commonly used in psychological studies employing SDT, relevant statements correspond to targets and irrelevant statements correspond to distractors. In SDT, there are four possible outcomes corresponding to success or failure in selecting targets and distractors. Selecting a target is a success and is labeled a *hit*. Not selecting a target is a failure and is labeled a *miss*. Selecting a distractor is a failure and is labeled a *false alarm*. Not selecting a distractor is a success and is labeled a *correct rejection*.

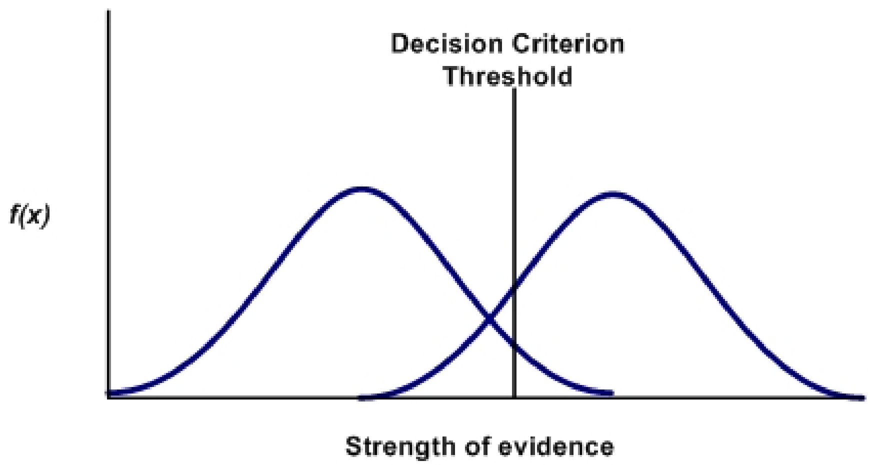


Figure 2: Noise and Signal Distributions

Notation

N_T total number of targets in the problem

N_D total number of distractors in the problem

n_H total number of hits made by a subject

n_M total number of misses made by a subject

n_F total number of false alarms made by a subject

n_R total number of correct rejects (i.e., irrelevant statements not selected by a subject)

H fraction of known targets that were correctly identified (hit rate)

F fraction of the number of times that a target was not present and a false alarm occurred (false alarm rate)

A problem is designed with known values for N_T and N_D. For each subject, n_H and n_F are recorded. Given these results, $n_M = N_T - n_H$ and $n_R = N_D - n_F$. H represents the probability of correctly recognizing a target and is estimated using n_H / N_T. It corresponds to the area under the signal distribution to the right of the decision criterion (see Figure 3), $1 - F_S(x)$. Similarly, F is estimated using n_F / N_D, corresponding to the area under the noise distribution to the right of the decision criterion, $1 - F_N(x)$. H and F are used to calculate measures of *sensitivity* and *decision bias.*

1.2.1.1 Calculating Signal Detection Theory Measures

SDT based on a Gaussian Models

This model assumes that both noise and signal distributions have the same variance (σ^2). A parametric measure of *sensitivity* (d') is defined as the normalized distance between the means of the noise and signal distributions based on the standard normal distribution. It represents a subject's ability to separate a signal from the noise. The standard deviation of the signal distribution and the standard deviation of the noise distribution are assumed to be equal and represent this common standard deviation as σ. Therefore, d' can be calculated as

$$d' = \frac{(\mu_S - \mu_N)}{\sigma},$$

where, μ_S is the mean of the signal distribution and μ_N is the mean of the noise distribution (Macmillan, 1993; Stanislaw and Todorov, 1999).

When $H < 1$ and $F > 0$, d' can be estimated by subtracting the Z value corresponding to F from the Z value that corresponds to H.

$$d' = Z_H - Z_F \quad . \tag{1.1}$$

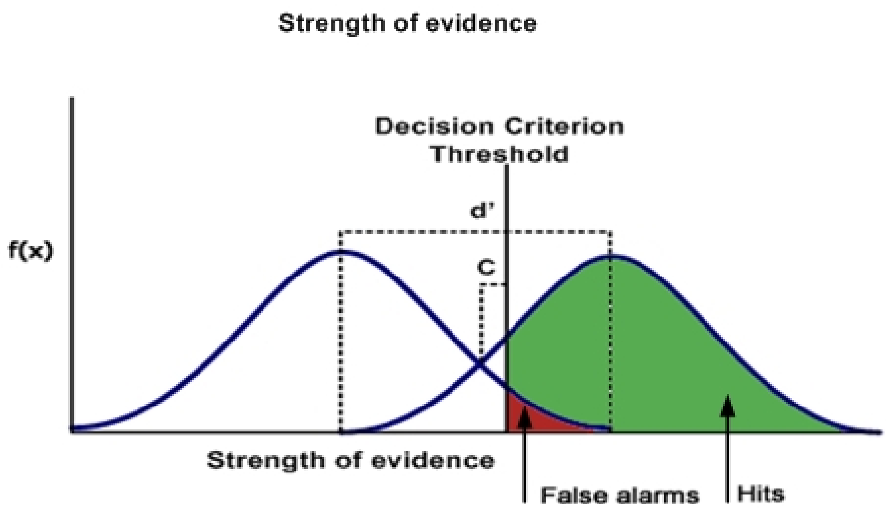


Figure 3: Definitions of C and d' in signal detection model

Decision bias measures a subject's tolerance for false alarms. A measure of decision bias for the normal SDT model, C , is the distance between the decision criterion threshold and the intersection of two distribution (Figure 3). C is found by averaging the Z value for H and the Z value for F (Snodgrass and Corwin 1988) and is given by

$$C = \frac{(Z_{FA} + Z_H)}{2} . \tag{1.2}$$

Receiver Operating Characteristics (ROC)

The assumptions of the SDT model can be evaluated by constructing the *receiver operating characteristics* (ROC) graph, sometimes referred to as *isosensitivity* curves (Macmillan and Creelman 2005). ROC is a plot of H as a function of F for all possible decision bias values for a respondent with one specific value of sensitivity (d'). Each value of d' is associated with a different ROC curve (Figure 4). Therefore, a point defined by a pair of values for H and F falls on a specific ROC curve, which is associated with a specific d' value. A diagonal ROC represents as subject who cannot discriminate the target at all (d'=0), and greater sensitivity forms a curve that bows more sharply to the upper left corner.

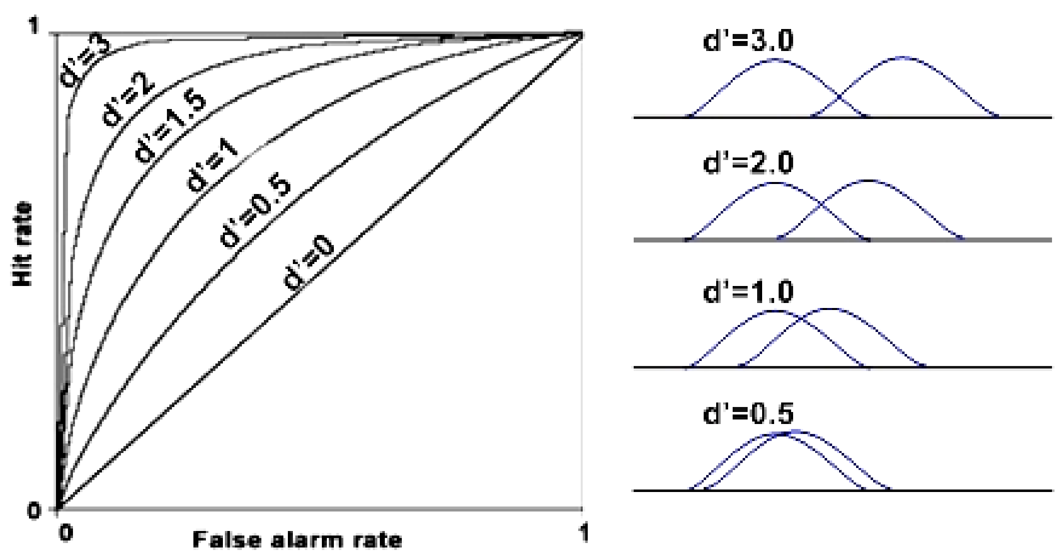


Figure 4: ROC Curve- Differing sensitivity.

The location of the point on the ROC curve is associated with the decision bias value for each specific d'. As shown in Figure 5, when the decision bias becomes positive (conservative), F and H would be very low (toward the lower left corner. A negative decision bias (liberal) would increase H and F (toward the upper right corner).

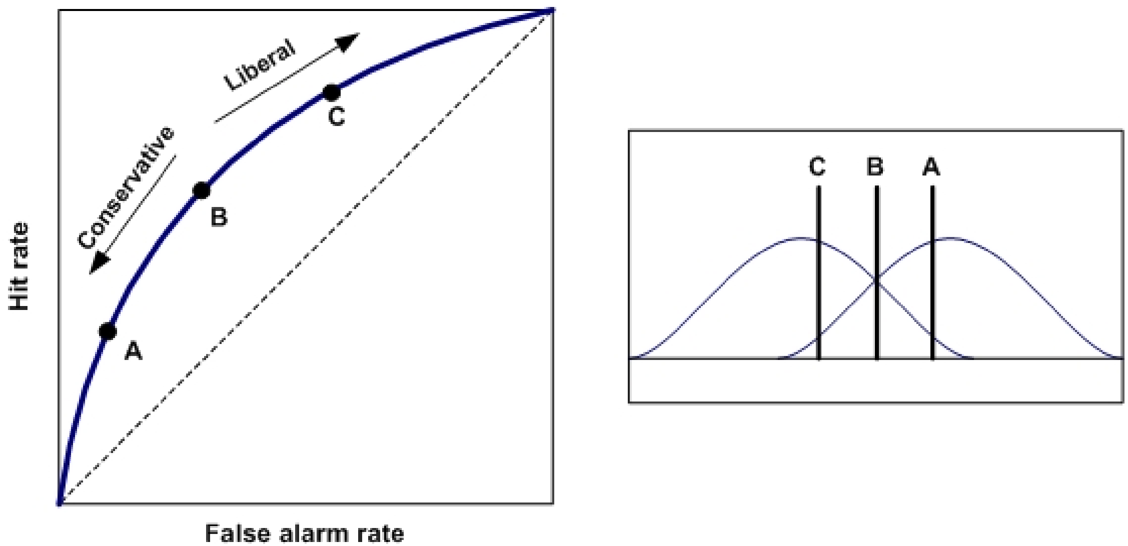


Figure 5. ROC Curve- Differing decision bias.

Nonparametric SDT Measure

In the situation where the underlying distributions are unknown (and therefore may not be normal distributions), a nonparametric SDT measure has been used as an alternative to measure the sensitivity and decision bias. Nonparametric SDT measures correspond to an area under the ROC curve as shown in Figure 6. For a given result of (F,H), the area is approximated by drawing lines from (1,1) and (0,0) that pass through (F,H).

A' is a nonparametric measure of sensitivity, or the separation between the two distributions (Stanislaw and Todorov, 1999). As A' approaches 1, discriminability increases while a value near 0.5 implies guessing. Norman (1964) suggested that this sensitivity measure (A') is given by

$$A' = I + 1/2\left(A_C + A_L\right)$$

where, A_L and A_C represent performance that is more liberal and more conservative, respectively.

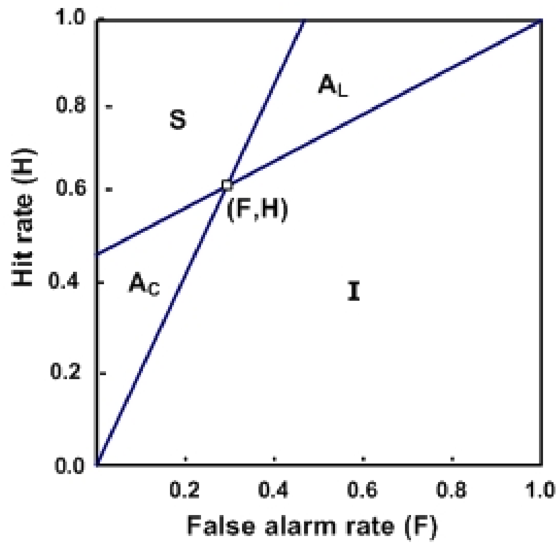


Figure 6. Area in the unit square used to define the nonparametric SDT.

The computational formula is

$$A' = 0.5 + \left[sign(H-F)\,\frac{(H-F)^2 + |H-F|}{4\max[H,F] - 4HF} \right]. \quad \textbf{(1.3)}$$

A measure of decision bias for nonparametric SDT generally is defined as the difference between two area ($(A_L - A_C)$) as a proportion of their combined areas $(A_L + A_C)$. Grier (1971) introduced B'' as a bias measure. Grier identified A_L as $(A_L + S)$ and A_C as $(A_C + S)$ when calculating bias. B'' is given by

$$B'' = \frac{(A_L + S) - (A_C + S)}{(A_L + S) + (A_C + S)}$$

which simplifies to

$$B'' = \frac{(A_L - A_C)}{(A_L + A_C + 2S)}.$$

Upon examination of the B'' formula, it should be noted that when discrimination decreases, the area S becomes larger and increasingly limits the possible range of B''. Therefore, Donaldson (1992) suggested B''_d as another alternative measure of decision bias for nonparametric SDT. B''_d, is given by

$$B''_d = \frac{(A_L - A_C)}{(A_L + A_C)}$$

and is computed as

$$B''_d = \frac{(1-H)(1-F) - HF}{(1-H)(1-F) + HF}. \qquad \textbf{(1.4)}$$

B''_d can have a value between -1 and 1. When $B''_d = 0$, there is no bias. A positive value indicates less tolerance for false alarms and conversely, a negative value indicates greater tolerance for false alarms.

The advantage of using a nonparametric over the parametric measures (based on an underlying distribution model) is that assumptions about the signal and noise distributions are not necessary. However, nonparametric measures tend to overestimate at high levels of discrimination (Pastore et al. 2003).

1.2.2 Information acquisition measures based on time

Information acquisition can be characterized in a variety of ways. General information acquisition measures include the amount and pattern of information acquired and the time spent acquiring information (Payne et al. 1993; Klayman 1983). In this study, we measure information acquisition in terms of time, acquisitions and process selectivity.

Time

Time is a common measure that can reflect a subject's information acquisition performance. Time spent in acquisition can be described as shown in Figure 7.

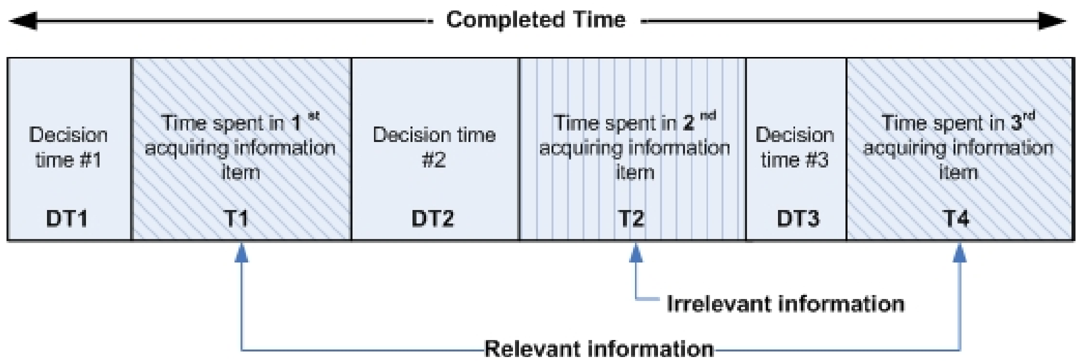


Figure 7: Time definition in information acquisition

A subject spends time deciding which item to open and then spends time looking at the item. Let DT_i be the time corresponding to the decision delay of deciding that item i should be opened and T_i.is the length of time that item i remains open. The completion time for all items, CT, is given by

$$CT = \sum_{\forall i} DT_i + T_i \quad \text{.} \tag{1.5}$$

The fraction of time spent on viewing relevant information, FRT, is given by

$$FRT = \frac{\sum_{\forall j} T_j}{CT} \tag{1.6}$$

where, T_j , is length of time on a relevant item.

Similarly, the fraction of time spent viewing irrelevant information is given by

$$FIT = \frac{\sum_{\forall k} T_k}{CT} \tag{1.7}$$

where, T_k , is length of time on a relevant item. Note that $FR + FI = 1$.

Acquisitions

Acquisitions can be used to determine how irrelevant information affects information acquisition. The following are the list of possible measures that can reflect a subject's information acquisition.

The fraction of total items viewed, *FTV*, is the number of items viewed, *NV*, divided by the total number of items,

$$FTV = \frac{NV}{N_T + N_D} \;. \qquad \textbf{(1.8)}$$

The fraction of viewed relevant items is *FVR* and the fraction of viewed irrelevant items is *FVI*.

The average information viewing time spent per acquisition, $\overline{VT}$, is given by

$$\overline{VT} = \frac{\sum_{j=1}^{m} T_j}{m} \,. \qquad \textbf{(1.9)}$$

where *m* is number of viewed information items.

Processing Selectivity

Processing Selectivity can be used to assess how the level of CS and level of DS affect selectivity in processing. The proportion of time spent acquiring information on relevant and irrelevant information and the variance in time spent acquiring each information item can be measured.

The fraction of viewing time spent on relevant information, *FVRT*, is given by

$$FVRT = \frac{\sum_{\forall j} T_j}{\sum_{\forall i} T_i}. \tag{1.10}$$

The fraction of viewing time spent on the irrelevant information, *FVIT*, is given by

$$FVIT = \frac{\sum_{\forall k} T_k}{\sum_{\forall i} T_i}. \tag{1.11}$$

The sample variance of the viewing time for each item can be determined for each subject and is given by

$$S_{VT}^2 = \frac{n\sum_{i=1}^{n} T_i^{\,2} - \left(\sum_{i=1}^{n} T_i\right)^2}{n(n-1)} \tag{1.12}$$

This measure indicates the strategy used in processing selectivity. A *compensatory strategy* implies a pattern of information acquisition that is consistent (low in variance) across information items; in contrast, a *non-compensatory strategy* implies more variance in processing.

1.3 EVALUATING SUBJECT BEHAVIOR

Clustering analysis and Markov models can used to discover subjects' information acquisition behavior. Clustering analysis is used to understand subject behavior by clustering subjects who exhibit similar behavior. Markov models are used to find subjects' acquisition patterns.

1.3.1 Markov models

Markov models have been used for stochastic processes and are well suited for modeling and predicting user navigation behavior (Pirolli et al. 1999). In general, the sequence of documents/information visited by a user is the input and the aim is to build Markov models that predict the likelihood of visiting the next document/information based on previous documents visited.

A Markov model consists of:

- ***States:*** States(s) represent a single item of information or a related collection of information. The set of all possible states for which the Markov models is built is given by S = $\{s_1,\ldots\ldots\ldots\ldots,s_n\}$.
- ***Action:*** The set of all possible actions (Different information items in the problem description) that can be performed by users are given as A = $\{a_1,\ldots\ldots\ldots\ldots,a_n\}$.
- ***Transition Probabilities***: A matrix, P, contains the conditional probabilities for a system to transition from one state to another. This matrix is given by P = $\{p_{1,1},\ldots p_{1,n},p_{2,1},\ldots p_{2,n},\ldots,p_{n,1},\ldots,p_{n,n}\}$.

The order of a Markov model depends on the number of previous states used in the conditional probability of the Markov process. The simplest Markov model (*first order*) predicts the next state from the current state. A First Order Markov models is easily extended to a second order model in which the probability of visiting the next state is based on the current state and previous state. This approach can be generalized to a K^{th} *- order Markov model*, which includes the last *K* states.

To estimate the values for P, the sequence of information items viewed by a subject is used as one realization of the Markov model. In the case of first order models, the states correspond to a single information item. Similarly, for the second-order models, the states correspond to all pairs of consecutive information items.

1.3.2 Clustering Analysis

Clustering is a data mining technique used to identify groups based on the similarities and dissimilarities in their characteristics. Standard clustering algorithms, such as K-Means (Steinbach et al. 2000), generally partition a data set into subsets (clusters) so that data in each subset are close to each other based on a measure of distance or similarity. K-means is an established clustering method that is efficient and fast in determining the clusters (Alsabti et al. 1998; Kanungo et al. 2002).

Clustering criteria are based on specific tasks or interests of the analyzers (Zhu, 2001). Cluster results can be used in further processing. In this study, we performed user clustering to discover user groups that have common characteristics based on their behaviors. Details on a subject's behavior are difficult to obtain, but we can learn or estimate subjects' characteristics based on their behaviors while they are performing information acquisition or information reduction.

CHAPTER2. RESEARCH DESCRIPTION

2.1 MOTIVATION

In a previous experiment (Kumsaikaew et al. 2006), it was found that the expertise level significantly affected a subject's performance. As expected, subjects with more expertise performed better in identifying relevant information compared to subjects with less expertise. Experienced subjects were more liberal than novices, as measured by B''_d and had higher values for H in the context of more false alarms.

Moreover, it was observed that the characteristics of irrelevant information played a significant role in a subject's performance (e.g., the relative amount of irrelevant information and the semantic similarity). Results also indicated that the structure of problem descriptions in terms of density and distribution could affect subject performance. Subjects performed well under high density and skewed distribution, which would represent a typical textbook problem. It became apparent in this study that more formal methods are needed to measure the nature of the irrelevant and relevant information in order to support further investigations on the nature of these effects in information reduction.

In this study, we examined two specific types of irrelevant information, namely, 1) when irrelevant information has a similar meaning as relevant information and 2) when concepts that appear in irrelevant information are related to the relevant information.

Data on information acquisition can provide insights into how subjects interact with problem content. The previous study did not consider the interaction between problem solving (i.e., moving through the problem space) and information reduction. In this study we also compare information reduction with and without solving the problem to determine any changes in performance or behaviors.

The results of this study should provide new insights into the information reduction process, which should lead to procedures and methods for improving problem solving skills. The formal methods used in this study can also provide guidance for constructing problem descriptions.

2.2 DEFINITIONS

Figure 8 describes semantic similarity for information items related to knowledge domains. Concepts a_1 and a_2 include different subsets of information items (and may share some items) but both lie within the same knowledge domain (domain A). Items in a_1 include a subset of relevant information (critical information used to solve a problem) and similar irrelevant information (items that are not needed to solve a specific problem). For example, if "*demand for 2006*" is relevant information, then "*demand for 1999*" may be irrelevant. In this case, both items are related to the same concept. Items in a_2 correspond to irrelevant information related to a different concept but still in the same knowledge domain (domain A). Items in b_1 include irrelevant information from another knowledge domain (domain B).

Semantic similarity is defined as the degree to which two information items have similar meaning (i.e., closeness in meaning).

Concept similarity (*CS*) is the degree to which irrelevant information is close in meaning to relevant information found in a specific concept. This corresponds to semantic similarity of an irrelevant information item (which may or may not appear within a concept) and a relevant information item (that appears within a concept). For example, if the relevant items are from a_1, then irrelevant items in a_1 would have high values for *CS*.

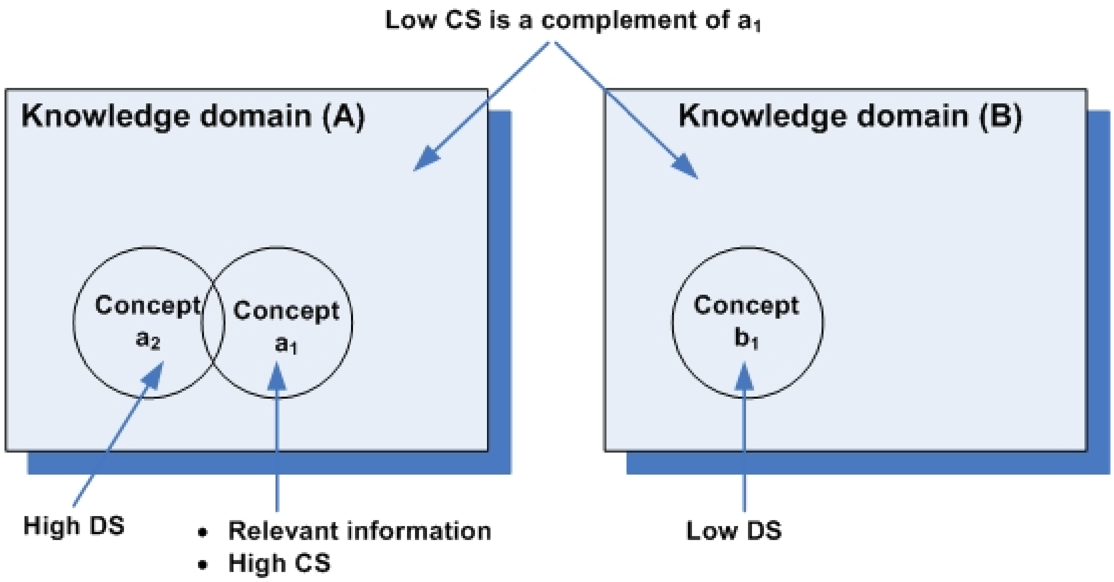


Figure 8: Similarity related to knowledge domain

Domain similarity (*DS*) is the degree to which the irrelevant information lies within the same knowledge domain. This corresponds to semantic similarity between irrelevant information and the knowledge (e.g., domain A).

Information reduction performance is defined as a subject's ability to differentiate relevant from irrelevant information.

Information acquisition strategy is defined as a subject's strategy used in scanning and identifying information from an information source. Subjects' acquiring strategy can be characterized by attributes such as the sequence of viewing information and time spent on individual information.

2.3 RESEARCH QUESTIONS

1. How do *CS* and *DS* in irrelevant information affect information acquisition and information reduction?

2. When a subject solves a problem, is there an effect on information reduction performance?

2.4 HYPOTHESIS

Hypothesis 1*: Higher values for CS may lead to more intensive search behavior in information acquisition.*

Hypothesis 2: *Higher values for CS will lead to more intensive search behavior in information acquisition.*

Hypothesis 3*: Lower values for CS will lead to better performance in information reduction.*

Hypothesis 4: *Irrelevant information* with a *higher value of DS will decrease subjects' performance especially for the experienced subjects since they are most likely to have internal schemas associated with the high DS information.*

Hypothesis 5: *More experienced subjects should have a better developed conceptual schema for a class of problems and they should have better performance in information reduction and acquisition.*

Hypothesis 6: *Subjects' information reduction performance should be improved when subjects are asked to solve a problem versus only identifying task relevant information.*

2.5 INFERENCES

1. If *CS* affects a subject's information acquisition strategy and information reduction performance, then we should see a significant effect in the ANOVA results

(performance) and clustering analysis should show different clusters depending on their acquisition strategy.

2. If *DS* affects a subject's information acquisition strategy and information reduction performance, we should see a significant effect in the ANOVA results (performance). In addition, clustering analysis should show different types of behaviors.

CHAPTER3. METHODOLOGY

The general procedure that was used is as follows.

1. Problem descriptions related to inventory control were formulated and evaluated.
2. An experiment was conducted using a web-based real time data collection system to collect and store the results in a database.
3. The results were analyzed using statistical methods, Markov models and clustering analysis.

3.1 FORMULATION OF PROBLEM CONTENT

To formulate problem content corresponding to different levels of *CS* and *DS*, six classes of information were used in the problem descriptions as shown in Table 1.

Table 1: Information classes and examples

Information class	Sample problem content
Relevant information	The total forecast demand for 2006 is 419
Common irrelevant information (Appears in all experimental conditions)	The MPBC history in the bicycle business began in 1981. It has pioneered many improvements to the industry, producing bikes for nearly 25 years
Irrelevant information with High CS	The total demand for 2005 is 391
Irrelevant information with Low CS	Company A's address is 22 West ST. New York, USA
Irrelevant information with High DS	Delivery lead time for company A is 2 weeks
Irrelevant information with Low DS	MARR of company is 9%

3.1.1 Background

In a previous experiment (Kumsaikaew et al. 2006), it was found that problem descriptions played a significant role in a subject's information reduction performance and that the structure and content of problem descriptions must be carefully formulated. Evaluation techniques such as concept maps and latent semantic analysis (LSA) can provide a basis for analyzing problem descriptions to determine similarities and differences between problems.

3.1.1.1 Concept Map

Concept maps are graphical descriptions used to represent relationships between concepts (Novak 2002). The concept diagram is a network structure consisting of nodes and links. Nodes correspond to concepts. Links are word phrases such as "results in", "represented as" or "consist of" that describes relationships between concepts. An example of a concept map for graphs (modified from Dürsteler 2004) is shown in Figure 9.

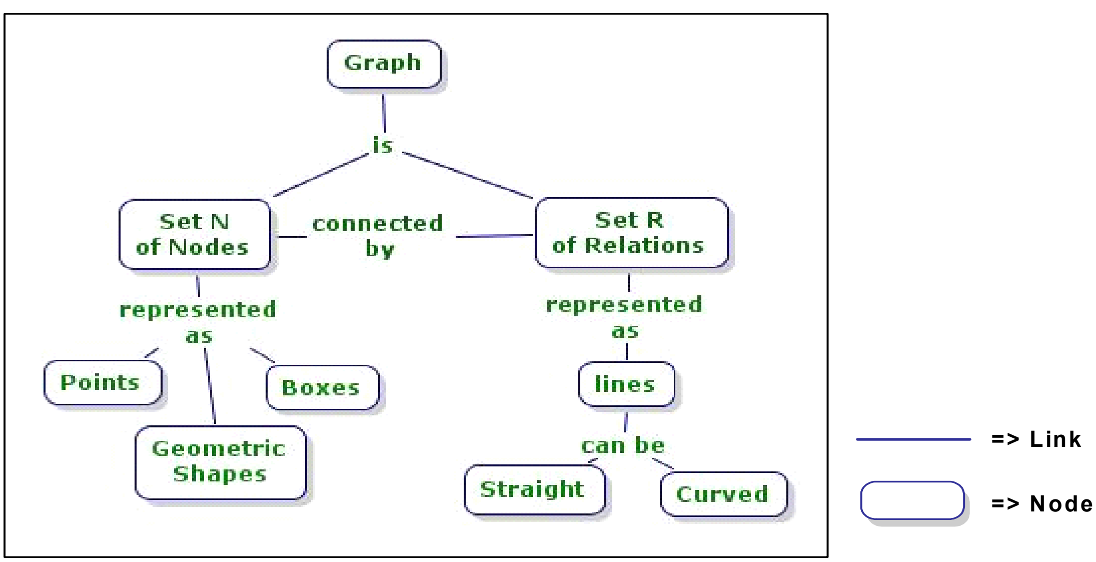


Figure 9: an example of concept map represented map of Graph Concept

Concept maps have been used in many domains such as business and education. For business, concept maps can help a team to develop a shared understanding or vision. In education, concept maps can aid learning by helping students to identify gaps in their knowledge (Novak 1998). In addition, since concept maps seek to capture the mental model of students, they can be used as an assessment tool (Novak 1990). Students are asked to construct a concept map for a specified topic. The mapping activity provides an external description of a student's internal schema for the topic. The map can be compared to a map of an expert to determine any deficiencies. Missing nodes and/or relationships between nodes would indicate a lack of understanding of the concepts. The evaluation is based on measuring the similarity between the student concept map and an expert map. McClure (1999) studied a number of different evaluation methods and found that they provided reasonable measures of similarity. Ruiz-Primo et al. (2001) observed that constructing maps using a blank form versus completing a partial map was a better indicator of differences in students' internal schemas. While concept maps can provide a representation of knowledge, variations can exist, even for experts.

Concept maps could provide a form of assessment of problem descriptions. A comparison of concept maps of the relevant information for different problem descriptions would indicate the degree of similarity. However, it would be difficult to assess the irrelevant information, which would appear as disconnected nodes in a concept map.

3.1.1.2 Latent Semantic Analysis (LSA)

Latent Semantic Analysis (LSA) is a method that produces quantitative measures for the meaning of a set of words based on a large corpus of text (Landauer and Dumais 1997).

A set of words can range from a phrase to a large body of text. The premise of LSA is that a text can be considered as an unordered set of words where the meaning of the text is based on "adding" the meaning of each word. Details of LSA used in this study can be found in Appendix A.

3.1.2 Formulation method

Four different problem descriptions were used in this study to examine four combinations (conditions) of high and low *CS* and *DS*. The structure of information in these problem descriptions is shown in Figure 10. The characteristics of information items are given in Table 2. There are five irrelevant information classes that were used to build four experimental conditions.

A method of evaluating the descriptions was needed in order to assess the suitability of the descriptions and make comparisons between conditions. The following steps were used to prepare problem descriptions.

Table 2: Characteristic of each information types

<table>
<tr><th colspan="2">Information classes</th><th>Description</th></tr>
<tr><td colspan="2">Relevant information</td><td>Setup cost, holding cost, production cost and demand on the current year</td></tr>
<tr><td rowspan="5">Irrelevant Information</td><td>Common</td><td>Company introduction, company address, salary, number of current distributions, order and delivery method</td></tr>
<tr><td>High CS</td><td>Setup cost, holding cost, production cost and demand on the previous year</td></tr>
<tr><td>Low CS</td><td>Future plan, vender contact information, package types, building rent. And company promotion.</td></tr>
<tr><td>High DS</td><td>Lead time, safety stock, selling product price, cost of product manufactured and service level information</td></tr>
<tr><td>Low DS</td><td>Average number of fork trucks, MARR, estimated new distribution and value of purchasing and using the equipment.</td></tr>
</table>

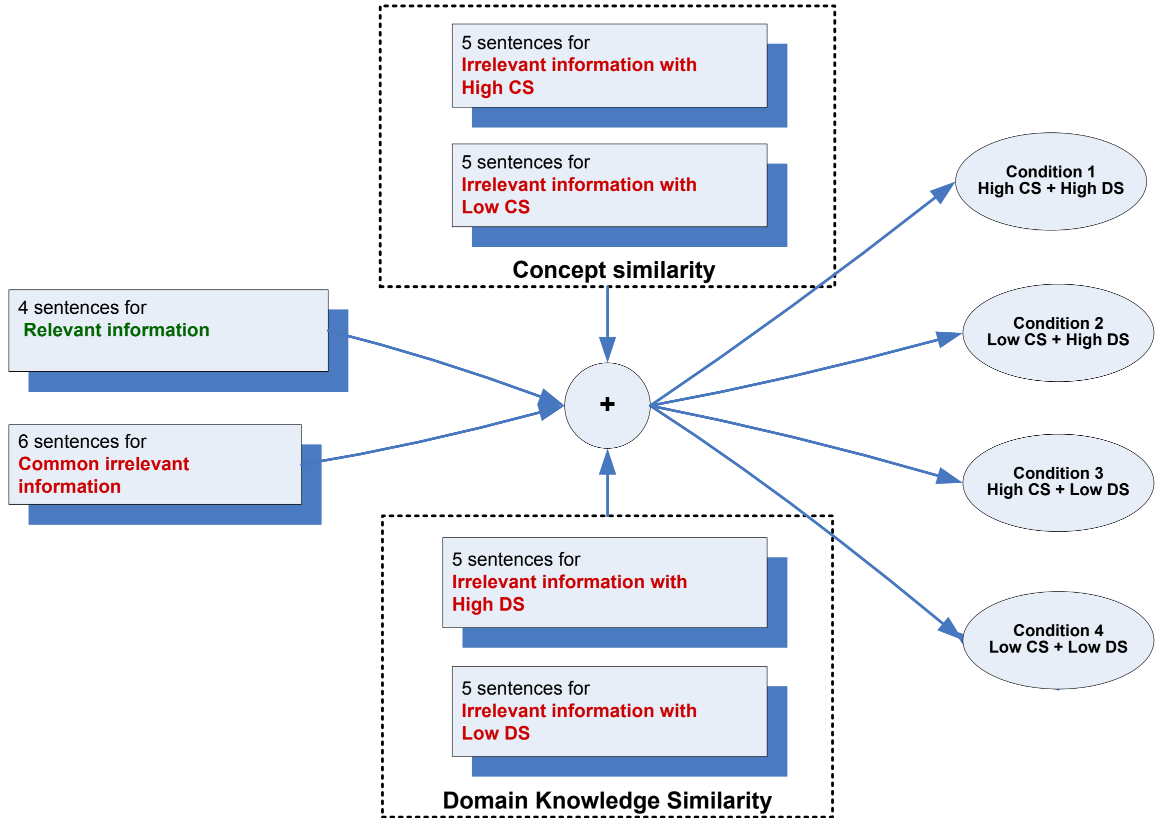


Figure 10: The structure of problem content in all four conditions

3.1.3 Data Preparation

3.1.3.1 Word extraction and preprocessing of documents

Words were extracted from each set of words by using a space as the delimiter. Each word was subsequently preprocessed to remove capitalization, most punctuation, and strings containing non- alphabetic characters such as digits and equations.

3.1.3.2 Removing common words

Words that could be found in a stop word list were removed. A stop word list includes words that do not carry a significant amount of semantic meaning and are primarily used to connect the main words in a sentence. Stop words include articles (e.g., a, an, the), conjunctions (e.g., and, or, but), interjections (e.g., oh, well), prepositions (e.g., in, on, over), pronouns (e.g., he, she, it), forms of the "to be" verb (e.g., is, am, are) and auxiliary verbs (e.g., should, may, will). We used the list of common words implemented by a WordNet Stop list (2006), along with some additions (DVL/Verity Stop Word List 2006; Snowball English Stop Word List 2006). A final list of 577 common stop words was used in this study.

3.1.3.3 Stemming

The next step of the process is to stem each word (eliminate plural endings, adverb endings, verb forms) so that all forms of a word occurrence have similar semantic interpretations. In this study, we used the Porter stemming algorithm (Porter 1980). This algorithm removes the common morphological and word suffixes and reduces a word to its *stem* or root form.

The algorithm ignores and removes the plural endings, adverb endings, verb forms; so that all forms of a word have similar semantic interpretations are considered as equivalent (root form) for the system. An existing implementation of the Porter stemming algorithm was used for this step (Christos 2005).

3.1.4 Building the domain dictionary

Domain knowledge can be characterized by a specific word set and the weight (frequency of appearance) of each word in the domain. A dictionary was constructed to represent knowledge domain. This domain dictionary is an abstraction of the internal schema that a knowledgeable subject should have in order to solve a problem in the domain.

Inventory control management was selected as the problem domain for this study. Therefore, six textbooks in Inventory Management were used to build the inventory domain dictionary. One textbook was from a textbook used for the initial problem content (Render 1997). Additional textbooks were used to insure coverage of the domain (Askin et. al 2002; Hopp and Spearman 1996; Van and Monhemius 1972; Smith 1989; Tersine 1982). The size of the domain dictionary was reduced further by limiting it to those sections of chapters related to the problem used in this study, namely, Economic Order Quantity (EOQ).

A word list was constructed separately for each text using the three steps previously described and then counting the word frequency. As a starting list, each text word list was compared to determine the number of new words that should be added to the composite list. Tables 3 and 4 along with Figure 11 and Figure **12** show that the number of new words decreased considerably for all words after the third textbook and after the second textbook for the higher frequency words, indicating convergence on a common set of words. Since the number of new words appears to be converging, the process was stopped after six textbooks.

All words except words having frequency < 3			
Textbook	Total number of words	Number of new words	% Of new words
T1	456	456	100.0%
T2	256	131	51.2%
T3	116	24	20.7%
T4	210	42	20.0%
T5	45	8	17. 8%
T6	129	16	12.4%

Table 3: The percentage of new words

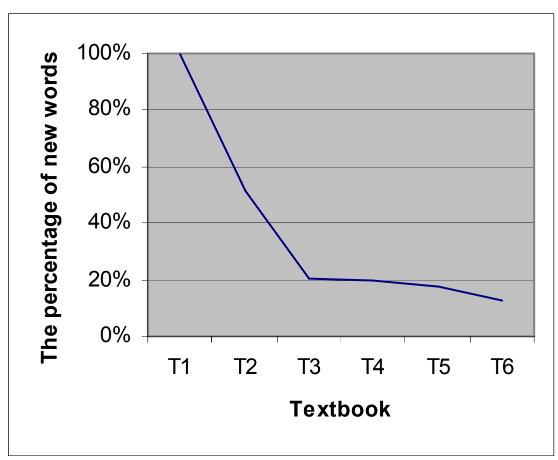


Figure 11: The percentage of new words

Number of words having frequency > 100			
Textbook	Total number of words	Number of new words	% Of new words
T1	101	101	100.0%
T2	149	32	21.5%
T3	185	23	12.4%
T4	209	20	9.6%
T5	222	11	5.0%
T6	233	7	3.0%

Table 4: The percentage of new words

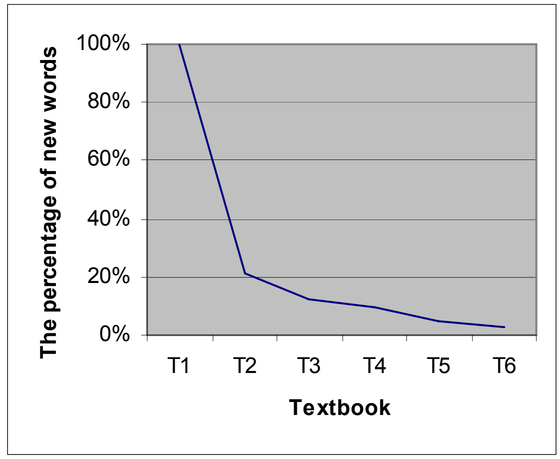


Figure 12: The percentage of new words

The degree of importance for a word in the domain was defined by its frequency of occurrence. The 200 most frequent words were initially placed in the domain dictionary. Some additional words were eliminated such as proper nouns (e.g., company name, person name, product name, etc). The final dictionary contained 111 words and each word's weight corresponded to the frequency of occurrence. The top ten most frequently occurring stemmed words are shown in Table 5. The complete list of words in the dictionary can be found in Appendix B.

Table 5: An example of stemmed words in dictionary

Top 10 of frequency words	
Words	Frequency
COST	1217
INVENTORI	913
TIME	565
DEMAND	538
PERIOD	472
PRODUCT	455
UNIT	452
QUANTITI	369
STOCK	328

3.1.5 Evaluating problem descriptions

In this study, we used latent semantic analysis (LSA) as an approach to measure the similarity between information items in all experimental conditions as described in Appendix A. The value for semantic similarity can vary between 0 and 1 (a 1 indicating complete similarity and a 0 indicating total dissimilarity). The information items for all problem descriptions were formulated under all four experimental conditions (see Appendix C). In order to formulate problem contents, we considered three semantic similarities as measured by LSA, between problem descriptions, *CS* within a problem and *DS* within a problem. Since problem descriptions were represented in a tabular format instead of plain text, each cell (in combination with the column heading and cell content) was considered as a separate information item for LSA.

The first step was to create an initial problem description for all four experimental conditions. The Economic Order Quantity problems were adapted from a problem by Render and Stair (1991). Then, we applied LSA to measure the semantic similarities. The problem descriptions were changed until reasonable values for semantic similarity were obtained for pair-wise comparisons of problem descriptions and high and low conditions for *CS* and *DS* (See Tables 6-9). Ideally, the semantic value for overall problem content should be the same under all conditions in all problems (i.e., a value of 1). Semantic values should be significantly different when we compare high versus low *CS* and high versus low *DS*.

Measuring between overall problem content

Table 6 shows the LSA similarity between problems in each condition and Table 7 shows the LSA similarity between experimental conditions in each problem. Equivalent semantics, it is not feasible, because the problem descriptions would be identical. The semantic values in Table 6 and Table 7 are reasonably close and indicate that there are no overall major differences between the problem descriptions in the same condition and between all conditions in each problem. There is some difference due to using a high *DS* versus a low *DS* as would be expected. The conditions having the same level of *DS* (1&2 and 3&4) are close in value (Table 7). Since each *DS* level contains different information items that do not overlap the other information, the values are different. Experimental conditions under low *CS* have similar information items as high *CS* but with fewer occurrences. Therefore, we obtain high semantic similarity values when we compare condition 1 versus condition 2 and condition 3 versus condition 4.

Table 6: The semantic similarity result for all problems in each condition

The semantic similarity result for overall problem content								
	Condition 1				Condition 2			
	Problem1	Problem2	Problem3	Problem4	Problem1	Problem2	Problem3	Problem4
Problem1		**0.970**	**0.969**	**0.963**		**0.968**	**0.953**	**0.971**
Problem2			**0.974**	**0.968**			**0.949**	**0.967**
Problem3				**0.967**				**0.952**
Problem4								
	Condition 3				Condition 4			
	Problem1	Problem2	Problem3	Problem4	Problem1	Problem2	Problem3	Problem4
Problem1		**0.963**	**0.937**	**0.973**		**0.945**	**0.90006**	**0.956**
Problem2			**0.918**	**0.964**			**0.867**	**0.920**
Problem3				**0.927**				**0.875**
Problem4								

Table 7: The semantic similarity result for all experimental conditions in each problem

The semantic similarity result for all experimental conditions								
	Problem 1				**Problem 2**			
	Condition1	Condition2	Condition3	Condition4	Condition1	Condition2	Condition3	Condition4
Condition1 *(High CS & High DS)*		**0.979**	**0.884**	**0.862**		**0.979**	**0.886**	**0.866**
Condition2 *(Low CS & High DS)*			**0.820**	**0.823**			**0.815**	**0.821**
Condition3 *(High CS & Low DS)*				**0.984**				**0.980**
Condition4 *(Low CS & Low DS)*								
	Problem 3				**Problem 4**			
	Condition1	Condition2	Condition3	Condition4	Condition1	Condition2	Condition3	Condition4
Condition1 *(High CS & High DS)*		**0.970**	**0.891**	**0.847**		**0.964**	**0.908**	**0.873**
Condition2 *(Low CS & High DS)*			**0.809**	**0.823**			**0.832**	**0.842**
Condition3 *(High CS & Low DS)*				**0.961**				**0.969**
Condition4 *(Low CS & Low DS)*								

Measuring *CS* within a problem description

The level of *CS* is a measure of the similarity between relevant information and irrelevant information. There are four sentences for relevant information that were compared with irrelevant information for four experimental conditions in each problem. As expected, irrelevant information under high *CS* condition has more similarity as compared to relevant information than under the low *CS* condition. Table 8 shows the semantic similarity comparisons for all four problem descriptions.

Table 8: Semantic similarity result for the level of CS

Document	Relevant information			
	Problem 1	Problem 2	Problem 3	Problem 4
Irrelevant information in condition 1 *(High CS & High DS)*	**0.719**	**0.688**	**0.700**	**0.728**
Irrelevant information in condition 2 *(Low CS & High DS)*	**0.409**	**0.379**	**0.369**	**0.439**
Irrelevant information in condition 3 *(High CS & Low DS)*	**0.822**	**0.770**	**0.775**	**0.779**
Irrelevant information in condition 4 *(Low CS & Low DS)*	**0.348**	**0.326**	**0.263**	**0.336**

Measuring *DS* within a problem description

To measure the level of *DS*, an additional step is needed. We compared the irrelevant information items from a related concept in the same knowledge domain as well as items from a concept in a different domain. The semantic similarity between the domain dictionary and irrelevant information from the concept in the same domain should be greater than the value for items from a different domain.

The goal state of the problems used in this study is to find the optimal order quality. Irrelevant information under the high *DS* condition includes lead time, selling product price and service level information. In the low *DS* condition, irrelevant information includes value of purchasing and using the equipment, MARR, average number of fork trucks and estimated new distributors (see Table 2). As expected, irrelevant information with a high *DS* has more similarity when compared to the domain dictionary. Table 9 shows the semantic similarity for the level of *DS* in all problem descriptions.

Table 9: Semantic similarity result for the DS Conditions

Document	*S*(*i*, Dictionary)			
	Problem 1	Problem 2	Problem 3	Problem 4
Irrelevant information in condition 1 *(High CS & High DS)*	0.513	0.531	0.500	0.530
Irrelevant information in condition 2 *(Low CS & High DS)*	0.470	0.487	0.452	0.494
Irrelevant information in condition 3 *(High CS & Low DS)*	0.427	0.447	0.432	0.450
Irrelevant information in condition 4 *(Low CS & Low DS)*	0.325	0.359	0.327	0.348

3.2 EXPERIMENT DESIGN

3.2.1 Independent Variables

Level of expertise: Two levels of expertise are considered, which we refer to as experienced and novice subjects. A pretest was used to determine the level of expertise (see Appendix H). Experienced subjects have more training and higher performance obtained from a pretest that assessed their understanding of the concepts in the knowledge domain. Novices had relatively little experience and lower performance in the pretest.

Level of CS: This corresponds to the level of semantic similarity between relevant information and irrelevant information.

Level of DS: This corresponds to the semantic similarity between irrelevant information and a domain dictionary.

Experimental session: There were two contiguous experiment sessions namely, information reduction and problem solving (only on the last problem in the sequence). In the information reduction session, subjects selected task relevant information. The second session was a problem solving session in which subjects solved the problem using a piece of paper and could revise their task relevant information (for that problem) selected in the first session.

Problem sequence: There were four problems presented in sequence.

3.2.2 Dependent Variables

3.2.2.1 Information reduction measures

The performance measures used in this study included H, F, A', and B''_d. All performance measures were used as dependent variables in the Analysis of Variance. Moreover, the numbers of selected items for each information type (DS items: *NSDS*; CS items: *NSCS*) were also used as dependent variable because they reflect a subject's information reduction.

3.2.2.2 Information acquisition measures

Information acquisition used performance measuring based on time, acquisitions and process selectivity.

3.2.3 Method

3.2.3.1 Subjects

The subjects were students who were enrolled in the IE 101, IE 148, IE 248 and IE 341 courses in Fall 2006. This experiment was an extra credit assignment. Students who participated not only earned an extra credit in their course, but also were eligible to win a cash door prize ($50*2). The sample was selected based on estimates found in appendix D.

The final list of participants included 48 experienced (14 females, 34 males) and 48 novice (14 females, 34 males) students. The subjects ranged age from 18 to 35 years ($\overline{X}$ =21.02, S = 2.98).

Subject selection

In the previous study, subjects were categorized as experienced based on their having passed a course. However, the results suggested that this was not a consistent criterion. In this experiment, it was necessary to have experienced and novice subjects equally distributed in all conditions to provide a basis of comparison. A pretest was used to assess expertise level prior to the experiment. An online pretest was implemented and given to subjects prior to the experiment (See Appendix H for pretest questions). The pretest was a set of twelve multiple choice questions from the inventory management domain (3 related to Economic Order Quantity (EOQ) and 3 related to Reorder Point) and the Engineering Economy domain (6 questions). EOQ questions assessed a subject's understanding (i.e., internal schema) of terms and concepts in the inventory control management domain that were present in the dictionary. Only the pretest scores on EOQ questions were used to differentiate a group of experienced subjects from a group of novices.

Threshold values were used to classify the expertise level. In this study, subjects who score above the upper threshold (2 out of 3) on the pretest were classified as experienced subjects. They are likely to understand all terms and concepts because their internal schema contains terms in this knowledge domain. Those who score less than the lower threshold (1 out of 3) were classified as novices (See Appendix H for pretest scores).

3.2.3.2 Stimuli

The four problems (each having four conditions) that were constructed as described in the previous section were used in this study.

3.2.3.3 Procedures

The experiment was a controlled experiment that took place in an IMSE computer lab. Each subject was seated in front of a computer having the same configuration of hardware, software, and Internet connection. The experimental procedure is described in Figure 13 and Figure 14.

The experimental session began with subjects reading a set of instructions followed by a pretest. After submitting a pretest, the correct answers and score were shown to the subjects. Moreover, the system automatically assigned the expertise level to subjects based on their pretest score. A short training session was given in which they practiced the mechanics of using the web-based system with an unrelated sample problem. After training, the students proceeded to the experimental phase. The experimental phase consisted of two sessions, information reduction and problem solving session. Each subject selected relevant information for all four different problem descriptions with randomized problem orders and each problem had a different combination of two independent variables. Subjects were asked to solve the last problem in the sequence and could revise their selected information (for that problem) after solving the problem.

In the information reduction session, all subjects were told to look at the given problem description. In contrast to the previous experiment, this experiment did not show all problem descriptions at the same time. Problem descriptions were divided into information items based on a tree structure as shown in Figure 15 and Figure 16. Headings correspond to information content that appeared in the display panel. Headings were equivalent across all conditions but the information content was varied depending on the experimental condition.

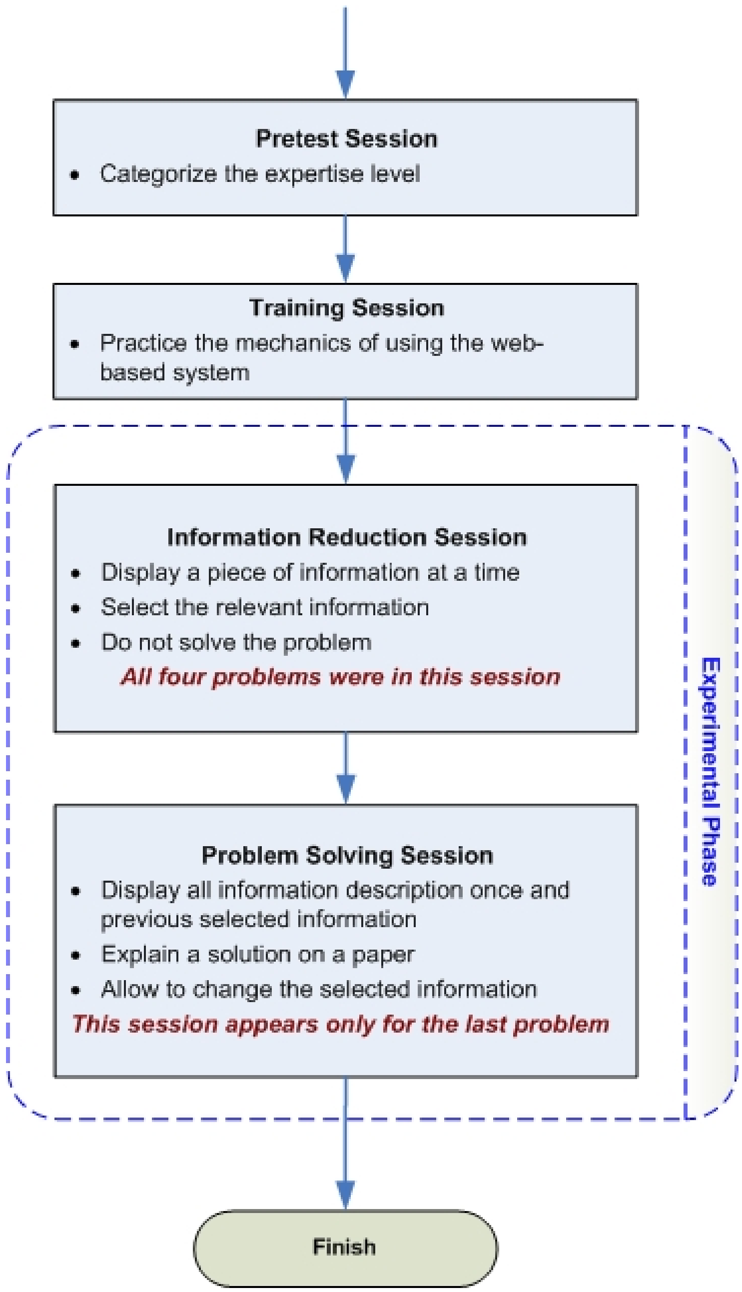


Figure 13: Overall experiment sessions.

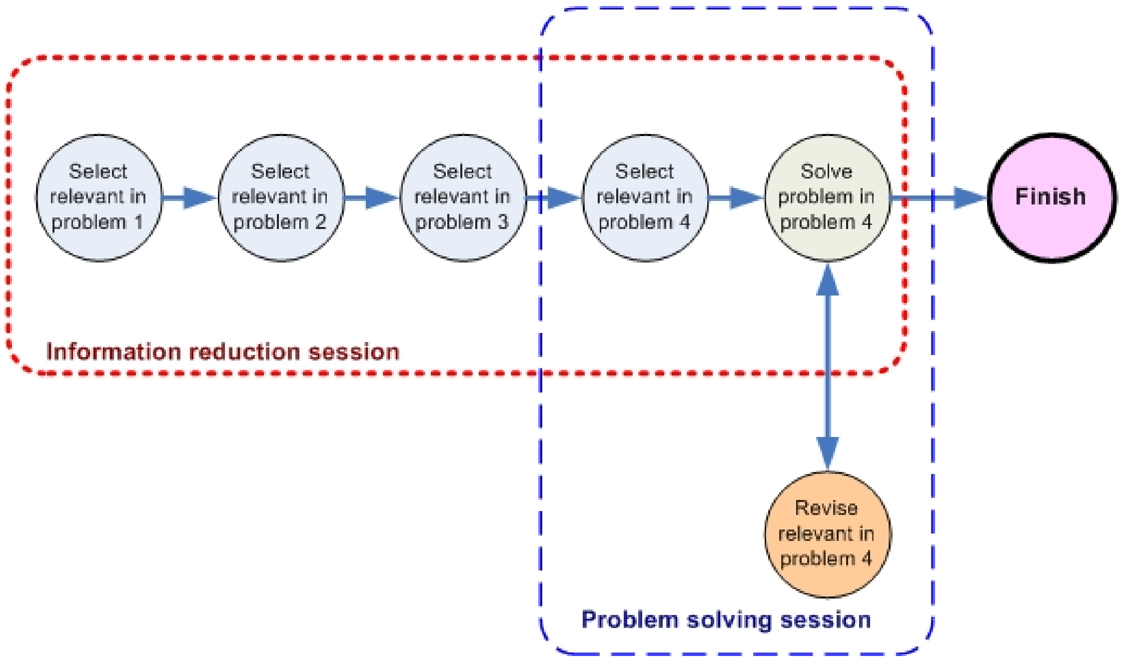


Figure 14: The experimental procedures/steps

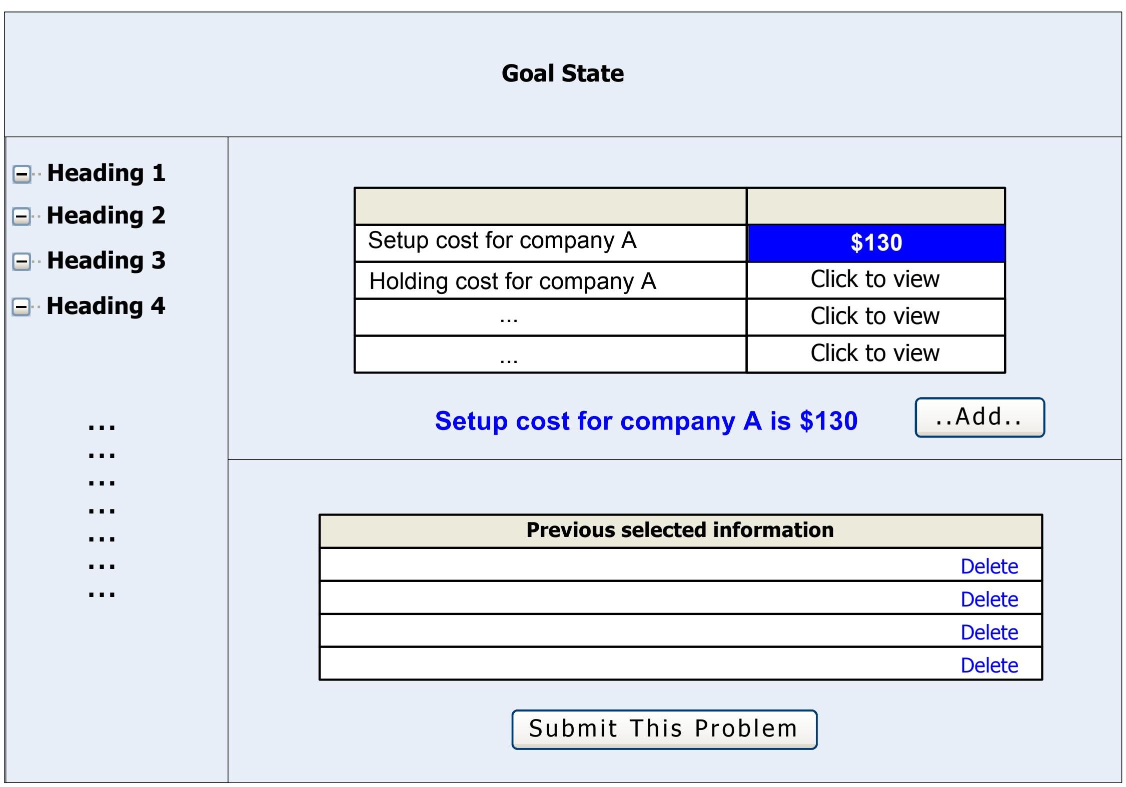


Figure 15: The layout of web-based system

An information item was shown only when subjects selected it (i.e., clicking the second column). The item was hidden when another selection was made. The goal state was displayed at the top of the problem description. Subjects were asked to identify relevant information items that are necessary to solve a problem by selecting the Add button. Subjects could add or delete an information item at any time. Once they were satisfied, subject must complete the problem by clicking the "submit this problem" button. However, subjects were not asked to solve the problem in this session.

After subjects finished the information reduction session on four problems, subjects proceeded to the problem solving session (Figure 14). In this session, subjects were asked to explain their solution on a piece of paper and were allowed to revise selected information made in the previous session. There was no time limitation in this experiment.

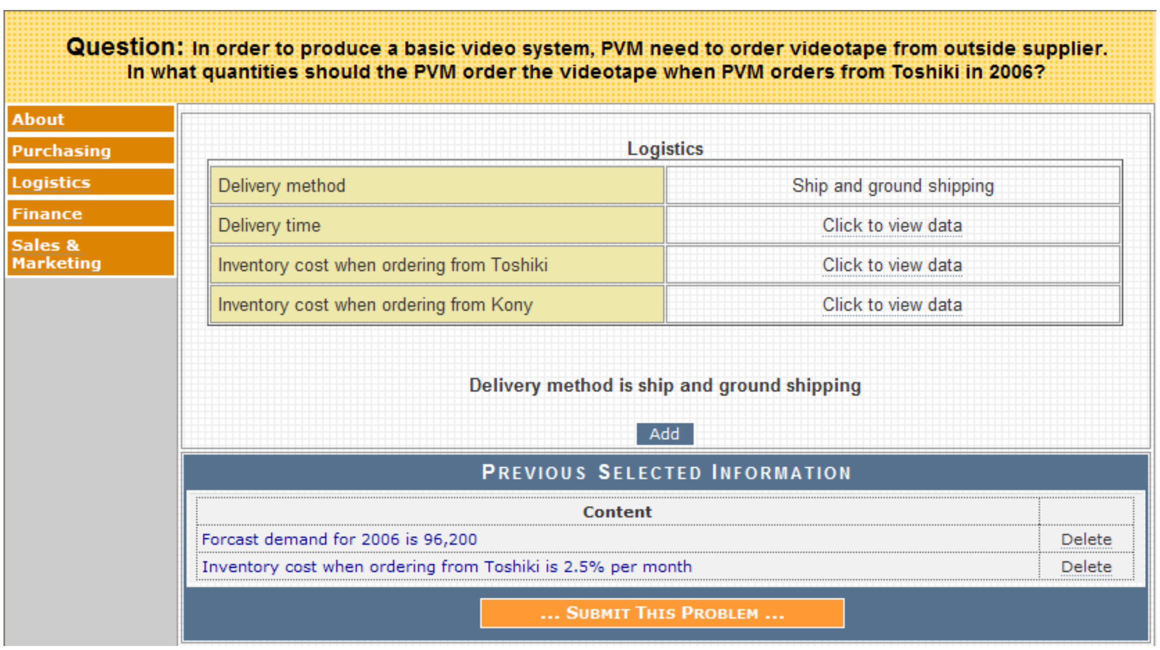


Figure 16: The web-based system

3.3 ANALYSIS OF RESULTS

3.3.1 Analysis of variance

Analysis of variance (ANOVA) was used to identify any significant main effects or interaction effects of the independent variables. The experiment was configured as a 2 (high *CS* versus low *CS*) x 2 (high *DS* versus low *DS*) using a within subjects design. We also examined the expertise level (experienced subject versus novice) and the actual problem solving (experimental sessions: information reduction versus problem solving) in between-subjects design.

3.3.2 Markov Model

Using the approach explained in the previous chapter, 1st, 2nd and 3rd order Markov models were implemented and analyzed. The support and confidence were used to measure the prediction quality. Support is a measure of prediction significance in a data set. Confidence is a measure of likelihood of prediction relative to the data set. The confidence and support for the prediction were calculated as follows.

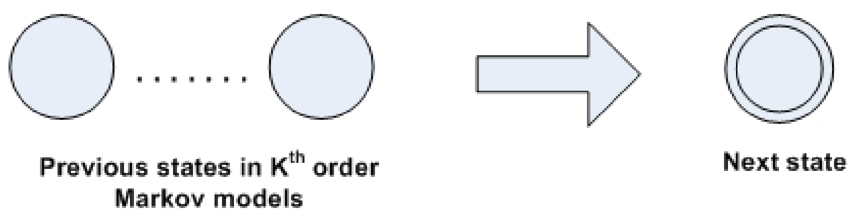


Figure 17: State diagram of Kth – order Markov model

$$\textbf{\textit{Support}} = \frac{\textit{Number of users whose pattern includes all states used } K^{th} - \textit{order Markov models}}{\textit{Total number of users}} \quad \textbf{(3.1)}$$

$$\textbf{\textit{Confidence}} = \frac{\textit{Occurrences of information element in the next state}}{\textit{Occurrences of previous states used } K^{th} \textit{ - order Markov models}} \quad \textbf{(3.2)}$$

3.3.3 Clustering Analysis

The K-means algorithm (Steinbach et al. 2000) was used for clustering analysis as implemented in the Waikato Environment for Knowledge Analysis (WEKA) system. Clustering begins with the identification of a set of attributes (and their values) for each individual. Using each information item (current state in 1st order Markov models) as an attribute the analysis was performed and will be referred to as *simple clustering analysis*. This represents a simple pattern of selection or acquisition. Information patterns were obtained using 3rd order Markov models (only previous states) as an attribute and will be referred to as *Markov clustering analysis*. This pattern is a sequence of three information items. The attributes are represented as V_{ij}, where i is the subject and j is the information pattern number. The data set used in this project for clustering can be generalized as

$$V_{ij} = \begin{cases} 0 & if\ \ information\ \ pattern\ \ j\ \ is\, observed\ \ for\ subject\ \ i \\ 1 & if\ \ information\ \ pattern\ \ j\ \ is\ observed\ \ for\ subject\ \ i \end{cases}.$$

Each row in the set shown in Table 10 represents one subject. The value of V_{ij} indicates whether the pattern was observed for that subject.

Table 10. A sample data set for clustering using Weka

Subject	Pattern1	Pattern2	Pattern	……
1	0	0	0	……
2	0	0	1	……
3	1	0	1	……
:	:	:	:	……

Compactness (i.e., density) and separation among clusters are commonly used to measure the quality of the cluster (Ray and Turi 1999). In this study, the average and variance of pair-wise similarity between each member and the cluster's centroid were used as measures of compactness of a cluster. Separation corresponds to distance between clusters and is calculated by taking the average of pair-wise similarities between cluster centroids. In a good clustering result, members of a cluster should be as close to each other as possible (low average and variance of compactness value) and clusters should be significantly separated from each other (i.e., high separation value). Compactness for cluster *j* is given by

$$Compactness = \frac{1}{N} * \sum_{i=1}^{N} d_i(x_i, \mu_j) \qquad \textbf{(3.3)}$$

where, *N* is number of instances in the cluster and $d_i(x_i, \mu_j)$ is the distance between instance *i* and the cluster centroid. This distance is given by

$$d_i(x_i, \mu_j) = \sqrt{\sum_{j=1}^{M} \left(x_{ij} - \mu_j\right)^2}$$

where, μ_j = centroid of cluster *j* and *M* is the number of attributes. For the *K* clusters, the separation is given by

$$Separation = \frac{\sum_{\forall i,j \; i \neq j} d(\mu_i, \mu_j)}{\binom{K}{2}}. \qquad \textbf{(3.3)}$$

CHAPTER4. ANOVA RESULTS FOR SDT MEASURES

The information reduction and information acquisition measures were computed for each subject. In all analyses, the standard level of significance used to indicate a statistically significant effect was α = 0.05. Our presentation of results is divided into two sections. Analysis of Variance (ANOVA) was used to examine the effect of the independent variables on SDT measures of sensitivity and bias. First we used all subjects' data (*Overall*) and then performed the analysis using the two levels of expertise (*Novice* and *Experienced*). Table 11 provides a description of the independent variables.

Table 11: List of independent variables

Variable	Values
Expertise	Novice, Experienced
CS	Low, High
DS	Low, High
Experimental session	Information reduction, Problem solving
Problem Sequence	1,2,3,4

4.1 SUMMARY OF RESULTS

Expertise effect

Experienced subjects performed better in identifying relevant information and were more liberal as compared to novices. Moreover, experienced subjects spent more time on relevant information than novices.

DS effect

- Subjects showed poorer performance when irrelevant information was information in the same domain.

- Only experienced subjects appeared to be more liberal when information in the same domain was present.
- In the high *DS* condition, only experienced subjects spent more time on irrelevant information and their average viewing time per acquisition increased.
- Both novices and experienced subjects tend to use an inconsistent pattern of information acquisition across information items (non-compensatory strategy) in the high *DS* condition and exhibit a more consistent pattern of information acquisition (compensatory strategy) when low DS information are present.

CS effect

- Only experienced subjects tend to do more acquisitions and spend less time on relevant information under low *CS* condition.
- In the low *CS* condition, only novices were more likely to use an inconsistent pattern of information acquisition across information items (non-compensatory strategy).

Solving problem effect

- Only experienced subjects' information reduction performance was improved and become more conservative after they solved the problem.
- Subjects tend to perform a few acquisitions after they solve the problem. Experienced subjects mainly remove the false alarms.
- A positive correlation between *H* and problem solving score was found.

Learning effect

- Only experienced subjects tend to have a liberal bias in the 1st problem and become more conservative as they complete subsequent problems

- As the problem sequence increased, completion time, average viewing time per acquisition, and fraction of total items viewed decreased. In addition, subjects spent more time on relevant information and use a more consistent pattern of information acquisition across information items as the problem sequence increased.

4.2 EFFECTS OF CS AND DS

4.2.1 Information reduction

Table 12 provides a description of the dependent variables for information reduction measures.

Table 12: List of dependent variables for information reduction measures

Information Reduction	
Variable	**Description**
H	Hit rate
F	False alarm rate
A'	Nonparametric sensitivity
B''_d	Nonparametric decision bias
d'	Gaussian sensitivity
C	Gaussian decision bias
NSDS	number of selected DS items
NSCS	number of selected CS items

A summary of the results for the dependent variables is given in Table 13. Some of the effects for the independent variables are shown in Figure 18 and 19 for sensitivity and bias. The results of the ANOVA are shown in Table 14, 15, and 16 and a discussion of those results follows.

Table 13: Performance measures as a function of expertise, level of CS, and level of DS.

Expertise	Level of DS	Level of CS	*H*		*F*		*A'*		B''_d		*d'*		*C*	
			Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Novice	high	high	0.67	0.04	0.25	0.02	0.79	0.02	0.0	0.11	2.3	0.28	-0.3	0.19
	high	low	0.67	0.04	0.26	0.02	0.80	0.02	0.1	0.11	2.1	0.25	-0.2	0.17
	low	high	0.71	0.03	0.20	0.02	0.84	0.01	0.0	0.12	2.8	0.29	-0.1	0.19
	low	low	0.65	0.03	0.18	0.02	0.83	0.01	0.2	0.12	2.5	0.27	0.1	0.2
Experienced	high	high	0.92	0.04	0.23	0.02	0.92	0.02	-0.6	0.11	4.3	0.28	-1.1	0.19
	high	low	0.90	0.04	0.19	0.02	0.92	0.02	-0.5	0.11	4.2	0.25	-1.1	0.17
	low	high	0.92	0.03	0.13	0.02	0.94	0.01	-0.4	0.12	5.5	0.29	-0.6	0.19
	low	low	0.90	0.03	0.10	0.02	0.95	0.01	-0.3	0.12	5.2	0.27	-0.5	0.2

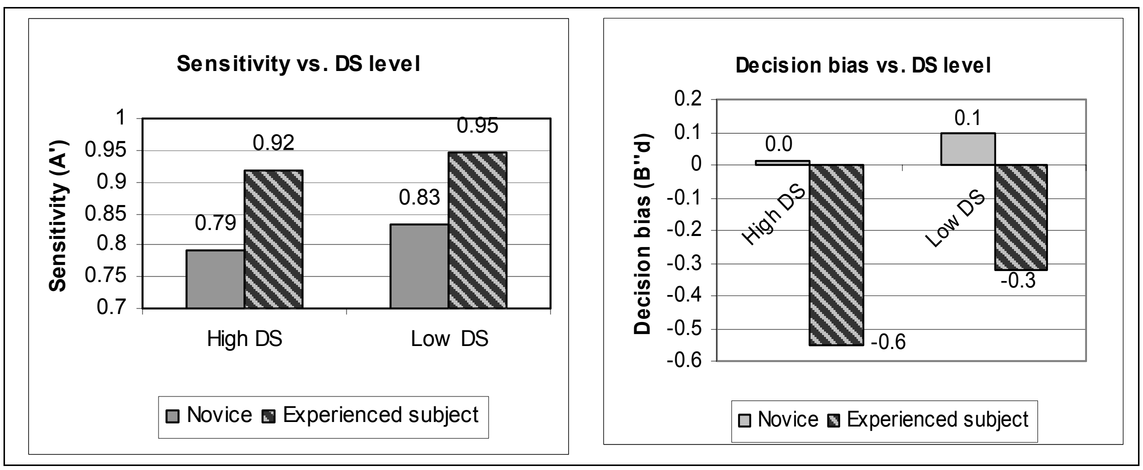


Figure 18: A' and B''_d as a function of expertise and level of DS

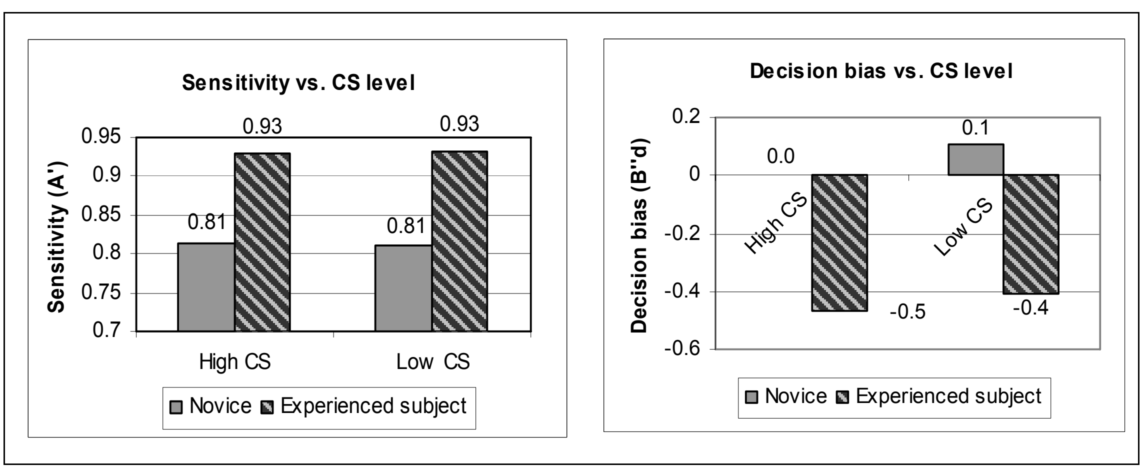


Figure 19: A' and B''_d as a function of expertise and level of CS

Table 14: The P-value for main effects and interaction in overall group.

P-value from ANOVA							
Measure	Level of Expertise (E)	Level of DS)	Level of CS	E*DS	E*CS	DS*CS	E*DS*CS
H	<0.001	0.738	0.072	0.616	0.741	0.408	0.321
F	0.026	<0.001	0.034	0.055	0.213	0.722	0.329
A'	<0.001	<0.001	0.958	0.480	0.799	0.388	0.425
B''_d	<0.001	0.006	0.090	0.183	0.663	0.708	0.990
d'	<0.001	<0.001	0.198	0.079	0.817	0.710	0.860
C	0.020	<0.001	0.109	0.059	0.537	0.676	0.796

Table 15: The P-value for main effects and interaction in novice and experienced subject group.

P-value from ANOVA						
Measure	Experienced subject			Novice		
	Level of DS	Level of CS	DS*CS	Level of DS	Level of CS	DS*CS
H	0.871	0.237	0.878	0.627	0.176	0.283
F	<0.001	0.027	0.598	<0.001	0.498	0.413
A'	<0.001	0.678	0.924	0.021	0.914	0.379
B''_d	0.005	0.378	0.807	0.297	0.129	0.775
d'	<0.001	0.479	0.640	0.081	0.259	0.904
C	<0.001	0.497	0.910	0.126	0.109	0.635

A', sensitivity

As expected, the main effect of expertise for A' was significant (F (1, 94) = 61.548, MSE = 0.22, p < .001) with experienced subjects showing higher sensitivity (.93) than novices (.81) as seen in Table 14. Both experienced subjects and novices were above chance (A' = .5). We expected that experienced subjects would perform better than novices in discriminating between relevant and irrelevant information, and they did.

Table 16: Number of selected items for low/high *DS* and low/high *CS* items.

Expertise	Level of DS	Level of CS	# of selected Low/High DS items (*NSDS*)		# of selected Low/High CS items (*NSCS*)	
			Mean	Std. Error	Mean	Std. Error
Novice	high	high	2.0	.2	1.2	.2
	high	low	2.2	.2	1.0	.1
	low	high	1.1	.1	1.4	.2
	low	low	1.3	.1	.9	.1
Experienced	high	high	2.7	.2	.9	.2
	high	low	2.6	.2	.4	.1
	low	high	.7	.1	1.1	.2
	low	low	.7	.1	.7	.1

We also expected that discrimination would be more difficult, especially for experienced subjects, when irrelevant information was information in the same knowledge domain (High *DS*) and when the irrelevant information had high semantic similarity to relevant information (High *CS*). However, *CS* was not significant (Overall (*A*'): High *CS*: .87; Low *CS*: 87), only *DS* was significant (F (1, 94) = 14.573, MSE = 0.008, p < .001) as subjects showed poorer performance with high *DS* (.85) than low *DS* (.89). Examination of *F*, *NSDS*, and *NSCS*, shows that subjects seem to have difficulty identifying irrelevant information in the same knowledge domain as irrelevant information as show in Table 16. This finding is still valid even for each expertise level. The main effect of *DS* was significant on *A*' for experienced subjects (F (1, 47) =24.985, MSE = .002, p < .001) and novice groups (F (1, 47) =5.671, MSE = .015, p = .021) as seen in Table 15.

B"d, Response Bias

For B''_d, there was a significant main effect of expertise (F (1, 94) = 14.040, MSE = 1.661, p < .0001) with experienced subjects showing a somewhat liberal bias (-.5) while novices showed a conservative bias (.1) as seen in Table 14. A significant main effect was found for the level of DS (F (1, 94) = 8.038, MSE = .293, p =. 006) with little evidence of bias on problems with low DS (-.1) but evidence of a liberal bias on problems with high DS (-.3). When the irrelevant information was information in the same problem domain, participants tended to select more information. No interactions were significant. For expertise level, only experienced subjects had similar results; DS was significant on $B''_{d,}$ (F (1, 47) = 8.759, MSE = .292, p =. 005, High DS: -0.55; Low DS: -0.32) as seen in Table 15.

These results indicating that novices were conservative (selecting less information overall) are not surprising. However, the finding of a liberal bias in experienced subjects was unexpected. We expected that *H* would be higher for experienced subjects, but we also expected *F* to decrease. That is, we expected little or no bias. Instead, experienced subjects were generally more willing to select more information. However, the fact that *A*' also was higher means that the increase for *H* was relatively higher than the increase for *F*. The increase in *F* for more experienced subjects as compared to novices may be an example of the U-shaped function that sometimes characterizes performance as one progress from novice to expert (Baylor 2001). That is, false alarms may increase as the person moves from a novice into an intermediate stage of expertise before decreasing again as true expertise is developed. Someone at an intermediate level of expertise may realize that information in a statement is often useful in problems of this general class, but may not realize until developing a higher level of expertise that this particular information is not relevant in this particular problem.

4.2.2 Information Acquisition

Similar to information reduction, a mixed ANOVA was run on all information acquisition measures. Table 17 provides a description of the dependent variables for information acquisition measures.

Table 17: List of dependent variables for information acquisition measures

Information acquisition	
Variable	Description
CT	Completion time
FRT	Fraction of total time on relevant items
FIT	Fraction of total time on irrelevant items
FVRT	Fraction of viewing time for relevant items
FVIT	Fraction of viewing time for irrelevant items
$\overline{VT}$	Average viewing time per acquisition
S_{VT}^2	Sample variance of viewing time
FTV	Fraction of total items viewed
FVR	Fraction of relevant items viewed
FVI	Fraction of irrelevant items viewed
TC	Total number of visits (clicks)

Time

The descriptive statistics for the results are shown in Table 18 and in Figures 20 and 21. Even though we expected that experienced subjects should spend less time than novices (because experienced subjects should know from the beginning which information items they need to select), there was no significant main effect of expertise level on CT (Equation 1.5). However, for FRT (Equation 1.6), the main effect of expertise level was significant, (F (1, 94) = 10.323 MSE = .015, p = .002) with experienced subjects showing longer time spent on relevant information (.236) than novices (.196) as shown in Table 19.

Table 18: Time spent as a function of expertise, level of CS, and level of DS.

Expertise	Level of DS	Level of CS	*CT* (Second)		*FRT*		*FIT*	
			Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Novice	high	high	130	11.8	0.19	0.013	0.44	0.024
	high	low	128	12.3	0.21	0.013	0.44	0.026
	low	high	126	9.9	0.22	0.014	0.38	0.027
	low	low	131	9.8	0.17	0.014	0.45	0.026
Experienced	high	high	153	11.9	0.23	0.013	0.45	0.024
	high	low	154	12.3	0.22	0.013	0.45	0.026
	low	high	138	9.9	0.26	0.014	0.35	0.027
	low	low	137	9.8	0.23	0.014	0.42	0.026

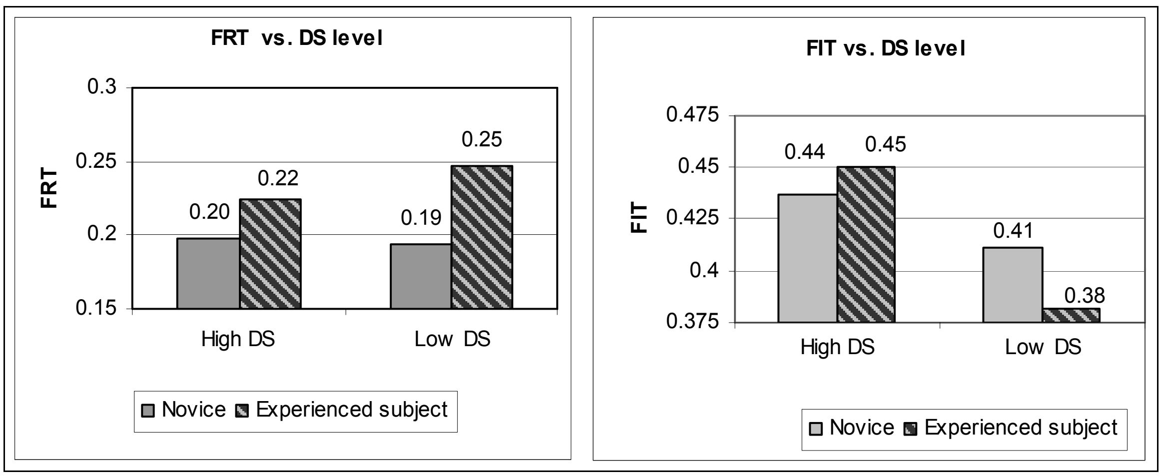


Figure 20: Time spent as a function of expertise and level of DS.

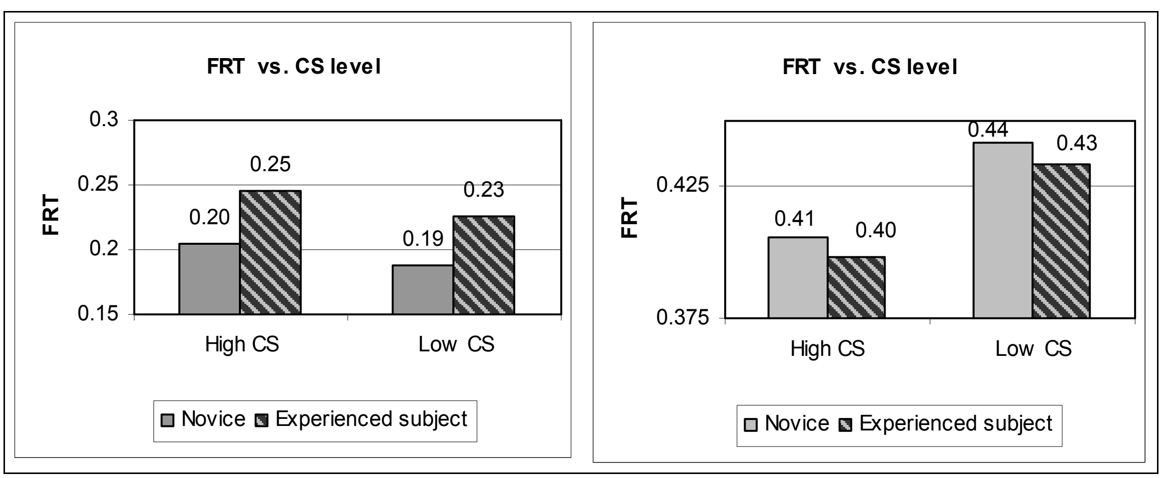


Figure 21: Time spent as a function of expertise and level of CS.

We found a significant main effect for DS on *FIT* (Equation 1.7) *Overall* (F (1, 94) = 17.809 MSE = .012, p < .001) and for experienced subjects (F (1, 47) = 15.973 MSE = .014, p < .001) as shown in Table 20. Subjects spent more time on irrelevant information under high *DS* (Overall: .44; Experienced subjects: .45) than low *DS* (Overall: .40; Experienced subjects: .38) conditions. This finding supports our information reduction result that subjects (especially experienced) had difficulty discriminating between relevant and irrelevant information that is in the same knowledge domain.

Table 19: The P-value in time spent for main effects and interaction in overall group.

P-value from ANOVA							
Measure	Level of Expertise (E)	Level of DS (DS)	Level of CS (CS)	E*DS	E*CS	DS*CS	E*DS*CS
CT	0.121	0.183	0.868	0.231	0.92	0.851	0.766
FRT	0.002	0.287	0.034	0.127	0.854	0.006	0.182
FIT	0.78	< 0.001	0.02	0.062	0.988	0.018	0.852

Table 20: The P-value in time spent for main effects and interaction in novice and experienced subject group.

P-value from ANOVA						
Measure	Experienced subject			Novice		
	Level of DS (DS)	Level of CS (CS)	DS*CS	Level of DS (DS)	Level of CS (CS)	DS*CS
CT	0.105	0.961	0.942	0.916	0.856	0.715
FRT	0.062	0.12	0.313	0.749	0.153	0.004
FIT	< 0.001	0.131	0.079	0.077	0.073	0.112

The main effect for *CS* was significant for both *FRT* (F (1, 94) = 4.613 MSE = .007, p = .034) and *FIT* (F (1, 94) = 5.562 MSE = .021, p = .020). Subjects spent more time on relevant information (High *CS*: .23; Low *CS*: .20) and less time on irrelevant information (High *CS*: .40; Low *CS*: .49) under high *CS*. This finding seems to be reasonable as high *CS* used mostly the same words as relevant information. Therefore, subjects spent more time on relevant information to compare relevant information and high CS information.

We could also see an interaction effect between *DS* level and *CS* level on both *FRT* (Overall: $F(1, 94) = 8.015$ $MSE = .008$, $p = .006$; Novice: $F(1, 47) = 9.261$ $MSE = .007$, $p = .004$) and *FIT* (Overall: $F(1, 94) = 5.849$ $MSE = .020$, $p = .018$). Low DS with high CS condition caused subjects to spend more time on relevant information and less time on irrelevant information compared to other conditions. Since Low DS might not influence subjects to spend time on low *DS* information and cased irrelevant information time deceased. Table 21 shows that subjects (especially novices) have a higher percentage of relevant information visited (*FVR*) and lower percentage of irrelevant information visited (*FVI*) under high *CS* than low *CS* condition. It is not clear why high *CS* could make novices pay more attention to relevant information. Therefore, further research may be warranted for this phenomenon.

Table 21: Fraction of visited relevant and irrelevant information items as a function of level of CS, and level of DS.

	Experienced subject				**Novice**			
	Level of DS		Level of CS		Level of DS		Level of CS	
	High	Low	High	Low	High	Low	High	Low
FVR	.958	.951	.964	.945	.776	.810	.805	.781
FVI	.594	.582	.540	.636	.533	.519	.497	.555

Acquisitions

To determine how the independent variables affected information acquisitions, the number of acquisitions (*Fraction information acquisitions: FTV*) and the amount of time spent acquiring information per information item (*Average viewing time per acquisition:* $\overline{VT}$) were measured.

The ANOVA results in Table 23 show that the *DS* level had a significant main effect on $\overline{VT}$, in the overall group (F (1, 94) = 57.054 MSE = 7.662, p = .008) and for experienced subjects (F (1, 47) = 6.184 MSE = 8.456, p = .017). Table 23 shows that high DS increased the viewing time per acquisition in both groups (Overall: high DS: 7.9; low DS: 7.1). However, we did not find any significant difference for the *FTV* (Overall: high *DS*: .62; low *DS*: .61). This result suggests that subjects seem to need more time to decide the next action when irrelevant information is in same knowledge domain.

In contrast to *DS*, the main effect of *CS* level on *FTV* was significant (F (1, 94) = 10.645 MSE = 0.03, p = .002) for the overall group and (F (1, 47) = 7.256 MSE = .036, p = .010) for the experienced subject group (Table 23 and 21). The high CS condition led to a decrease in the *FTV* (Overall: High CS: .59; Low CS: 65) and an increase in $\overline{VT}$ (Overall: High CS: 7.6; Low CS: 7.3), but $\overline{VT}$ is not significant in both overall and the experienced subject group. This ANOVA result indicates that subjects had more visits under the low CS condition. This suggests that subjects examined the new information when similar words did not appear in relevant information (See Appendix C for problem descriptions). However, they spent less time.

Table 22 : Acquisitions and processing selectivity as a function of expertise, level of CS, and level of DS.

Expertise	Level of DS	Level of CS	*FTV*		$\overline{VT}$		*FVRT*		*FVIT*	
			Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Novice	high	high	0.57	0.037	7.6	0.58	0.31	0.026	0.69	0.026
	high	low	0.60	0.04	7.6	0.61	0.35	0.028	0.65	0.028
	low	high	0.55	0.039	7.2	0.46	0.40	0.033	0.60	0.033
	low	low	0.60	0.042	7.1	0.45	0.31	0.03	0.70	0.03
Experienced	high	high	0.63	0.037	8.4	0.58	0.36	0.026	0.65	0.026
	high	low	0.70	0.04	7.8	0.61	0.35	0.028	0.65	0.028
	low	high	0.62	0.039	7.2	0.46	0.49	0.033	0.51	0.033
	low	low	0.70	0.042	6.9	0.45	0.38	0.03	0.63	0.03

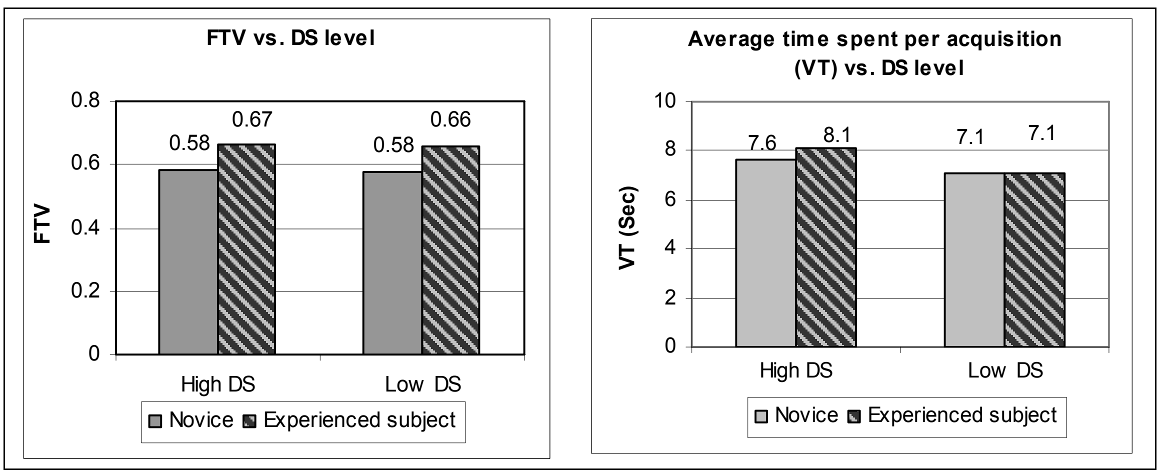


Figure 22: Acquisitions as a function of expertise and level of DS.

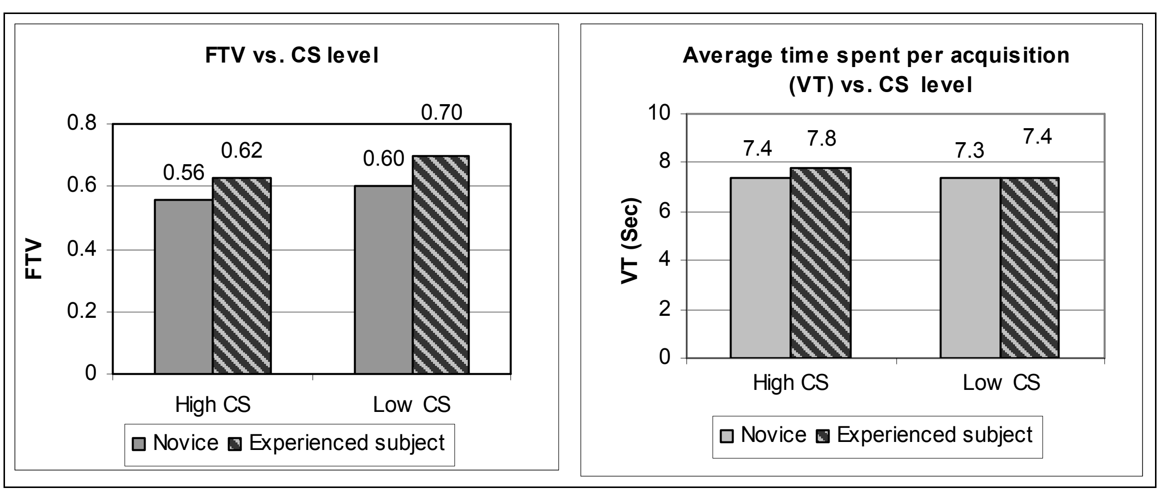


Figure 23: Acquisitions as a function of expertise and level of CS.

Table 23: The P-value in acquisition and processing selectivity for main effects and interaction in overall group.

P-value from ANOVA							
Measure	Level of Expertise (E)	Level of DS (DS)	Level of CS (CS)	E*DS	E*CS	DS*CS	E*DS*CS
FTV	**0.085**	0.59	0.002	0.829	0.38	0.717	0.979
$\overline{VT}$	0.668	0.008	0.373	0.337	0.423	0.931	0.774
FVRT	0.088	0.002	0.023	0.055	0.426	0.001	0.778
FVIT	0.088	0.002	0.023	0.056	0.426	0.001	0.778

Table 24: The P-value in acquisition and processing selectivity for main effects and interaction in novice and experienced subject group.

P-value from ANOVA						
Measure	Experienced subject			Novice		
	Level of DS (DS)	Level of CS (CS)	DS*CS	Level of DS (DS)	Level of CS (CS)	DS*CS
FTV	0.64	0.01	0.828	0.785	0.069	0.76
$\overline{VT}$	0.017	0.243	0.8	0.194	0.949	0.882
FVRT	0	0.048	0.04	0.38	0.249	0.006
FVIT	0	0.048	0.04	0.38	0.249	0.006

Processing Selectivity

To assess how independent variables affect selectivity in processing, the fraction of viewing time spent on relevant information: $FVRT$ (Equation 1.10) and irrelevant information: $FVIT$ (Equation 1.11) and the sample variance in time spent viewing information for each information item: S_{VT}^2 (Equation 1.12) were measured.

The ANOVA results in Table 23 and 24 show that there was a significant main affect for DS (Overall: F (1, 94) = 10.426 MSE = .021, p = .002; Experienced subject group: F (1,

47) = 14.204 MSE = .020, p < .001) and CS level (Overall: F (1, 94) = 5.309 MSE = .031, p = .023; Experienced subject group: F (1, 47) =4.118 MSE = .037, p = .048;) on *FVRT*. High DS led to a decrease in the *FVRT* (Overall: high DS: .344; low DS: .391). In contrast, high CS led to an increase in the *FVRT* (Overall: high CS: .39 vs. low CS: .34). This could indicate that experienced subjects were confused by irrelevant information from the same domain, causing them to spend proportionally more time on analyzing irrelevant information.

We used the F-Test to determine differences for S_{VT}^{2} (Table 25). There were significant differences for *DS* level in all three groups (Overall: F (1, 191) =2.830, p < .001; Experienced subject group F (1, 95) =3.396, p < .001; Novice group: F (1, 95) =2.279, p < .001). High *DS* consistently led to increase estimated variance in all groups. This suggests that subjects tend to use an inconsistent pattern (high variance) of information acquisition across information items (non-compensatory strategy) under high *DS* condition and more consistent pattern (low variance) of information acquisition (compensatory strategy) when information from different knowledge domain are present.

For the *CS* conditions, there was significant effect for *CS* only in overall group (F (1, 191) =0.673, p = .003) and novice group (F (1, 95) =0.380, p < .001). Novices were more likely to use non-compensatory strategy under the low *CS* condition (High *CS*: 35.970 vs. Low *CS*: 40.364). Even though there was not a significant effect for the experienced subjects, we found that this group has the opposite behavior of using non-compensatory strategy under the high *CS* condition (High *CS*: 47.782 vs. Low *CS*: 44.094).

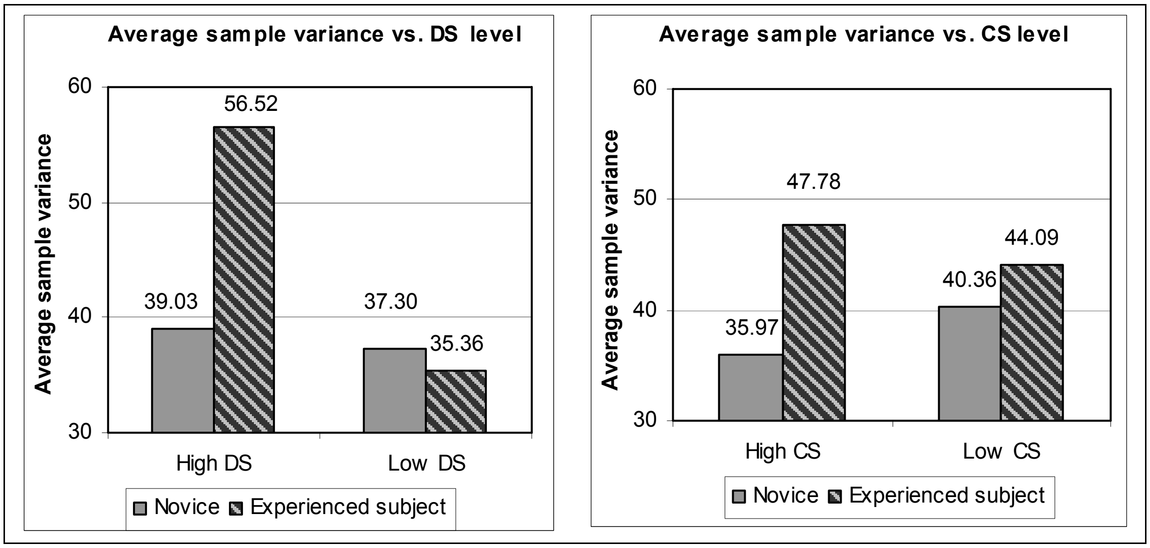


Figure 24: Average sample variance (S_{VT}^2) in time spent acquiring information as a function of expertise, level of CS, and level of DS.

Table 25: The P-value from F-Test in S_{VT}^2.

P-value from F-Test							
Measure	Overall			Experienced subject		Novice	
	Level of Expertise (E)	Level of DS (DS)	Level of CS (CS)	Level of DS (DS)	Level of CS (CS)	Level of DS (DS)	Level of CS (CS)
S_{VT}^2	0.095	<0.001	0.003	<0.001	0.466	<0.001	<0.001

4.3 EFFECTS OF SOLVING THE PROBLEM

As discussed in the previous chapter, subjects wrote down their solution for the fourth problem in the sequence. The following criteria were used to grade their solution. The scores along with the information reduction measures are shown in Table 26.

$$Solution\ Score = \begin{cases} 1.00, & \text{If solution contains correct problem formulation} \\ 0.75, & \text{If solution contains correct problem formulation with minor mistake} \\ 0.50, & \text{If solution contains only correct defined variable list but not formulation} \\ 0.00, & \text{If solution doesn't contain any meaningful information} \end{cases}$$

Table 26: Subjects' solution score and performance measure

Expertise level	Experimental condition	Score	Before solving problem				After solving problem			
			A'	B''_d	H	F	A'	B''_d	H	F
Novice	1	0.000	0.738	-0.160	0.672	0.281	0.720	0.022	0.625	0.260
	2	0.083	0.803	0.024	0.667	0.276	0.828	-0.026	0.750	0.266
	3	0.000	0.835	0.100	0.714	0.229	0.839	0.162	0.667	0.193
	4	0.063	0.820	-0.039	0.651	0.255	0.803	0.045	0.667	0.255
Expert	1	0.750	0.919	-0.414	0.917	0.219	0.911	-0.190	0.833	0.151
	2	0.771	0.932	-0.505	0.917	0.172	0.962	-0.389	0.958	0.104
	3	0.792	0.947	-0.611	0.958	0.167	0.970	-0.417	0.979	0.099
	4	0.833	0.968	0.056	0.917	0.042	0.972	0.111	0.917	0.021

As expected, experienced subjects tended to be able to formulate problem correctly and use the correct principle (EOQ). In contrast, novices were not able to solve or formulate the problem. Based on subjects' solutions, novices identified the ordering elements such as inventory cost and delivery time, but their solutions did not show that the EOQ principle was used.

In addition, we also see a correlation between the score and H (see Table 27). The weaker correlation between score and F was found for the experienced subject group. Therefore, the ability to identify relevant information may serve as a predictor of problem solving ability. The process of solving the problem appears to cause refinements, mainly in eliminating false alarms for experienced subjects. The correlation between score and A' is small and correlation for experienced subjects essentially the same as novices. The following section describes problem solving process effects on information reduction and information acquisition.

Table 27: Pearson correlation (r) between *H* and problem solving score

	Pearson correlation (R)	
	Experienced subject	Novice
	Score	Score
H before problem solving	0.379	-0.040
H after problem solving	0.318	0.053

Table 28: Pearson correlation (r) between *F* and problem solving score

	Pearson correlation (R)	
	Experienced subject	Novice
	Score	Score
F before problem solving	-0.213	-0.167
F after problem solving	-0.355	-0.245

4.3.1 Information reduction

As shown in Table 30, there is a slight difference between performance measures obtained from SDT based on Gaussian models (d' : sensitivity, C: decision bias) and from nonparametric SDT measures (A' : sensitivity, B''_d : decision bias). We could find a significant effect on d' and C in the experienced subject group but not in A′ and B''_d. However, both types of measures show the same trend. Experienced subjects' information reduction performance (d', sensitivity) was affected by the problem solving process (F (1, 47) = 4.539 MSE = 2.466, p = .038).

Experienced subjects' information reduction performance improved after they solved the problem (before: 5.092 vs. after: 5.775). Moreover, the main effect of session type was significant only on *C* (decision bias) for experienced subjects (F (1, 47) = 4.302 MSE = .705, p = .044). Experienced subjects seem to be more conservative after solving the problem (before: -.732 vs. after: -.377). The performance improvement and conservative behavior were caused by a significant reduction in *F* (F (1, 47) = 12.531 MSE = .006, p = .001).

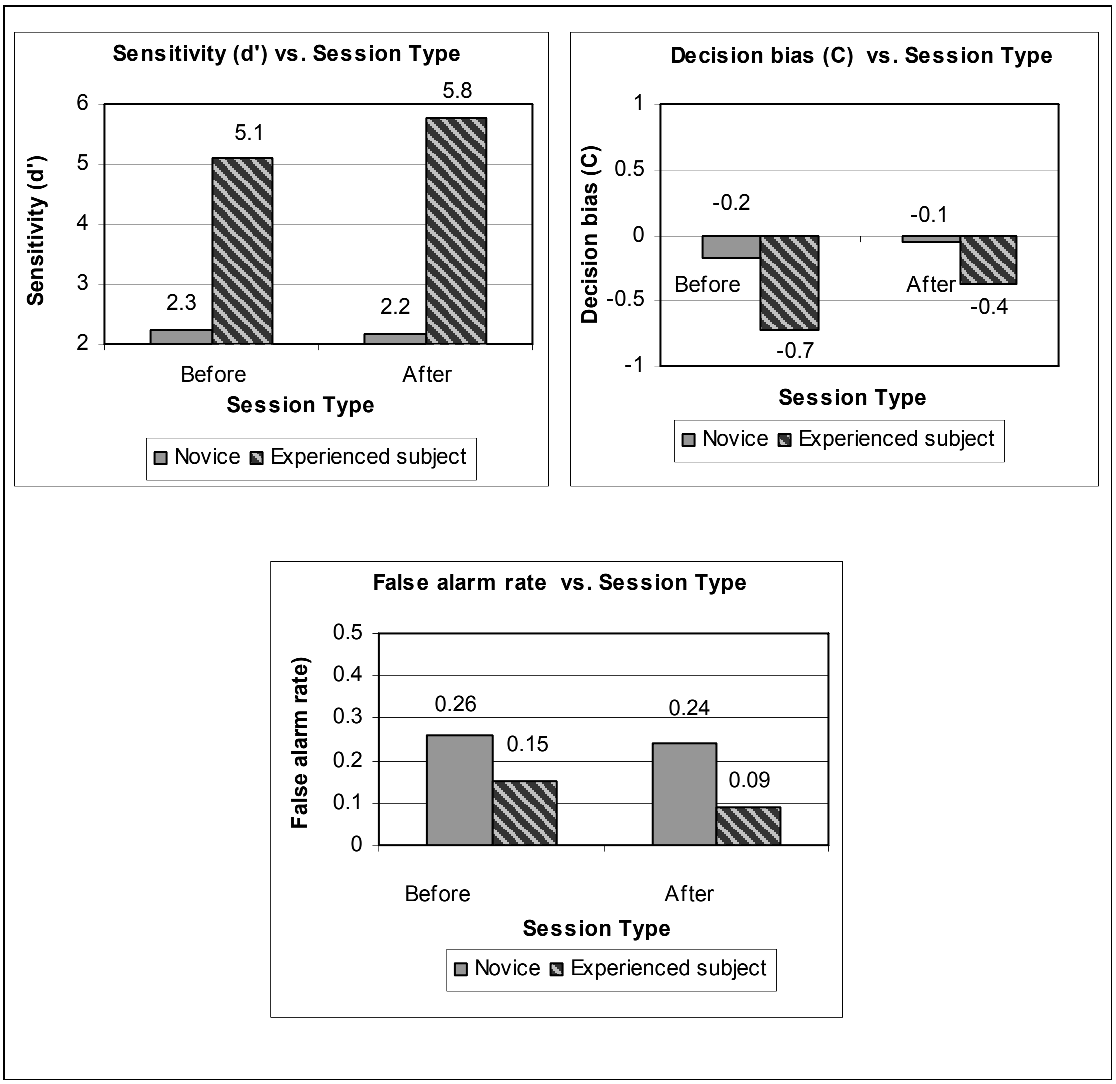


Figure 25: *D′, C* and *F* as a function of expertise and section type.

Table 29: Performance measures as a function of expertise and section type.

Expertise	Session (Before/After problem solving)	*H*		*F*		*A'*		*B"$_d$*		*d '*		*C*	
		Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Novice	Before	0.69	0.03	0.26	0.02	0.80	0.02	0.0	0.12	2.3	0.29	-0.2	0.21
	After	0.68	0.03	0.24	0.02	0.80	0.02	0.1	0.11	2.2	0.31	-0.1	0.20
Experienced	Before	0.93	0.03	0.15	0.02	0.94	0.02	-0.4	0.11	5.1	0.28	-0.7	0.18
	After	0.92	0.03	0.09	0.02	0.95	0.02	-0.2	0.11	5.8	0.32	-0.4	0.18

Table 30: The P-value in performance measure and total number of clicks for main effects and interaction in all groups.

P-value			
	Overall	**Experienced subject**	**Novice**
Measure	**Session Type (Before/After problem solving)**	**Session Type (Before/After problem solving)**	**Session Type (Before/After problem solving)**
H	0.659	0.830	0.688
F	0.000	0.001	0.135
A'	0.402	0.097	0.892
B"$_d$	0.113	0.185	0.366
d'	0.098	0.038	0.612
C	0.017	0.044	0.196
Total number of clicks	0.001	0.035	0.013

4.3.2 Information acquisition

The main effect of session type was significant for *total number of clicks* (*TC*) for both experienced subjects ($F(1, 47) = 4.732$ MSE = 7.926, $p = .035$) and novices ($F(1, 47) = 6.698$ MSE = 15.243, $p = .013$) as shown in Table 30. According to the mean total number of clicks (shown in Table 31), novices seem to have more acquisitions than experienced subjects (novice: 2.1 vs. experienced subject: 1.3).

Table 31: Total number of clicks as a function of expertise and section type.

Expertise	Session (Before/After problem solving)	Total number of clicks (*TC*)	
		Mean	Std. Error
Novice	Before	10.8	.8
	After	12.9	1.2
Experienced	Before	11.7	.8
	After	12.9	1.2

Information reduction and information acquisition results indicate that experienced subjects realized that they had included some irrelevant information. After solving the problem, they removed false alarm items with little additional information acquisition/revisit activity. Novices had difficulty solving the problem and did more information acquisition (revisiting information items) but had less adding and removing actions as compared with experienced subjects.

4.4 LEARNING EFFECTS

Given that the same set of relevant information items were present in each of the four problems, it is possible that learning occurred over the sequence of problems. Analysis of variance (ANOVA) was used to identify any significant main effects on information reduction performance and information acquisition behavior in all three groups, namely, all subjects (overall), the experienced subject group and the novice group. Problem sequences were used as the independent variable in a within subjects design. Expertise level (experienced subject versus novice) was also analyzed in a between-subjects design.

4.4.1 Information reduction

The results for the mean and standard deviation are summarized in Table 32. No significant main effect for problem sequence was found on A' in all three groups. For B''_d, a significant main effect of problem sequence was found for the experienced subjects' group (F (1, 47) = 4.850, MSE = .369, p = .033) as seen in Table 33. Experienced subjects were more liberal in the first problem and became more conservative as they completed subsequent problems, indicating a learning curve effect (Table 32).

Table 32: Performance measures as a function of expertise and problem sequence.

Expertise	Problem sequence	H		F		A'		B''_d		d'		C	
		Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Novice	1	0.64	0.04	0.20	0.02	0.79	0.02	0.2	0.11	2.4	0.29	0.1	0.19
	2	0.68	0.04	0.22	0.02	0.82	0.01	0.1	0.12	2.6	0.27	-0.2	0.19
	3	0.70	0.03	0.21	0.02	0.84	0.01	0.1	0.12	2.5	0.27	-0.2	0.19
	4	0.69	0.03	0.26	0.02	0.80	0.02	-0.0	0.11	2.3	0.29	-0.2	0.20
Experienced	1	0.92	0.04	0.17	0.02	0.93	0.02	-0.6	0.11	4.6	0.29	-1.0	0.19
	2	0.91	0.04	0.16	0.02	0.93	0.01	-0.5	0.12	4.9	0.27	-0.9	0.19
	3	0.88	0.03	0.16	0.02	0.92	0.01	-0.3	0.12	4.5	0.27	-0.6	0.19
	4	0.93	0.03	0.15	0.02	0.94	0.02	-0.4	0.11	5.1	0.29	-0.7	0.20

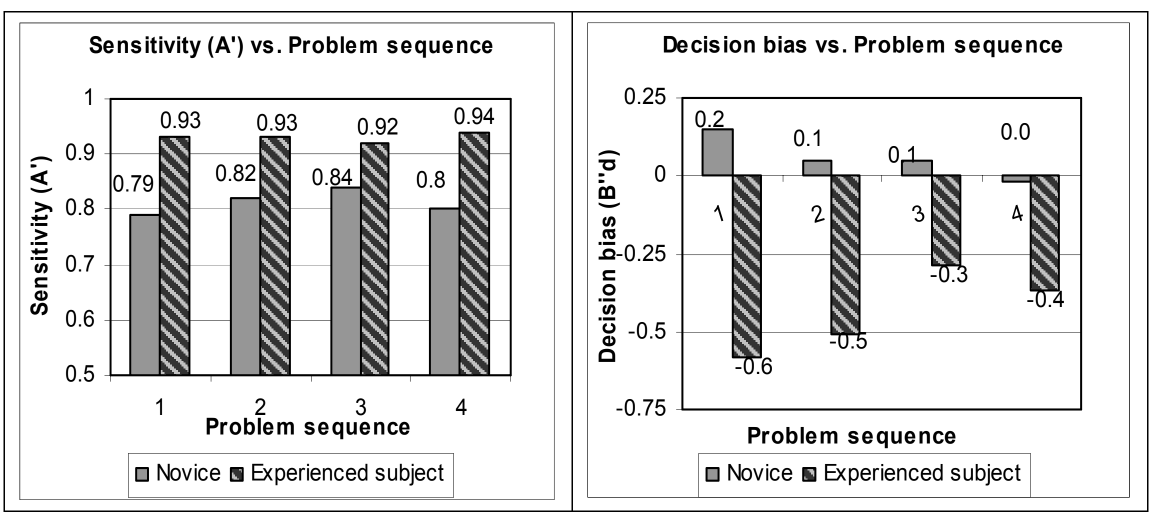


Figure 26: A' **and** B''_d **as a function of expertise and problem sequence.**

Table 33: The P-value in performance measure for main effects in all groups

P-value			
	Overall	Experienced subject	Novice
Measure	Problem Sequence	Problem Sequence	Problem Sequence
H	0.379	0.835	0.279
F	0.331	0.281	0.022
A'	0.575	0.436	0.704
B"d	0.520	0.033	0.191
d'	0.757	0.194	0.634
C	0.554	0.087	0.365

4.4.2 Information acquisition

Results (summarized in Tables 34 and 35) for *completion time* (*CT*), a*verage viewing time spent per acquisition* ($\overline{VT}$) and *fraction of total items viewed* (*FTV*) were similar across all three groups. The significant main effect of problem sequence on *CT* for the overall group (F (1, 94) = 161.359, MSE = 3041.172, p < .001) shows that subjects spent more time in the first problem (194 seconds) than the last problem (97 seconds). Significant main effects of problem sequence on $\overline{VT}$ (F (1, 94) = 53.161 MSE = 8.745, p < .001) and *FTV* significant (F (1, 94) = 78.258 MSE = .031, p < .001) were found. As the problem sequence increased, it led to a decrease in time per acquisition as well as a decrease in fraction of total information items viewed (see Table 34).

Table 34: Time and acquisitions as a function of expertise and problem sequence.

Expertise	Problem sequence	***CT*** **(Second)**		***FTV***		$\overline{VT}$		***FVRT***	
		Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Novice	1	181	12.5	.67	.037	9.2	.52	0.31	0.027
	2	131	11.3	.60	.039	7.5	.49	0.38	0.032
	3	109	7.3	.54	.039	6.6	.50	0.34	0.032
	4	93	6.2	.51	.037	6.1	.50	0.34	0.028
Experienced	1	206	12.5	.81	.037	9.4	.52	0.35	0.027
	2	155	11.3	.71	.039	7.5	.49	0.36	0.032
	3	120	7.3	.59	.039	7.0	.50	0.43	0.032
	4	101	6.2	.54	.037	6.4	.50	0.43	0.028

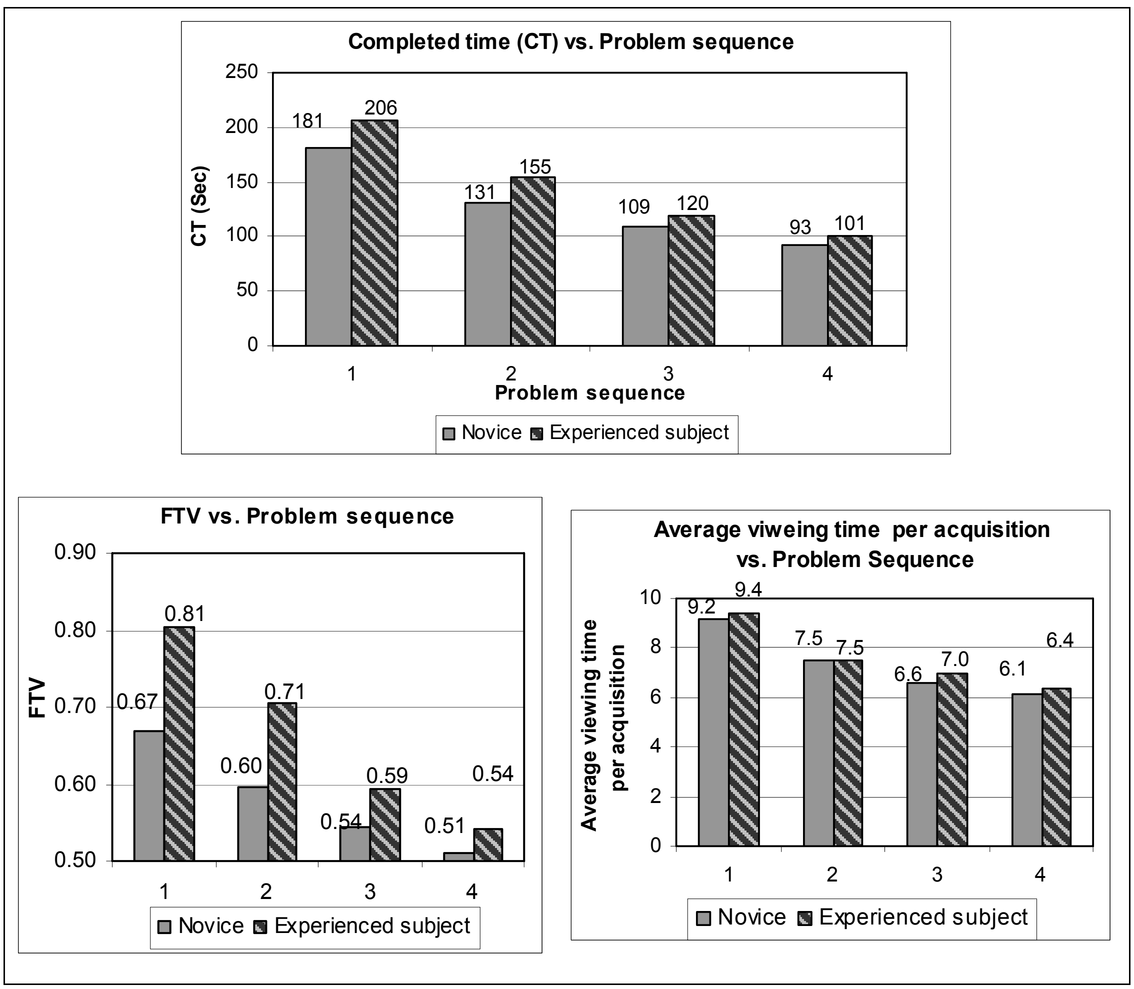


Figure 27: Graphs of time and acquisitions VS expertise level and problem sequence.

Table 35: The P-value in time and acquisition for main effects in all groups

P-value			
Measure	Overall	Experienced subject	Novice
	Problem Sequence	Problem Sequence	Problem Sequence
CT	< 0.001	< 0.001	< 0.0019
FTV	< 0.001	< 0.001	< 0.001
$\overline{VT}$	< 0.001	< 0.001	< 0.001
FVRT	0.006	0.002	0.059

For processing selectivity, results (in Table 35) show a significant main effect of problem sequence on *FVRT* (F (1, 94) = 10.426 MSE = .021, p = .002). F-test results also show a significant effect in *the estimated variance in time spent acquiring information* (S^2_{VT}), F (1, 95) =8.589, p < .001 (see Table 36). Subjects spent more time on relevant information and used a more consistent pattern of information acquisition across information items (compensatory strategy) as they progressed through the problems.

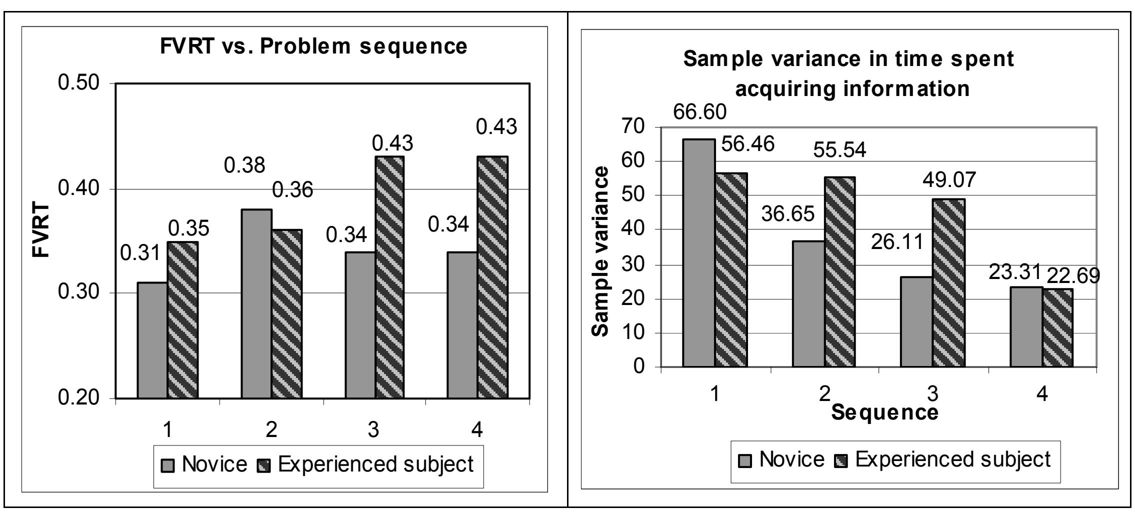


Figure 28: Graphs of Process Selectivity VS expertise level and problem sequence.

Table 36: The P-value from F-Test in estimated variance in time spent acquiring information.

Measure	Overall	Experienced subject	Novice
	Problem Sequence	Problem Sequence	Problem Sequence
S_{VT}^2	< .001	< .001	< .001

ANOVA results for *completion time and acquisition* show that learning occurred as subjects spent less time to complete a problem and acquire information and also performed fewer acquisitions (see Figure 28). For *processing selectivity,* both relevant information time and irrelevant information time decreased. However, there was a larger relative decrease in irrelevant information time as compared to relevant information time, especially in the experienced subjects' group. This suggests that subjects learn to ignore irrelevant information during acquisition (as found by Haider and Frensch 1999b). Moreover, subjects' patterns of information acquisition across information became more consistent after the second problem.

CHAPTER5. INFORMATION REDUCTION AND ACQUISITION PATTERN ANALYSIS

In this study, we applied the 1st and 3rd order Markov models to obtain subjects' pattern in selecting and acquiring information. Consequently, we used the patterns obtained from the Markov model result as attributes for cluster analysis. The presentation of results in this section is represented as a combination of information type and the vertical sequence in which the information appeared in the problem description. For example notation R5 refers to irrelevant information with high DS appearing in the fifth position of the sequence.

$$\mathit{Information\ symbol} = \mathit{Information\ type} + \mathit{vertical\ sequence\ in\ problem\ content}$$

$$\mathit{Information\ type} \begin{cases} T\text{, if Information type is relevant Information} \\ C\text{, if Information type is Common Irrelevant Information} \\ R\text{, if Information type is Irrelevant Information in High DS condition} \\ U\text{, if Information type is Irrelevant Information in Low DS condition} \\ H\text{, if Information type is Irrelevant Information in High CS condition} \\ L\text{, if Information type is Irrelevant Information in Low CS condition} \end{cases}$$

5.1 SUMMARY OF RESULTS

5.1.1 Information reduction behavior

- Experienced subjects' pattern of selecting information contained more relevant information items and they selected relevant information in a sequence.
- Subjects' patterns of selecting information corresponded to the sequence in which the information was presented.

- Subjects selected information with high DS as well as information corresponding to ordering, selling, cost and expense as false alarms.
- Subjects had less common patterns in selecting information with low DS than those with high DS. In the same way, subjects had less common patterns in selecting information with low CS and high CS.

5.1.2 Information acquisition behavior

Markov model results show that novices and experienced subjects had relatively similar behavior in acquiring information. Subjects' information acquisition behavior is based on the order in which information items were presented.

Based on information acquisition clustering analysis results, we make the following observations.

The first problem

- Subjects (especially experienced subjects) performed exhaustive searches.
- Information items in the "About" section and those with high CS were most likely to be ignored.

The last problem

- Subjects performed less exhaustive searches as compared to the first problem.
- Information items in the "About" section were almost completely ignored by subjects who are not in the visit-all group. This finding agrees with the results in the starting page analysis.

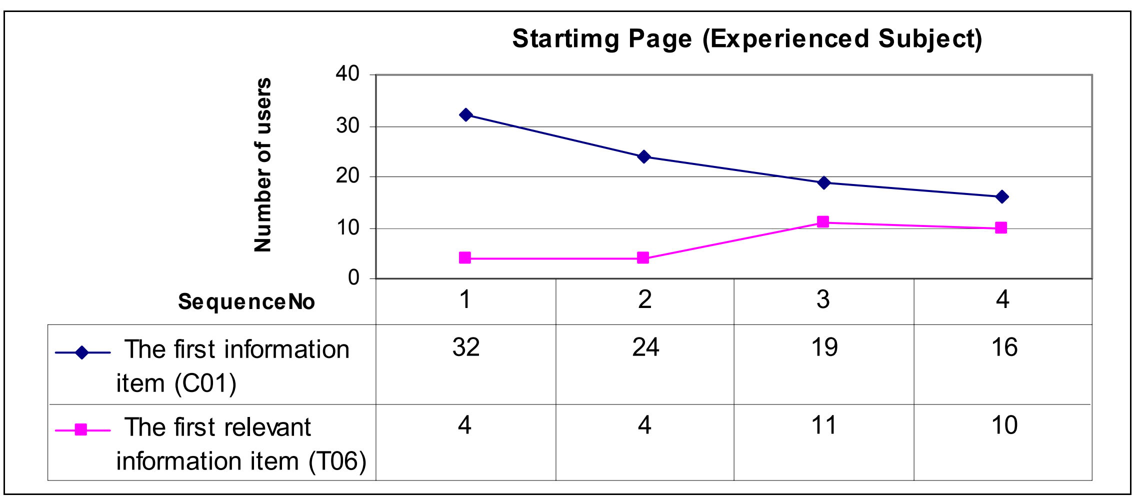
High vs. Low CS

- The low CS condition shows a steeper leaning curve.

- First problem: subjects performed more exhaustive searches under the low CS condition.
- Last problem: subjects under the high CS condition continue to perform more exhaustive searches than under the low CS condition.

5.2 STARTING PAGE ANALYSIS

ANOVA results in the previous chapter indicated that learning occurred in information acquisition. *Completion time* (*CT*) and *fraction of total items viewed* (*FTV*) decreased as problem sequence increased. The starting document report is another way to analyze a subject's learning effect. Figure 29 and Figure 30 show the starting page reports for experienced subjects and novices, respectively. It can be seen that learning related to relevant information occurred for experienced subjects. As the problem sequence increases, experienced subjects and novices learned to ignore the first information item (common irrelevant information). However, only experienced subjects ignored the first five irrelevant information items and jumped to visit the first relevant information item as their staring page.



SequenceNo	1	2	3	4
The first information item (C01)	32	24	19	16
The first relevant information item (T06)	4	4	11	10

Figure 29: Starting page report for experienced subject

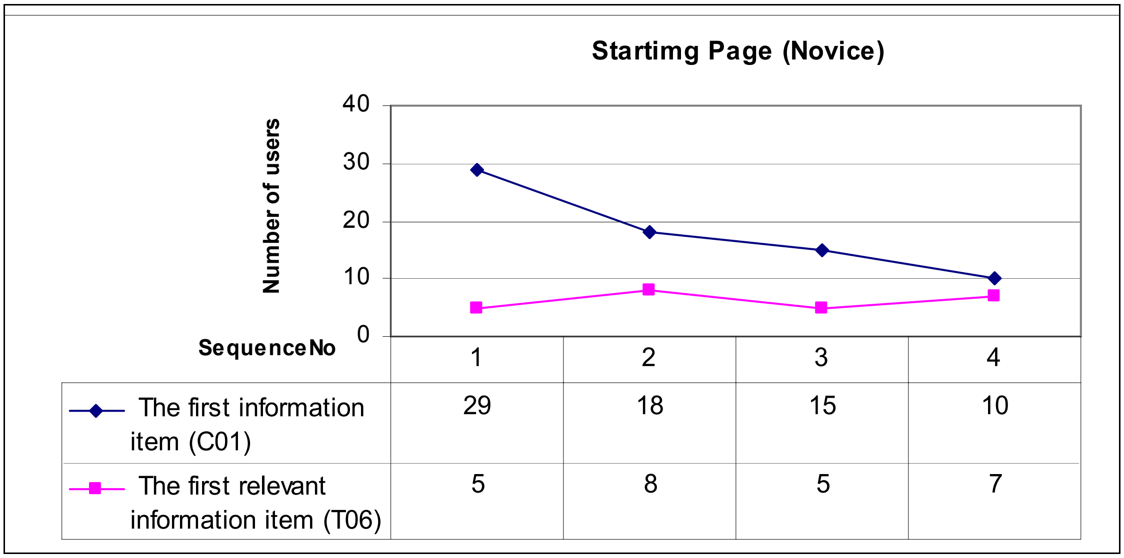


Figure 30: Starting page report for novice

5.3 MARKOV MODEL ANALYSIS

5.3.1 Information reduction

First, second and third order Markov models were used to analyze information reduction behavior. The complete Markov model results can be found in Appendix E. Different behaviors can be observed for novices and experienced subjects as they selected information. The results show that experienced subjects' selecting pattern contains more relevant information items and they selected relevant information in sequence as compared to novices.

5.3.2 Information acquisition

Novices and experienced subjects have relatively similar behavior in acquiring information. Subjects' information acquisition behavior is based on the sequence in which information items appear. The complete Markov model results can be found in Appendix E.

5.4 CLUSTERING ANALYSIS

The following section shows the results of simple clustering analysis first followed by Markov-clustering analysis results. Given the ANOVA results from Table 13, it appears that the experimental conditions have different levels of difficulty. Therefore, we applied a clustering method to discover information reduction and acquisition behavior in each experimental condition.

5.4.1 Information reduction

The mean and sample variance for compactness (Equation 3.3) along with the separation (Equation 3.4) were used to determine the number of clusters (details of the clustering quality measure calculation can be found in Appendix F). For simple and Markov clustering analyses, 4 and 7 clusters were used, respectively.

Condition 1 (High DS + High CS)

Simple clustering analysis

Clusters for condition 1 are shown in Figure 31. Decision bias and high CS information items are the main factors that differentiate the clusters. Results in Table 37 show that subjects in cluster 4 are mostly novices and had a conservative bias with a lower number of selected information items, as well as lower values for H and F. In addition, subjects in cluster 3 usually missed one hit item and selected a few false alarm items. High DS information items were the common false alarm that occurred in clusters 1-3. In addition; subjects in cluster 2 selected more false alarms with high CS.

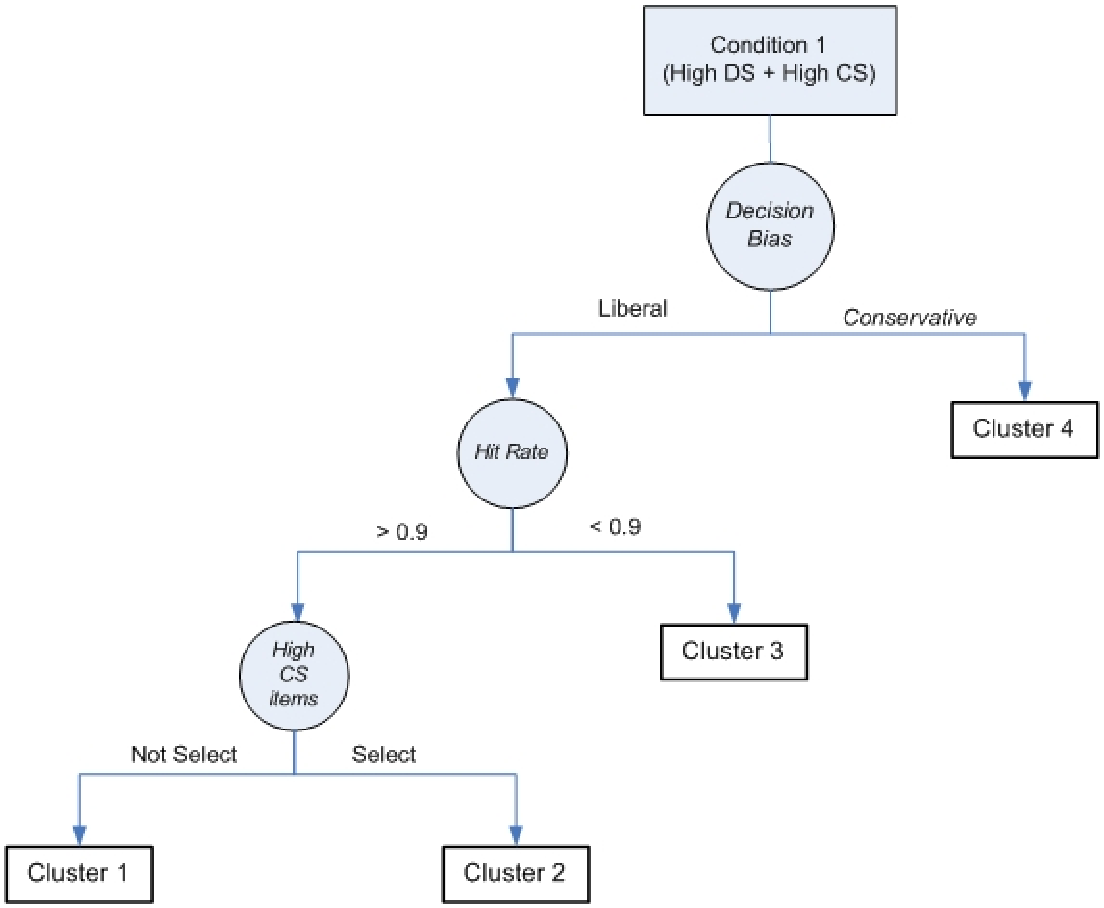


Figure 31: Simple clustering result in condition 1 (High DS + High CS)

Table 37: Cluster Characteristics for Condition 1 (High DS + High CS)

Cluster No	Average number of selected items	Expertise level		Performance measures			
		Novice	Experienced subject	*H*	*F*	*A'*	B''_d
1	8.40	11	19	0.967	0.283	0.914	-0.881
2	11.44	10	8	0.944	0.479	0.834	-0.900
3	5.62	7	19	0.837	0.142	0.904	-0.169
4	3.36	20	2	0.398	0.111	0.712	0.820

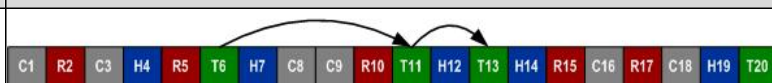
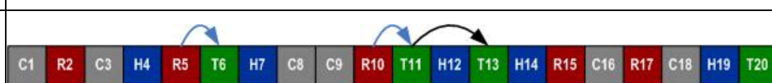
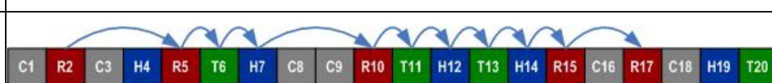
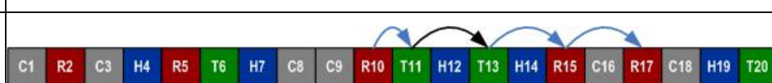
Markov clustering analysis

The behavior of the 7 clusters is more complex as seen in Table 38. It appears that relevant information (T), high DS information (R) and high CS information (H) are the main factors that differentiate the clusters except for the perfect performance group (cluster 1).

Subjects in clusters 2 and 4 can be considered to be a good performance group (*A' > 0.9*) and experienced users. Subjects in these two clusters were affected by high DS information (Cluster 2: R5 and R10 vs. Cluster4: R10, R15 and R17) and this effect led to a decrease in their information reduction performance. This finding is in agreement with the ANOVA results.

Subjects in cluster 3 are experienced subjects having poor performance since they added high CS irrelevant information into their relevant information list. Subjects in cluster 5 and 6 are mostly novices with very poor performance. Cluster 5 represents conservative novices with low values for *H* and *F*. Subjects in cluster 6 appear to be more liberal, producing higher values for *H* and *F*. Finally, cluster 7 represents a group of subjects whose selecting patterns do not fall within the common patterns obtained from the 3rd order Markov model.

Table 38: The Markov clustering result from K-Means (n=7) for related-high condition

No	Characteristic in information selection	*A'*	*B''d*	*H*	*F*	# of expert	# of novice
1		0.97	-0.3	0.96	0.08	6	0
2		0.94	-0.9	0.98	0.21	10	0
3		0.87	-0.9	0.97	0.45	8	0
4		0.91	-0.8	0.94	0.26	7	5
5		0.80	-0.2	0.75	0.29	0	5
6		0.83	-0.9	0.95	0.47	1	9
7	Match in some patterns but none of patterns containing 50% number of subjects	0.80	0.21	0.64	0.17	16	29

Condition 2 (High DS + Low CS)

Simple clustering analysis

Figure 32 shows the four clusters obtained from the K-Means method. For condition 2, decision bias, *H* and low CS information items are the main factors that differentiate the clusters. Similar to condition 1, high DS information items were common false alarms in clusters 1-3. Experienced subjects are mostly in clusters 1 and 3 which correspond to high performance subjects. Subjects in cluster 2 have higher values for *F* as they included low CS items as relevant information. Cluster 4 represents a conservative subjects group, mostly novices, who have low values for *H* and *F*.

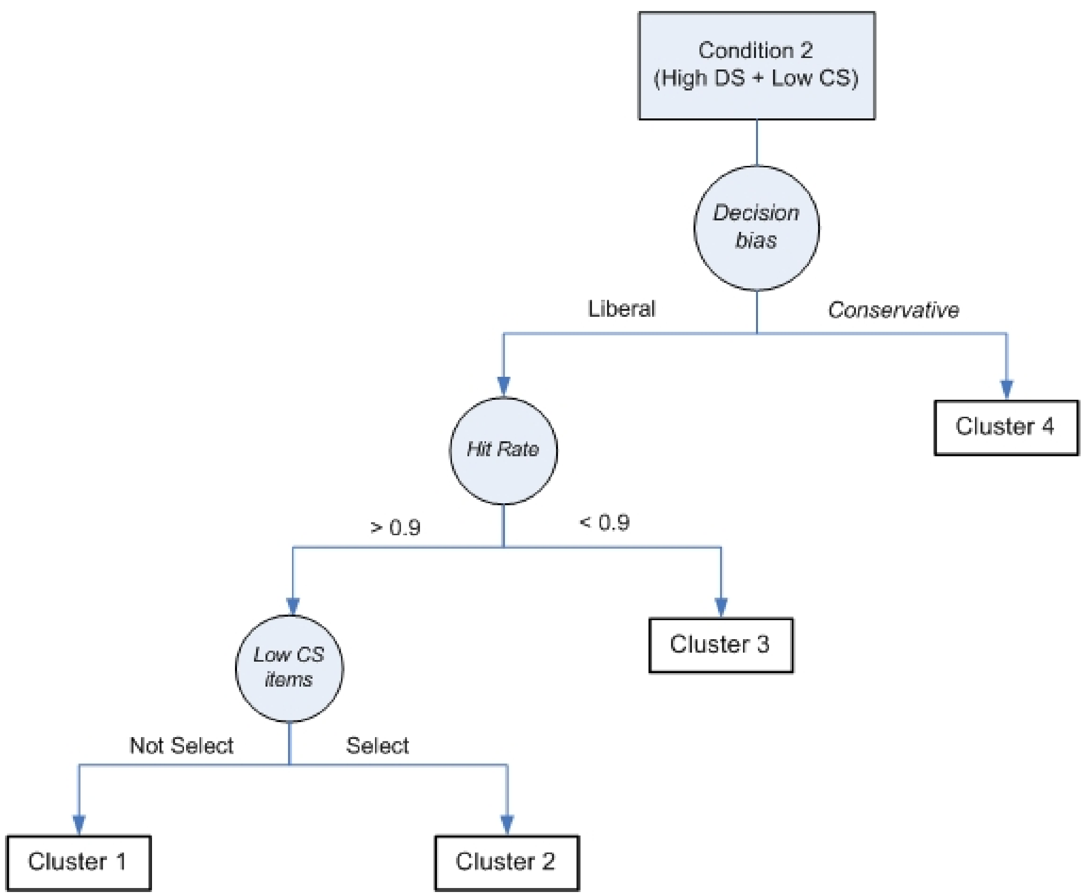


Figure 32: Simple clustering result in condition 2 (High DS + Low CS)

Table 39: Cluster Characteristics for Condition 2 (High DS + Low CS)

Cluster No	Average number of selected items	Expertise level		Performance measures			
		Novice	Experienced	*H*	*F*	*A'*	B''_d
1	8.069	13	16	0.914	0.276	0.889	-0.712
2	11.071	7	7	0.946	0.455	0.838	-0.926
3	5.963	7	20	0.852	0.160	0.907	-0.288
4	3.654	21	5	0.471	0.111	0.780	0.720

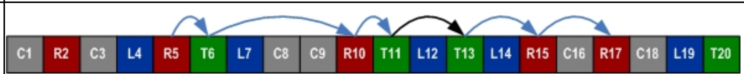
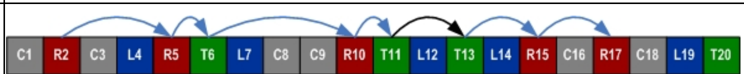
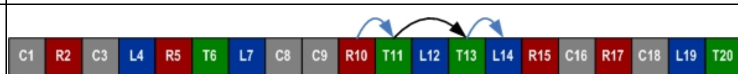
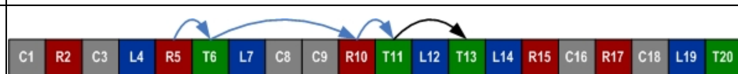
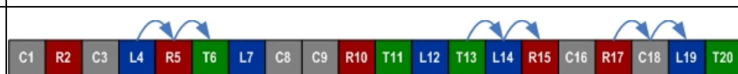
Markov clustering analysis1

Relevant (T) and high DS (R) information items differentiate the clusters shown in Table 40. Cluster 1 represents the perfect group in which the selecting pattern contains only relevant information items (T11 -> T13 -> T20). Clusters 2, 3 and 5 are good performance groups. Subjects in these three clusters were affected by high DS information items. All members of clusters 2 and 3 are experienced subjects, while members of cluster 5 are a mixture of experienced and novice subjects. Clusters 2 and 3 have slightly different selecting patterns (Cluster 2: R5->T6; Cluster 3: R2->R5->T6). For cluster 5, overall behavior is almost the same as behavior in cluster 2 except for actions after information item T13. The selecting pattern after T13 in cluster 5 was random.

The remaining clusters (Cluster 4, 6 and 7) represent a group of subjects having poor performance ($A' < 0.9$) with some difference in selecting patterns. Cluster 4 includes experienced subjects who not only included high DS items as relevant information but also included a low CS information item (L14). Cluster 6 corresponds to a novice group having liberal bias who selected all types of information items. Subjects in cluster 7 have a random pattern.

Unlike the condition 1 results, not all low CS information items are in the selecting pattern as seen for high CS information items in condition 1. This may imply that low CS information has less effect in information reduction behavior than high CS.

Table 40: The Markov clustering result from K-Means for condition 2 (High DS + Low CS)

No	Characteristic in information selection	*A'*	*B''d*	*H*	*F*	# of expert	# of novice
1		0.96	-0.33	0.94	0.08	4	0
2		0.94	-1.0	1	0.23	5	0
3		0.92	-1.0	1	0.31	5	0
4		0.89	-0.7	0.94	0.31	4	0
5		0.90	-0.7	0.91	0.25	11	3
6		0.82	-0.6	0.88	0.46	0	6
7	Match in some patterns but none of patterns containing 50% number of subjects	0.83	0.09	0.68	0.19	19	39

Condition 3 (Low DS + High CS)

Simple clustering analysis

Figure 33 indicates that subjects' behaviors were fairly consistent with condition 1. Decision bias, *H* and high CS information are the main factors in differentiating clusters. Subjects who did not select high CS information items as relevant information (Cluster 1) had higher performance than subjects who selected high CS information items (Cluster 2). Low DS information items were not selected by subjects as high DS information items were selected in condition1.

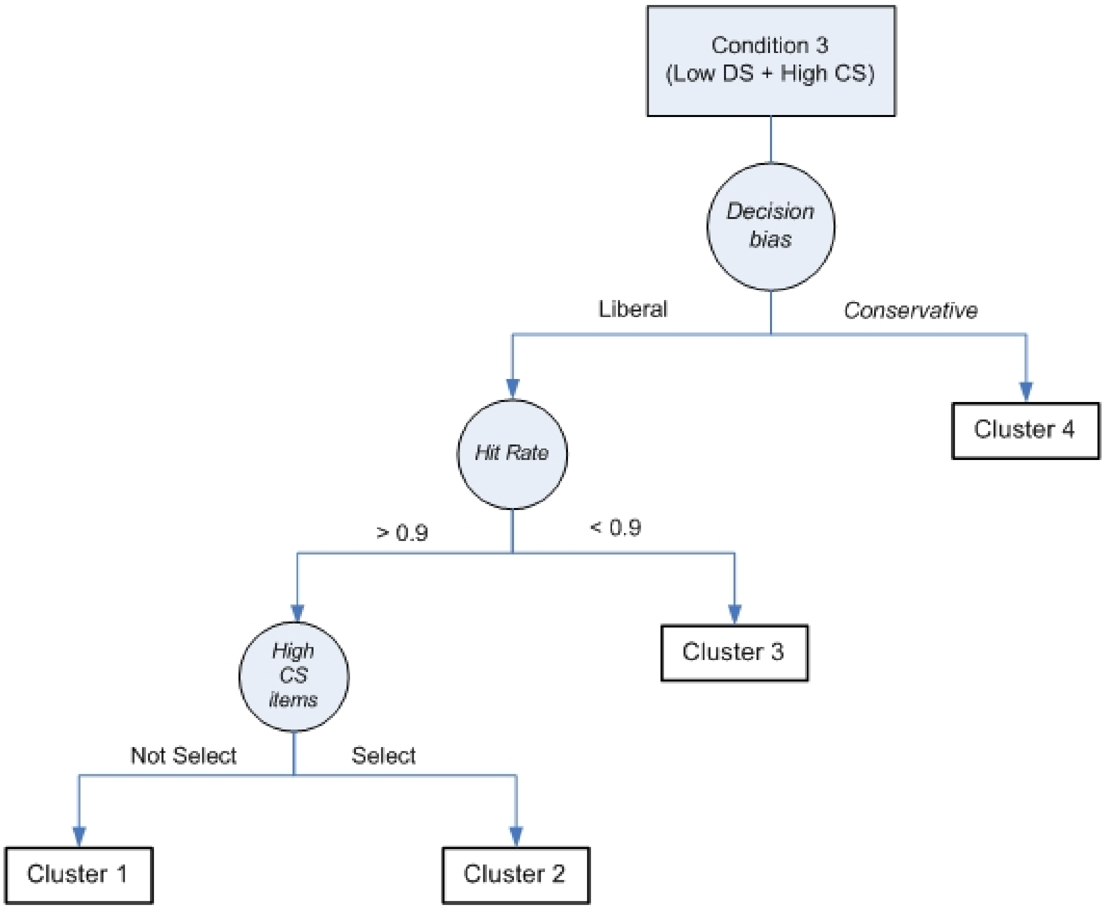


Figure 33: Simple clustering result in condition 3 (Low DS + High CS)

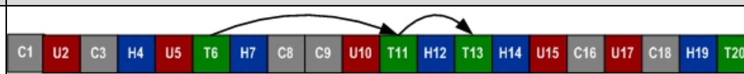
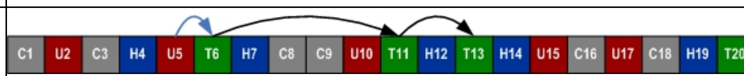
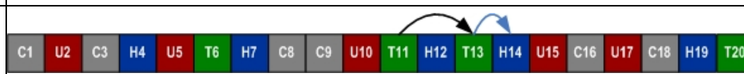
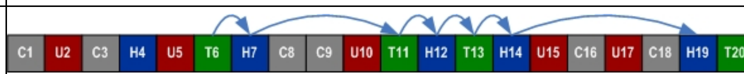
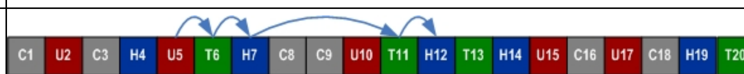
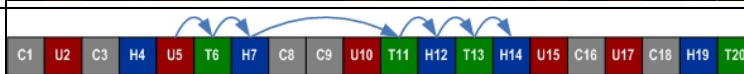
Table 41: Cluster Characteristics for Condition 3 (Low DS + High CS)

Cluster No	Average number of selected items	Expertise level		Performance measures			
		Novice	Experienced	*H*	*F*	*A'*	*B''$_d$*
1	5.375	10	22	0.969	0.094	0.967	-0.519
2	9.077	12	14	0.923	0.337	0.873	-0.768
3	6.600	7	3	0.825	0.206	0.881	-0.333
4	3.179	19	9	0.536	0.065	0.831	0.859

Markov clustering analysis

The seven clusters are shown in Table 42. The number of experienced subjects in the perfect performance group is relatively high as compared to conditions 1 and 2 (Condition 1: 6; Condition 2: 4; Condition 3: 11). This could be due to the substitution of high DS information for low DS information. Low DS information does not seem to affect the information reduction performance. This agrees with the simple clustering analysis.

Table 42: The Markov clustering result from K-Means for condition 3 (Low DS + High CS)

No	Characteristic in information selection	A'	B"d	H	F	# of expert	# of novice
1		0.99	-0.1	0.98	0.03	11	0
2		0.97	-0.8	1	0.14	6	0
3		0.97	-1.0	1	0.11	4	0
4		0.94	-0.8	1	0.23	4	0
5		0.91	-0.4	0.89	0.18	3	4
6		0.89	-1.0	0.98	0.35	6	7
7	Match in some patterns but none of patterns containing 50% number of subjects	0.85	0.2	0.68	0.14	14	37

Subjects in clusters 2, 3 and 4 are part of a good performance group (*A' > 0.94*). All members of these three clusters are experienced subjects and some in cluster 2 selected some low DS information such as U5. Subjects in clusters 3 and 4 ignored low DS information. However, they selected high CS information items instead (H14 in cluster 3 and all high CS information in cluster 4). Subjects in clusters 4 and 5 have a bit lower performance as subjects in these clusters produced more false alarms by including both low DS and high CS information items.

Condition 4 (Low DS + Low CS)

Simple clustering analysis

Similar to other conditions, B''_d and H differentiate the clusters. However, for this condition, the differentiating attributes for clusters 1 and 2 are a mix of three types of irrelevant information as shown in Figure 34. This suggests that none of irrelevant information types (low CS, low DS and common) dominated subjects' information reduction. In contrast to other conditions, there are two clusters with conservative bias and *H* separated clusters under conservative bias but not liberal bias. This suggests that subjects with liberal bias had better performance and higher values for *H*. In addition, subjects with conservative bias had relatively low performance.

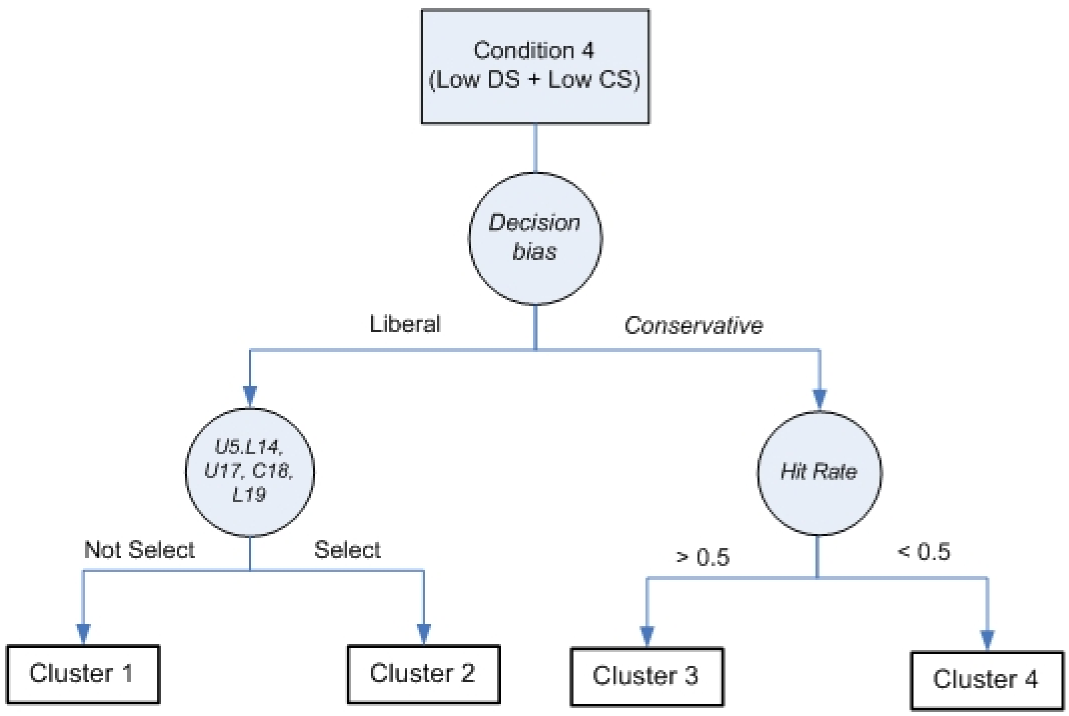


Figure 34: Simple clustering result in condition 4 (Low DS + Low CS)

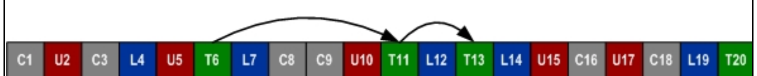
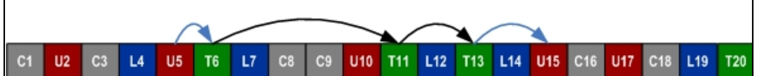
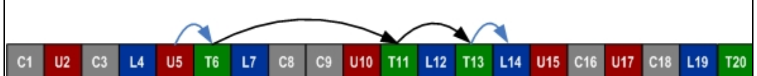
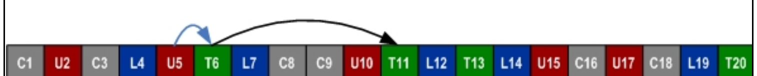
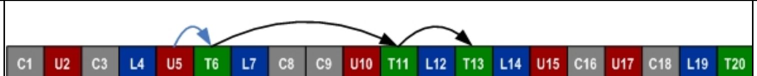
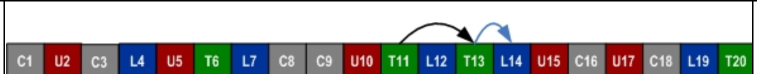
Table 43: Cluster Characteristics for Condition 4 (Low DS + Low CS)

Cluster No	Average number of selected items	Expertise level		Performance measures			
		Novice	Experienced	*H*	*F*	*A'*	B''_d
1	4.895	11	27	0.895	0.082	0.948	-0.204
2	8.321	15	13	0.946	0.283	0.904	-0.802
3	4.600	4	6	0.675	0.119	0.854	0.607
4	2.350	18	2	0.350	0.059	0.761	0.920

Markov clustering analysis

Table 44 shows cluster results for condition 4. Similar to other conditions, one cluster represents the perfect group (Cluster1). The higher performance group (clusters 2-6) added U5 before T6 and this caused poorer performance as compared to cluster 1. Subjects in cluster 2, 3 and 5 had nearly the same selecting pattern (U5->T6->T11->T13). However, their selecting patterns after T13 were different (Cluster 2: T13-> U15; Cluster 3: T13-> L14; Cluster 5: random pattern). Cluster 6 represents subjects having high values for *F* with a random selecting pattern.

Table 44: The Markov clustering result from X-Means for condition 4 (Low DS + Low CS)

No	Characteristic in information selection	A’	B”d	H	F	# of expert	# of novice
1		0.99	-0.3	0.98	0.03	12	0
2		0.97	-1.0	1	0.14	5	0
3		0.97	-1.0	1	0.14	4	0
4		0.96	-1.0	1	0.16	2	0
5		0.95	-0.5	0.92	0.08	3	0
6		0.89	-0.8	0.94	0.30	5	7
7	Match in some patterns but none of patterns containing 50% number of subjects	0.85	0.3	0.65	0.13	17	41

Common selecting pattern

The clustering results for information reduction have a large number of subjects in the last cluster with a random selecting pattern. In addition, for patterns having support greater than 0.1 in 3rd order Markov models(Table 45), subjects had less common selecting patterns under low DS conditions than under high DS conditions (condition 1 vs. condition 3; condition 2 vs. condition 4).. In the same way, subjects had less common selecting patterns under low CS conditions than the high CS conditions (condition 1 vs. condition 2; condition 3 vs. condition 4). Based on this finding, subjects may have been confused by high DS and high CS information items, thus, the selecting patterns became more similar. The selected information items for these two information types were fairly random which decreased the support. In contrast, low DS and low CS have little effect on information reduction.

Table 45: Number of pattern having support grater than 5 in 3rd order Markov model

Condition	# of subjects in last cluster (random pattern)			# of pattern having support >0.1 in 3rd order Markov model			Average A'
	Novice	Expert	All	Novice	Expert	All	
1 (High DS + High CS)	29	16	45	17	10	21	0.851
2 (High DS + Low CS)	39	19	58	10	10	16	0.857
3 (Low DS + High CS)	37	14	51	9	5	9	0.890
4 (Low DS + Low CS)	41	17	58	4	1	4	0.890

False alarm characteristics

Simple and Markov cluster analysis results show that certain information items led to a false alarm for each information type are shown in Table 46. The location of information had little effect on selecting since problem content is fairly short, containing twenty information items. In general, it was found that two information characteristics led to a false alarm.

- Information in the same knowledge domain with relevant information (High DS).
- Information corresponded to ordering, selling, cost or expense.

Table 46: False alarm information item in each information type

Information type	Information trend to selected as false alarm	Information trend to do NOT selected as false alarm
Common	C18 : Number of distributors	C1 : Company description C3 : Company address C8 : Order method C9: Delivery method
High DS	R5 : Safety stock R10 : Delivery time R15 : Cost of products manufactured R17 : Average selling product price	-
Low DS	U5 : Value of using equipment U17 : Estimated new distributors	U10 : Average number of fork trucks U15 : MARR of company
High CS	H7 : Purchase price from other company H12 : Inventory cost from other company H14 : Order cost from other company H19 : Demand in other year	-
Low CS	L14 : Building rents L19 : Promotion for this company	L4 : Packaging types L7 : Supplier address

5.4.2 Information acquisition

ANOVA results showed that problem sequence affects information acquisition. Therefore, clustering analysis was applied to explore subjects' information acquisition behaviors in the first problem (Sequence No =1) and last problem (Sequence No =4). The number of clusters based on compactness and separation (see Appendix F) was determined to be 4 for a simple clustering analysis.

Based on the sample Markov clustering analysis results shown in Appendix F, Markov clustering did not provide meaningful information as only a small fraction of information acquisition patterns could be clustered. This may be due to a greater variety in acquisition patterns. Therefore, only simple clustering analysis was used to cluster subjects' information acquisition behavior.

Condition 1 (High DS + High CS)

Table 47 shows the four clusters for condition 1. In the first problem, experienced subjects and novices visited all information items (Cluster 1 in sequence 1), referred to as the *visit-all* group. Another group visited almost all information items (Cluster 2,3 in sequence 1), referred to as the *visit-almost-all* group. In this group, subjects' behavior was nearly the same as the *visit-all* group except that they did not visit high CS information. The last group represents a subject group who visit some information, referred to as the *visit-some* group. Relatively few subjects are in this last group and they had low performance.

After subjects reached the last problem, their behavior changed. They performed less acquisitions and disregarded information in the "Logistic" section (Cluster 2 in sequence 4). For Clusters 3 and 4, subjects completely ignored the "About" section. This is a good indication of their learning as the "About" section always contained only irrelevant information. In addition, the number of subjects in the *visit-all* group decreased while the number of subjects in the *visit-some* group increased. Experienced subjects had a higher learning curve effect than novices. In the first problem, only one experienced subject did not visit irrelevant information. This number increased to 5 in last problem.

Table 47: Simple clustering result for information acquisition in condition 1 (High DS + High CS)

	No	About				Purchasing				Logistics				Finance				Sale & Marketing				Average # of visit	Performance				# of users	
		C1	R2	C3	H4	R5	T6	H7	C8	C9	R10	T11	H12	T13	H14	R15	C16	R17	C18	H19	T20		H	F	A	BD	E	N
Sequence 1	1	1	0.9	0.9	0.9	0.9	1	1	1	1	0.9	1	0.7	0.9	0.4	0.9	0.6	0.7	0.8	0.8	1	17.10	0.81	0.22	0.88	-0.18	5	4
	2	1	1	1	1	1	1	0	0.7	1	1	1	0.3	1	0	1	1	0.3	0.7	0.7	1	15.70	1	0.19	0.95	-1	2	1
	3	0.6	0.4	0	0	1	0.9	0.6	1	0.9	0.9	0.8	0.3	0.8	0	0.7	0.3	0.9	0.9	0.9	1	12.80	0.81	0.28	0.83	-0.54	4	5
	4	0	0	0	0	0.3	0.7	0	0.3	0.3	0.3	0.7	0	0.7	0	0.7	0	1	0.7	0.7	1	7.33	0.25	0.19	0.58	0.86	1	2

	No	About				Purchasing				Logistics				Finance				Sale & Marketing				Average # of visit	Performance				# of users		Score	
		C1	R2	C3	H4	R5	T6	H7	C8	C9	R10	T11	H12	T13	H14	R15	C16	R17	C18	H19	T20		H	F	A	BD	E	N	E	N
Sequence 4	1	0.8	1	1	0.8	1	1	1	0.8	0.8	1	1	0.8	1	0.7	1	0.7	0.8	0.8	1	1	18.17	1	0.46	0.89	-1	3	3	0.67	0
	2	1	1	1	1	1	0.7	0	0.3	0	0.3	0.3	0.3	0.7	0	1	0	0.3	0	0.7	1	10	0.67	0.19	0.81	0.17	2	1	0.88	0
	3	0.4	0.4	0	0	0.6	0.8	0	1	1	1	1	0	0.8	0	0.8	0	0.6	0.2	0.4	0.8	9.8	0.85	0.24	0.88	-0.42	2	3	0.5	0
	4	0	0.1	0	0	0.4	0.7	0.1	0.3	0	0.3	0.7	0.1	0.6	0.1	0.6	0.2	0.4	0.1	0.6	0.8	6.1	0.7	0.15	0.78	0.07	5	5	0.8	0

Table 48: Simple clustering result for information acquisition in condition 2 (High DS + Low CS)

	No	About				Purchasing				Logistics				Finance				Sale & Marketing				Average # of visit	Performance				# of users	
		C1	R2	C3	L4	R5	T6	L7	C8	C9	R10	T11	L12	T13	L14	R15	C16	R17	C18	L19	T20		H	F	A	BD	E	N
Sequence 1	1	1	0.9	0.9	1	1	1	1	1	0.9	1	1	0.9	1	0.8	1	1	0.9	1	1	1	19.42	0.85	0.3	0.85	-0.6	8	4
	2	1	1	1	1	0.7	1	1	1	1	1	1	1	0.3	0.3	1	1	1	1	1	1	18.33	0.5	0.27	0.62	0.39	1	2
	3	1	1	0.8	1	0.5	0.8	0.5	0.8	0	0	0.3	0	0.5	0	0.5	0	0.5	0.3	0.5	0.8	9.5	0.44	0.06	0.7	0.85	1	3
	4	0.3	0.3	0	0.1	0.6	1	0.6	0.8	0.3	0.4	0.6	0.1	0.3	0	0.1	0	0.3	0.3	0.4	0.4	6.625	0.53	0.08	0.84	0.44	2	6

	No	About				Purchasing				Logistics				Finance				Sale & Marketing				Average # of visit	Performance				# of users		Score	
		C1	R2	C3	L4	R5	T6	L7	C8	C9	R10	T11	L12	T13	L14	R15	C16	R17	C18	L19	T20		H	F	A	BD	E	N	E	N
Sequence 4	1	1	0.8	0.7	1	0.8	1	1	0.8	0.7	0.8	1	0.7	1	0.5	1	0.3	0.7	0.3	0.8	1	16	0.96	0.34	0.9	-0.77	2	4	0.88	0
	2	0	0.1	0	0	0.9	1	1	0.7	0.4	1	1	0.9	0.9	0.7	1	0.1	0.7	0.4	0.3	0.9	12	0.89	0.27	0.88	-0.59	5	2	0.75	0
	3	0	0.1	0	0	0.6	1	0.3	0.1	0	0.6	0.9	0.4	0.7	0.3	0.4	0	0.1	0.3	0.3	1	7.143	0.82	0.13	0.91	-0.03	5	2	0.9	0
	4	0.3	0	0	0	0.8	0.8	0.3	0.3	0	0.5	0	0	0.3	0	0.5	0	0.3	0.3	0.3	0.5	4.75	0.38	0.14	0.72	0.8	0	4	-	0.3

Condition 2 (High DS + Low CS)

Table 48, subjects in the *visit-almost-all* group visited most of the items. Only L14 (Building rents) was a common information item that subjects in *visit-almost-all* group did not visit. A learning effect was observed for the fourth problem in the sequence. Subjects in the *visit-almost-all* group and visit-some group ignored the "About" section and some irrelevant information in "Sales & Marketing". The proportion of experienced subjects in the *visit-all* group decreased (Cluster 1 in sequence 1) and the proportion increased in the *visit-almost-all* group. The number of subjects in the *visit-all* group dropped from 8 to 2 subjects. This was not true for novices.

Condition 3 (Low DS + High CS)

Table 49 shows four clusters for condition 3. Similar to conditions 1 and 2, subjects (particularly experienced subjects) visited all information items or visited almost all information items in the first problem. Subjects in the *visit-almost-all* group typically did not visit high CS information.

Subjects adjusted their behavior in the last problem. In general, subjects increasingly ignored information in the "About" section (Cluster 2-4 in sequences 4) as well as some irrelevant information in "Sales & Marketing" (Cluster 3-4 in sequences 4). The number of subjects in the *visit-all* group decreased for both novice and experienced subjects. For the visit-some group, only the number of experienced subjects increased slightly.

Table 49: Simple clustering result for information acquisition in condition 3 (Low DS + High DS)

	No	About				Purchasing				Logistics				Finance				Sale & Marketing				Average # of visit	Performance				# of users	
		C1	U2	C3	H4	U5	T6	H7	C8	C9	U10	T11	H12	T13	H14	U15	C16	U17	C18	H19	T20		H	F	A	BD	E	N
Sequence 1	1	1	1	0.9	0.9	0.9	1	0.9	1	1	0.9	1	0.8	1	0.6	0.9	0.9	0.9	0.7	1	1	18.33	0.94	0.19	0.93	-0.57	7	5
	2	1	1	1	1	1	1	0	0.7	1	1	1	0	1	0	0.7	1	0.7	0.7	0.7	1	15.33	1	0.13	0.97	-0.67	2	1
	3	0.3	0.3	0.7	0.3	0.7	1	0.3	1	0	0.3	0.3	0	1	0.7	0.3	0	0.3	0.7	1	0.7	10	0.58	0.15	0.77	0.62	3	0
	4	0	0.2	0	0.2	0.5	0.8	0.3	0.5	0.5	0.3	1	0.3	1	0.3	0.7	0	0	0	0.2	0.7	7.5	0.79	0.08	0.91	0.1	3	3

	No	About				Purchasing				Logistics				Finance				Sale & Marketing				Average # of visit	Performance				# of users		Score	
		C1	U2	C3	H4	U5	T6	H7	C8	C9	U10	T11	H12	T13	H14	U15	C16	U17	C18	H19	T20		H	F	A	BD	E	N	E	N
Sequenc e 4	1	1	1	1	0.9	0.9	1	0.5	0.9	0.9	0.6	1	0.4	0.9	0.4	0.5	0.4	0.8	0.9	0.8	1	15.5	0.91	0.22	0.92	-0.62	5	3	0.8	0
	2	0.4	0.4	0	0	0.8	1	0.8	0.4	0.6	0.8	1	0.7	0.9	0.6	0.5	0	0.6	0.6	0.7	0.9	11.44	0.81	0.29	0.85	-0.21	1	5	0	0
	3	0.3	0.7	0	0	1	1	1	0.3	0.7	0.3	1	1	1	0.7	0.3	0	0	0	0	0.7	10	0.83	0.21	0.88	-0.1	2	1	0.75	0
	4	0.1	0	0	0	0.4	0.9	0	0.1	0.1	0	0.6	0	0.6	0.3	0.6	0.4	0.1	0	0.1	0.9	5.286	0.71	0.05	0.91	0.23	4	3	1	0

Table 50: Simple clustering result for information acquisition in condition 4 (Low DS + Low CS)

	No	About				Purchasing				Logistics				Finance				Sale & Marketing				Average # of visit	Performance				# of users	
		C1	U2	C3	L4	U5	T6	L7	C8	C9	U10	T11	L12	T13	L14	U15	C16	U17	C18	L19	T20		H	F	A	BD	E	N
Sequence 1	1	1	1	0.9	1	1	1	1	1	0.9	0.9	1	1	1	1	1	1	0.8	0.8	0.8	0.9	19.23	0.92	0.21	0.92	-0.65	8	5
	2	0.6	0.2	0	0.2	1	1	1	1	1	1	1	0.8	0.8	0.6	0.8	0.6	1	0.8	0.6	1	15	0.8	0.13	0.91	-0.03	3	2
	3	0.5	0.5	0.5	0.5	0.5	0.8	0.8	1	0	0	0	0	0.5	0.3	0.5	0.3	0.8	0.5	0.5	0.8	9	0.44	0.05	0.83	0.84	1	3
	4	0.5	0.5	0.5	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0.5	3	0.13	0.06	0.49	0.98	0	2

	No	About				Purchasing				Logistics				Finance				Sale & Marketing				Average # of visit	Performance				# of users		Score	
		C1	U2	C3	L4	U5	T6	L7	C8	C9	U10	T11	L12	T13	L14	U15	C16	U17	C18	L19	T20		H	F	A	BD	E	N	E	N
Sequence 4	1	0.4	0.8	0.4	0.8	1	1	1	0.6	1	1	1	1	1	1	1	0.4	1	1	0.8	0.8	17	0.9	0.39	0.86	-0.66	1	5	0.75	0
	2	1	1	1	1	0.8	1	1	0.5	1	0.5	1	0.5	1	0	0	0	0.3	0.8	1	1	14.25	0.88	0.16	0.9	0.02	3	1	0.92	0
	3	0.2	0.2	0	0.5	1	1	0.7	0.5	0.7	0.8	0.8	0.5	0.7	0	0.3	0	0.5	0.3	0.3	1	10	0.88	0.11	0.93	-0.21	3	3	0.92	0.3
	4	0	0.1	0	0	0.3	0.7	0.2	0.1	0	0	0.6	0	0.6	0	0	0	0.2	0.2	0.4	1	4.444	0.67	0.03	0.89	0.52	5	3	0.9	0

Condition 4 (Low DS + Low CS)

According to clustering results for condition 4 (see Table 50), most of subjects (especially experienced) visited all information items in their first problem (Cluster 1 in sequences 1). Cluster 3 represents a group of novices who completely ignored the "Logistics" section. For cluster 4, subjects in this cluster are novices having very low performance as they completely ignored three sections - purchasing, logistics ad finance.

As in the other conditions, subjects' behavior changed in the last problem. The number of visited information items generally decreased and irrelevant information in the "Finance" section was ignored (Cluster 2-4 in sequence 4). For Clusters 3 and 4, subjects were able to ignore the "About" section as well. Furthermore, it can be seen that the proportion of experienced subjects in the *visit-all* group decreased and the proportion in the *visit-some* group increased. The number of novices appearing in the groups remained relatively constant.

High vs. Low CS condition

Under the same DS condition (Condition 1 vs. 2; Condition 3 vs. 4), we found that in the first problem, subjects performed more exhaustive searches under the low CS condition than the high CS condition. However, in the last problem, subjects under the high CS condition appear to have performed more exhaustive search than in the low CS condition. For example, in condition 1, there are 9 subjects (5 experienced subjects and 4 novices) performing exhaustive search in the first problem. However, only 6 subjects (3 experienced subjects and 3 novices) still do exhaustive search in the last problem. Therefore, it appears that learning occurred in the low CS condition.

Table 51: Number of subject in the visit-all group.

Number of subject in the visit-all group.				
Condition No	First problem		Last problem	
	Experienced subject	Novice	Experienced subject	Novice
1 (High DS + High CS)	5	4	3	3
2 (High DS + Low CS)	8	4	2	4
3 (Low DS + High CS)	7	5	5	3
4 (Low DS + Low CS)	8	5	1	5

CHAPTER6. CONCLUSIONS AND FUTURE WORK

Problems are defined by the information used to describe and solve them. In this study, the effects of concept similarity (CS) and knowledge domain similarity (DS) on a problem solver's ability to identify information relevant to solving a problem were investigated. In the methodology for the experiment, a new heuristic approach was developed for constructing problem descriptions with certain semantic characteristics. Latent semantic analysis (LSA) was used in this approach to measure the similarity between problem contents in all experimental conditions. Performance measures from signal detection theory were used to measure a subject's ability to identify task relevant information in problem solving. Information acquisition is related to information reduction and corresponds to a subject's exploration of information available about the problem. Established performance measures from the information acquisition literature were used.

ANOVA and clustering analysis (based on Markov models) provided insights into the nature of groups of subjects based on their information reduction and information acquisition behavior. These results indicate that both the expertise level and problem contents (that differed in terms of CS and DS) significantly affected performance in both information acquisition and reduction behaviors.

As expected, subjects with more expertise performed better (i.e., higher A' scores) in identifying relevant information compared to subjects with less expertise. It should also be noted that experienced subjects were more liberal than novices, as measured by B''_d. Experienced subjects had higher values for H in the context of more false alarms, higher F. A similar result on B''_d was also observed by Allen et al. (2004). In their study, they investigated the effect of expertise level on a subject's ability to supervise aircraft in term of tracking targets among distractors. Their result showed that professional radar operators (experts) appeared to be more liberal than undergraduate students (novices) and increasingly more liberal when the task becomes more difficult (number of targets increased).

We found that experienced subjects spent more time on relevant information than novices. Taken together (the higher A', higher B''_d and more time spent on relevant information), these indicators suggest that while more experienced subjects may choose more statements overall as being relevant, the proportion of chosen statements that are relevant is higher than for novices. This finding is in agreement with Perkins and Rao (1990) who found that experience could affect the ability to prioritize important information. Their result indicated that subjects with more expertise (e.g., a senior manager) used more relevant information and needed less time prior to making a decision than a subject with less expertise (e.g., an assistant manager).

In this study, a new approach was used to investigate the effects of irrelevant information content (concept similarity: CS and domain knowledge similarity: DS) on information reduction (performance and selecting information pattern) and information acquisition (performance and navigation). The results indicate that DS plays a significant role in a subject's performance and behavior. Both experienced subjects and novices showed poorer performance and were more liberal with high DS items than with low DS items. It should also be noted that experienced subjects spent more time on irrelevant information and used an inconsistent pattern of information acquisition across information elements (non-compensatory strategy) under the high DS condition. In general, it can be said that subjects (especially experienced subjects) had difficulty identifying high DS information as irrelevant information and became more liberal when the difficulty increased (Allen et al. 2004).

Concept similarity (CS) affected information acquisition behavior. Experienced subjects spent more time on irrelevant information and performed more acquisitions under low CS. This suggests that experienced subjects were aware of the problem's goal state which leads them to ignore high CS information element. Given that experienced subjects were more liberal, a possible explanation is that new information was investigated when similar words do not appear in relevant information. However, we did not find the same significant effect in the novice group.

Solving the problem had an effect only on experienced subjects' information reduction performance, which improved because they became more conservative after they had solved the problem. Both experienced subjects and novices performed a few acquisitions after solving the problem. Taking into account the information reduction and acquisition behavior, different behaviors for experienced subjects and novices can be seen. After solving the problem, experienced subjects became aware that they had included some irrelevant information. Consequently, they generally removed false alarm information items. Novices had difficulty both in identifying relevant information and solving the problem. Therefore, they revisited a few information items but had fewer adding and removing actions. In addition, it was found that there are some experienced subjects who were able to solve problem correctly but had low sensitivity (*A'*). While most of novices were not able to solve the problem; some had high sensitivity. Therefore, additional study is warranted to investigate other aspects of the problem solving process for experienced subjects with low sensitivity and novices with high sensitivity. A possible extension would be to measure the sensitivity by considering the information used in a subject's solution rather than a separate relevant information list.

The results indicate that a learning effect occurred, particularly on information acquisition behavior. As the problem sequence increased, it led to a decrease in completion time, average viewing time per acquisition as well as a decrease in fraction of information acquisition. Moreover, subjects spent more time on relevant information and used a more consistent pattern of information acquisition across information items. This result is consistent with Soetens et al. (2004) who found that sequence learning was tied to a decrease in the mean reaction time.

As seen in the ANOVA results, the experimental conditions have different levels of difficulty. The results from clustering showed that an experienced subject should be more successful in discriminating the relevant information from irrelevant information for all problems. The influence of DS was consistent with our expectation that subjects would be less successful with high DS problems. High DS information items were commonly included as relevant information. Clustering results showed that a smaller percentage of subjects selected a majority of the high CS elements if they selected this type of information. This could imply that subjects (including experienced subjects) continued to be confused by high DS irrelevant information. Real world problems are considered to be much more ill structured in terms of information diversity. These types of problems could potentially pose greater difficulties for experienced subjects in finding relevant information and formulating the problem. These findings suggest that in the design of user interfaces, information from the same domain knowledge (but different in concept) should be separated in order to avoid or reduce user confusion. In addition, it was also observed that when irrelevant information contained high DS items corresponding to ordering, selling, cost or expense, then it led to a false alarm.

To obtain a better understanding of the effects of concept integration within the same knowledge domain, a possible extension would be to investigate how well subjects integrate related concepts in a given domain. Additionally, assessment techniques could be developed (based on the approach used in this study) to analyze the level of integration to determine similarities and differences in DS between different problem descriptions. The use of performance measures in information reduction for this assessment may prove to be an effective approach.

Information reduction and information acquisition performance measures were considered as dependent variables in the ANOVA to identify any significant main effects or interaction effects of the independent variables. Future work could consider the correlation between information reduction and information acquisition performance measures. For example, do specific information acquisition behaviors lead to better or poorer information reduction performance?

Results from Markov models have shown that there are no significant differences in the overall selecting and acquiring information pattern. Experienced subjects and novices acquisition pattern appears to follow the order of the information presentation sequence. This finding is also supported by the work of Camel et al. (1992). They found that there was no significant different between experts and novices in overall browsing strategy in hypertext.

In addition, Markov models and clustering results confirm that problem sequence can have an affect on learning in information acquisition, particularly in the experienced subject group. Subjects performed an exhaustive search in the first problem and became more focused when they reached the last problem. In the last problem, subjects usually ignored the "About" section. This is a good indication of learning because the "About" section contained only irrelevant information. Since there was no time limitation in the experiment, subjects (especially experienced subjects) were liberal and tended to visit all information under all experimental conditions. Another possible extension is to investigate subjects' behavior when time is limited or when each information item has a different cost or penalty.

Results from the Markov clustering analysis in information acquisition behavior indicated that subjects' acquisition patterns were quite random. Future work could focus on the nature of this apparent random behavior, perhaps extending the Markov clustering analysis using higher orders, varying the support value used as common pattern criterion, or examining additional factors.

The results for the CS and DS effects on discriminating targets suggest that in developing problem solving expertise, it might be more effective to start with simple information conditions, namely, low CS and low DS. As performance improves, the difficulty could be increased by changing to higher levels of CS and DS.

In contrast to findings that subjects' ability in separating task relevant from task-irrelevant information could be improved through practice (Haider and Frensch 1996; Green and Wright 2003), we found that learning occurred only on information acquisition but not in information reduction. It remains to be seen if information reduction performance can be improved in more complex problems, as subjects still had difficulty identifying relevant information with high DS even though they had reached the fourth problem or had solved the problem. Vendlinksi and Stevens (2002) had similar results, finding that without instruction intervention, subjects are not likely to change their problem solving strategies even though those strategies might not provide the correct solution. In order to improve problem solving skills, additional emphasis must be placed on clarifying the differences between concepts or principles in same knowledge domains.

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APPENDIX A. LATENT SEMANTIC ANALYSIS

NOTATION

A word frequency matrix (m x n)

m number of words

n number of documents

d_j column vector j in **A**

f_{ij} frequency of appearance of word i in document j

$\hat{\mathbf{A}}$ weighting functions matrix

$\hat{d}_j$ column vector j in $\hat{\mathbf{A}}$

l_{ij} local weighting function presents the weighting of word i document j

g_i global weighting function is used to measure the weighting of a word i across all documents

$\hat{a}_{ij}$ element in row i and column j of $\hat{\mathbf{A}}$, calculated from the two weighting functions, local and global weight functions

df_i number of documents in which word i appears

gf_i total frequency of appearance of word i in all documents

p_{ij} conditional probability of document j given that word i appears.

$\mathbf{A}^*$ single value decomposition matrix (SVD)

U matrix of word vectors

S diagonal matrix of singular values ordered by size

V matrix of document vectors

k number of dimensions

The LSA process begins by representing the set of documents as a word document matrix A. Matrix A is an m x n matrix where m is the number of words, and n is the number of documents.

$$\mathbf{A} = \begin{bmatrix} f_{11} & \cdots & f_{1n} \\ \vdots & & \\ f_{m1} & & f_{mn} \end{bmatrix}$$

where f_{ij} is the frequency of appearance of word i in document j. Each row is associated with an individual word, and each column is an individual document. **A** is transformed into $\hat{\mathbf{A}}$ using a weighting function resulting in

$$\hat{\mathbf{A}} = \begin{bmatrix} \hat{a}_{11} & \cdots & \hat{a}_{1n} \\ \vdots & & \\ \hat{a}_{m1} & & \hat{a}_{mn} \end{bmatrix}.$$

The transformation is a product of two weighting functions, local and global. Each element of $\hat{\mathbf{A}}$ is determined by

$$\hat{a}_{ij} = l_{ij} * g_i ,$$

where l_{ij} is a local weighting function representing the weighting of word i in document j, and g_i is a global weighting function used to measure the weighting of a word i across all documents.

WEIGHTING FUNCTIONS

Local Weighting functions

The local weight indicates the importance of a word within a document. Three common local weighting functions (Dumais, 1991; Jones 1972) are as follows.

1. *Term of frequency* - frequency of word *i* in the document *j*

$$l_{ij} = f_{ij}$$

2. *Logarithmic* - represents the logarithm of the word frequency.

$$l_{ij} = \log_2\left(f_{ij} + 1\right) \tag{A.1}$$

3. *Binary* - indicates a frequency greater than zero.

$$l_{ij} = \begin{cases} 1 & when \quad f_{ij} \rangle 0 \\ 0 & when \quad f_{ij} = 0 \end{cases}$$

Global weighting functions

The global weight is used to indicate the importance of a word across an entire set of documents. Numerous global weighting functions have been used in LSA such as, normal and entropy. Typical weighting functions are as follows.

1. *Normal* is a normalization of the local weights.

$$g_i = \frac{1}{\sqrt{\sum_j l_{ij}^2}}$$

2. *Inverse document frequency (idf):*

$$g_i = 1 + \log\left(\frac{n}{df(i)}\right)$$

Where: df_i is the number of documents in which word *i* appears and *n* is the total number of documents.

3. *Ratio of the global frequency of term (word) and the number documents (GfIdf):*

$$g_i = \frac{gf_i}{df_i} \tag{A.2}$$

Where gf_i is the total frequency of appearance of word *i* in all documents.

3. *Entropy*

$$g_i = 1 + \frac{\sum_j^n p_{ij} \log(p_{ij})}{\log(n)} \tag{A.3}$$

Where: $p_{ij} = f_{ij} / gf_i$ is the conditional probability of document *j* under condition that the word *i* appears.

4. *Real entropy of the conditional distribution:*

$$g_i = -\sum_j^n p_{ij} \log(p_{ij}) \tag{A.4}$$

Some studies have indicated that LSA with the entropy global weighting function produced high correlation with human performance (Lee et al. 2005; Nakov et al 2001). In many applications such as information retrieval, LSA is partially confounded by variability in word usage. This problem can be addressed by either creating a dictionary containing focus words or using a Single Value Decomposition (SVD). Both methods aim to capture most of underlying semantic structure in the association of words and documents and at the same time ignore minor differences in vocabulary and word count. For the dictionary option, the term of frequency is a typical method to select words for the dictionary.

For the SVD process, $\hat{\mathbf{A}}$ is transformed to $\mathbf{A}^*$ via a Single Value Decomposition (SVD), given by

$$A^* = U \quad S \quad V^T$$

where **U** (m x k) is the matrix of word vectors, **S** (k x k) is the diagonal matrix of singular values ordered by size, and **V** (n x k) is the matrix of document vectors when k is the number of dimensions and $k \leq Max(m,n)$, and $m > n$.

The goal of SVD is to reduce relationships between words that appear in large passages. This can be done by keeping only the k largest singular values and setting the rest to zero. By multiplying the truncated matrices back together, we obtain $\mathbf{A}^*$, a reduced dimension term document matrix. Berry (1995) reported that the information retrieval performance is greatly improved with SVD technique as compared to the original matrix.

Document similarity

To compare the similarity between documents either in the $(k * m)$ reduced latent semantic space or in the $(n * m)$ full space, the cosine measure, the Jaccard coefficient, or variants have been used. The cosine measure is commonly used for measuring document/text similarity. To compare documents i and j, the similarity, $S(i,j)$, is the cosine of the angle (θ) between the two vectors, $\hat{d}_i$ and $\hat{d}_j$. Using the standard relationship between two vectors,

$$S(i,j) = \cos(\theta) = \frac{\hat{d}_i \bullet \hat{d}_j}{\left\|\hat{d}_i\right\| \left\|\hat{d}_i\right\|}. \quad \textbf{(A.5)}$$

Note that $0 \le S(i,j) \le 1$, because all elements of the vectors are zero or positive. Dissimilarity is indicated when $S(i,j) = 0$, representing orthogonal vectors (i.e., one vector has one or more elements with a value of zero, indicating the word does not appear in the document). When $S(i,j) = 1$, the documents are the most similar in meaning, but not necessarily equivalent.

ILLUSTRATION OF LSA CALCULATION

This example is adapted from a LSA example used in previous studies (Deerwester et al, 1990; Landauer et al 1997). Table A.1 is a sample data set consisting of multiple word phrases that are treated as “documents.” In this example, the LSA calculation is performed using a dictionary. Stop words (shown in italics) such as articles and conjunctions are ignored.

Table A.1: A sample data set

Document No.	Document content
1	Human machine interface *for* Lab ABC computer management applications
2	*The* EPS user interface management system
3	System *and* user interface system testing *of* EPS

The first step is to create **A** by counting the word occurrences as shown in. Table A.2

Table A.2: Word frequency matrix A

	d_1	d_2	d_3
human	1	0	0
machine	1	0	0
interface	1	1	1
lab	1	0	0
ABC	1	0	0
computer	1	0	0
application	1	0	0
EPS	0	1	1
user	0	1	1
management	1	1	0
system	0	1	2
test	0	0	1

Local weighting function: Using (A.1), the local weights, l_{ij}, are determined as shown in Table A.3.

Table A.3: Logarithmic local weights

	l_{i1}	l_{i2}	l_{i3}
human	1	0	0
machine	1	0	0
interface	1	1	1
Lab	1	0	0
ABC	1	0	0
computer	1	0	0
application	1	0	0
EPS	0	1	1
user	0	1	1
management	1	1	0
system	0	1	1.585
test	0	0	1

Global weighting function: The global entropy is used in this example. The first step is to calculate the conditional probabilities shown in the first three columns of Table A.4. The global weight in the last column is found using (A. 2) for each word. The results are shown in Table A.4.

Table A.4: The calculation step of global entropy weighting function

	p_{i1}	p_{i2}	p_{i3}	g_i
human	1	0	0	**1**
machine	1	0	0	**1**
interface	0.3333	0.3333	0.3333	**0**
lab	1	0	0	**1**
ABC	1	0	0	**1**
computer	1	0	0	**1**
application	1	0	0	**1**
EPS	0	0.5	0.5	**.369**
user	0	0.5	0.5	**.369**
management	0.5	0.5	0	**.369**
system	0	0.3869	0.7737	**.485**
test	0	0	1	**1**

$\mathbf{A}$ is transformed into $\hat{\mathbf{A}}$ (shown in Table A.5) by using the product of the two weighting functions.

Table A.5: The weight function matrix $\hat{\mathbf{A}}$

	$\hat{d}_1$	$\hat{d}_2$	$\hat{d}_3$
human	1	0	0
machine	1	0	0
interface	0	0	0
Lab	1	0	0
ABC	1	0	0
computer	1	0	0
application	1	0	0
EPS	0	0.36907	0.36907
User	0	0.36907	0.36907
management	0.36907	0.36907	0
system	0	0.484893	0.664372
Test	0	0	1

The final step is to compute $S(i,j)$ for each pairing of documents using (A.5). The results are given in Table A.6.

Table A.6: The similarity between documents.

Similarity between document			
Document No.	1	2	3
1		0.068534	0
2			0.56606
3			

Two local weighting functions, term of frequency and logarithm were used for this study. For the global weighting function, we used normalization, the ratio of global frequency of a term and the number of documents in which it appears (Equation A.2), the real entropy of the conditional distribution (Equation A.3) and entropy (Equation A.4). We investigated all combinations between local weight functions and global weight functions. Our results agreed with others (Lee et al. 2005; Nakov et al 2001) in that LSA using the entropy global weighting function produced high correlation as compared to human performance. Therefore, in this study, the logarithm local weighting function and the entropy global weighting function were used in LSA to calculate the word-document vector matrix.

APPENDIX B. THE COMPLETE LIST OF WORDS IN DICTIONARY

This table shows the completed list of words with their frequency in Inventory Management domain dictionary.

Table B. 1: Inventory management domain dictionary.

Dictionary					
Words	**Frequency**	**Words**	**Frequency**	**Words**	**Frequency**
COST	1217	DECIS	86	COMPANI	40
INVENTORI	913	WEEK	85	DETERMINIST	40
TIME	565	BATCH	82	LOST	38
DEMAND	538	POLICI	81	PARAMET	36
PERIOD	472	FIX	79	SUPPLI	36
PRODUCT	455	STOCKOUT	78	ARRIV	35
UNIT	452	INCLUD	73	START	35
QUANTITI	369	MINIM	72	SALE	33
STOCK	328	DISTRIBUT	68	ACCOUNT	32
PRODUC	223	PROCESS	68	FINISH	32
OPTIM	197	DISCOUNT	64	CONSUMPT	31
ITEM	195	APPROXIM	63	LIMIT	30
TOTAL	191	HOUR	62	PROFIT	30
SETUP	189	POSIT	62	RATIO	30
SIZE	172	REDUC	62	CONSTRAINT	28
CONTROL	167	MATERI	61	HAND	28
REPLENISH	166	ESTIM	58	LENGTH	28
LEAD	162	FORECAST	57	MAXIMUM	28
HOLD	160	MANUFACTUR	57	CURRENT	27
RATE	155	CHANG	56	RESPECT	27
CARRI	152	SCHEDUL	56	ASSUMPT	25
EOQ	148	MINIMUM	55	CALL	25
PURCHAS	119	CURV	54	MEASUR	25
ASSUM	118	DELIVERI	54	DAI	24
SHORTAG	118	MACHIN	53	FACIL	24
PLAN	114	RANDOM	52	FEASIBL	24
PRICE	109	AVAIL	51	NATUR	24
REORDER	105	CONSTANT	50	SATISFI	24
CYCL	104	PROBABL	50	DYNAM	23
REQUIR	103	NORMAL	49	FREQUENC	23
SAFETI	103	CAPAC	46	LOW	22
Q*	102	BACKORD	45	PROVID	22
ANNUAL	98	DERIV	45	STORE	22
ECONOM	90	REVIEW	45	ENTIR	21
SERVIC	90	RECEIV	44	EQUAT	21
AVERAG	88	PERCENT	43	EXAMIN	21
CUSTOM	87	INTERV	41	EXTRA	21

APPENDIX C. PROBLEM DESCRIPTION

This appendix presents all four sample problem descriptions in each of the four conditions. Each of the target sentences included in the analyses is represented by an identifier, *Ti* where *i* is a position of information in sequence. Each of the distractor sentences included in the analyses is represented by an identifier as follow.

- *Ci* for common irrelevant information
- *Ri* for high DS
- *Ui* for low DS
- *Hi* for high CS
- *Li* for low CS

In addition, the relevant information is presented in italics. The words in gray shade represent a heading and the words in the first column are the sub-headings. The second column are the information content hidden behind the cells. Subjects can reveal this information by clicking the cell. Finally, the third columns represent information symbol and information type.

The goal state for this problem generally is to find the optimal order quantity for 2006 and is displayed at the top of problem description in condition 1.

PROBLEM 1

QUESTION: How many bicycles should MPBC order for 2006 when it orders units from Company A?.

Condition 1: High DS + High CS		
About		
Introduction	Martin-Pullin Bicycle Corp. (MPBC) is a wholesale distributor of bicycles and bicycle parts. The most popular model is the Air Wing.	C1 (Common)
Mission	The firm wants to maintain a 95% service level with its customers to minimize losses due to lost orders.	R2 (High DS)
Company address	99 N. Pearl St. Dallas, TX 75243.	C3 (Common)
Contact us	If you have a question regarding pricing or ordering, please send us an email at sale@MPBC.com	H4 (High CS)
Purchasing		
Safety stock	100	R5 (High DS)
The purchase price (per bicycle) for Company A	*$120*	*T6*
The purchase price (per bicycle) for Company B	$95	H7 (High CS)
Order method	Telephone, fax or email	C8 (Common)
Logistics		
Delivery method	Ground shipping	C9 (Common)
Delivery time	2 weeks	R10 (High DS)
Inventory cost for Company A	*1% per month*	*T11*
Inventory cost for Company B	2% per month	H12 (High CS)
Finance		
Cost of communication and paperwork (per order) for Company A	*$65*	*T13*
Cost of communication and paperwork (per order) for Company B	$80	H14 (High CS)
The cost of products manufactured	$120	R15 (High DS)
Salary/employee/yr	$60,000	C16 (Common)
Marketing		
The average selling product price (per bicycle)	$155	R17 (High DS)
Total number of current distributors	200	C18 (Common)
Total demand in 2005	343	H19 (High CS)
Forecast demand for 2006	*403*	*T20*

Condition 2: High DS + Low CS		
About		
Introduction	Martin-Pullin Bicycle Corp. (MPBC) is a wholesale distributor of bicycles and bicycle parts. The most popular model is the Air Wing.	C1 (Common)
Mission	The firm wants to maintain a 95% service level with its customers to minimize losses due to lost orders.	R2 (High DS)
Company address	99 N. Pearl St. Dallas, TX 75243.	C3 (Common)
Future plan	MPBC will offer the online catalog in the near future.	L4 (Low CS)
Purchasing		
Safety stock	100	R5 (High DS)
The purchase price (per bicycle) for Company A	*$120*	*T6*
Company A contact	22 West ST. New York, USA Phone: 212-999-8888	L7 (Low CS)
Order method	Telephone, fax or email	C8 (Common)
Logistics		
Delivery method	Ground shipping	C9 (Common)
Delivery time	2 weeks	R10 (High DS)
Inventory cost for Company A	*1% per month*	*T11*
Packaging types	Carton and Pallet	L12 (Low CS)
Finance		
Cost of communication and paperwork (per order) for Company A	*$65*	*T13*
Building rent (per month)	$7,000	L14 (Low CS)
The cost of products manufactured	$120	R15 (High DS)
Salary/employee/yr	$60,000	C16 (Common)
Marketing		
The average selling product price (per bicycle)	$155	R17 (High DS)
Total number of current distributors	200	C18 (Common)
Promotion for this year	10% off on $5,000 or more	L19 (Low CS)
Forecast demand for 2006	*403*	*T20*

Condition 3: Low DS + High CS		
About		
Introduction	Martin-Pullin Bicycle Corp. (MPBC) is a wholesale distributor of bicycles and bicycle parts. The most popular model is the Air Wing.	C1 (Common)
Mission	Our mission is to create innovative, quality products that inspire cyclists around the world.	U2 (Low DS)
Company address	99 N. Pearl St. Dallas, TX 75243.	C3 (Common)
Contact us	If you have a question regarding pricing or ordering, please send us an email at sale@MPBC.com	H4 (High CS)
Purchasing		
Value of purchasing and using the equipment for this year.	$6,000	U5 (Low DS)
The purchase price (per bicycle) for Company A	*$120*	*T6*
The purchase price (per bicycle) for Company B	$95	H7 (High CS)
Order method	Telephone, fax or email	C8 (Common)
Logistics		
Delivery method	Ground shipping	C9 (Common)
Average number of fork trucks	15	U10 (Low DS)
Inventory cost for Company A	*1% per month*	*T11*
Inventory cost for Company B	2% per month	H12 (High CS)
Finance		
Cost of communication and paperwork (per order) for Company A	*$65*	*T13*
Cost of communication and paperwork (per order) for Company B	$80	H14 (High CS)
MARR of company	9%	U15 (Low DS)
Salary/employee/yr	$60,000	C16 (Common)
Marketing		
Estimated new distributors	50	U17 (Low DS)
Total number of current distributors	200	C18 (Common)
Total demand in 2005	343	H19 (High CS)
Forecast demand for 2006	*403*	*T20*

Condition 4: Low DS + Low CS		
About		
Introduction	Martin-Pullin Bicycle Corp. (MPBC) is a wholesale distributor of bicycles and bicycle parts. The most popular model is the Air Wing.	C1 (Common)
Mission	Our mission is to create innovative, quality products that inspire cyclists around the world.	U2 (Low DS)
Company address	99 N. Pearl St. Dallas, TX 75243.	C3 (Common)
Future plan	MPBC will offer the online catalog in the near future.	L4 (Low CS)
Purchasing		
Value of purchasing and using the equipment for this year.	$6,000	U5 (Low DS)
The purchase price (per bicycle) for Company A	*$120*	*T6*
Company A contact	22 West ST. New York, USA Phone: 212-999-8888	L7 (Low CS)
Order method	Telephone, fax or email	C8 (Common)
Logistics		
Delivery method	Ground shipping	C9 (Common)
Average number of fork trucks	15	U10 (Low DS)
Inventory cost for Company A	*1% per month*	*T11*
Packaging types	Carton and Pallet	L12 (Low CS)
Finance		
Cost of communication and paperwork (per order) for Company A	*$65*	*T13*
Building rent (per month)	$7,000	L14 (Low CS)
MARR of company	9%	U15 (Low DS)
Salary/employee/yr	$60,000	C16 (Common)
Marketing		
Estimated new distributors	50	U17 (Low DS)
Total number of current distributors	200	C18 (Common)
Promotion for this year	10% off on $5,000 or more	L19 (Low CS)
Forecast demand for 2006	*403*	*T20*

PROBLEM 2

QUESTION: In what quantities should the Western Ranchman Outfitters order directly from Levi company in 2006?

Condition 1: High DS + High CS		
About		
Introduction	Western Ranchman Outfitters (WRO) is a retail supplier in Cheyenne, Wyoming. One of WRO's staple items is the blue jean made by Levi Strauss (model no. 501)	C1 (Common)
Mission	The firm wants to maintain a 90% service level with its customers to minimize losses due to lost orders.	R2 (High DS)
Company address	address is210 West Lincolnway Cheyenne, Wy 82001	C3 (Common)
Contact us	Do you have any questions a question regarding to product purchase price, ordering, please call us at (307) 775-7550	H4 (High CS)
Purchasing		
Safety stock	250	R5 (High DS)
The purchase price (per pair) for Levi	*$15.65*	*T6*
The purchase price (per pair) for Champ-Via Garment	$10.05	H7 (High CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ground shipping	C9 (Common)
Delivery time	3 weeks	R10 (High DS)
Inventory cost for Levi	*7% per month*	*T11*
Inventory cost for Champ-Via Garment	*8% per month*	H12 (High CS)
Finance		
Cost of communication and paperwork (per order) for Levi	*$100*	*T13*
Cost of communication and paperwork (per order) for Champ-Via Garment	$250	H14 (High CS)
The cost of products manufactured	$25.75	R15 (High DS)
Salary/employee/yr	$45,000	C16 (Common)
Marketing		
The average selling product price (per pair)	$37.45	R17 (High DS)
Total number of current distributors	75	C18 (Common)
Total demand in 2005	2045	H19 (High CS)
Forecast demand for 2006	*2100*	*T20*

Condition 2: High DS + Low CS		
About		
Introduction	Western Ranchman Outfitters (WRO) is a retail supplier in Cheyenne, Wyoming. One of WRO's staple items is the blue jean made by Levi Strauss (model no. 501)	C1 (Common)
Mission	The firm wants to maintain a 90% service level with its customers to minimize losses due to lost orders.	R2 (High DS)
Company address	address is210 West Lincolnway Cheyenne, Wy 82001	C3 (Common)
Future plan	To be worldwide apparel supplier.	L4 (Low CS)
Purchasing		
Safety stock	250	R5 (High DS)
The purchase price (per bicycle) for Levi	*$15.65*	*T6*
Levi contact	1155 Battery St. San Francisco, CA94111 phone is 1-800-872-5384	L7 (Low CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ground shipping	C9 (Common)
Delivery time	3 weeks	R10 (High DS)
Inventory cost for Levi	*7% per month*	*T11*
Packaging types	Carton	L12 (Low CS)
Finance		
Cost of communication and paperwork (per order) for Levi	*$100*	*T13*
Building rent (per month)	$5,000	L14 (Low CS)
The cost of products manufactured	$25.75	R15 (High DS)
Salary/employee/yr	$45,000	C16 (Common)
Marketing		
The average selling product price (per pair)	$37.45	R17 (High DS)
Total number of current distributors	75	C18 (Common)
Promotion for this year	12% off on $2,500 or more	L19 (Low CS)
Forecast demand for 2006	*2100*	*T20*

Condition 3: Low DS + High CS		
About		
Introduction	Western Ranchman Outfitters (WRO) is a retail supplier in Cheyenne, Wyoming. One of WRO's staple items is the blue jean made by Levi Strauss (model no. 501)	C1 (Common)
Mission	We will continue to provide the best possible product at reasonable prices	U2 (Low DS)
Company address	address is210 West Lincolnway Cheyenne, Wy 82001	C3 (Common)
Contact us	Do you have any questions a question regarding to product purchase price, ordering, please call us at (307) 775-7550	H4 (High CS)
Purchasing		
Value of purchasing and using the equipment for this year.	$4,500	U5 (Low DS)
The purchase price (per pair) for Levi	*$15.65*	*T6*
The purchase price (per pair) for Champ-Via Garment	$10.05	H7 (High CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ground shipping	C9 (Common)
Average number of fork trucks	5	U10 (Low DS)
Inventory cost for Levi	*7% per month*	*T11*
Inventory cost for Champ-Via Garment	*8% per month*	H12 (High CS)
Finance		
Cost of communication and paperwork (per order) for Levi	*$100*	*T13*
Cost of communication and paperwork (per order) for Champ-Via Garment	$250	H14 (High CS)
MARR of company	7.50%	U15 (Low DS)
Salary/employee/yr	$45,000	C16 (Common)
Marketing		
Estimated new distributors	23	U17 (Low DS)
Total number of current distributors	75	C18 (Common)
Total demand in 2005	2045	H19 (High CS)
Forecast demand for 2006	*2100*	*T20*

Condition 4: Low DS + Low CS		
About		
Introduction	Western Ranchman Outfitters (WRO) is a retail supplier in Cheyenne, Wyoming. One of WRO's staple items is the blue jean made by Levi Strauss (model no. 501)	C1 (Common)
Mission	We will continue to provide the best possible product at reasonable prices	U2 (Low DS)
Company address	address is210 West Lincolnway Cheyenne, Wy 82001	C3 (Common)
Future plan	To be worldwide apparel supplier.	L4 (Low CS)
Purchasing		
Value of purchasing and using the equipment for this year.	$4,500	U5 (Low DS)
The purchase price (per pair) for Levi	*$15.65*	*T6*
Levi contact	1155 Battery St. San Francisco, CA94111 phone is 1-800-872-5384	L7 (Low CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ground shipping	C9 (Common)
Average number of fork trucks	5	U10 (Low DS)
Inventory cost for Levi	*7% per month*	*T11*
Packaging types	Carton	L12 (Low CS)
Finance		
Cost of communication and paperwork (per order) for Levi	*$100*	*T13*
Building rent (per month)	$5,000	L14 (Low CS)
MARR of company	7.50%	U15 (Low DS)
Salary/employee/yr	$45,000	C16 (Common)
Marketing		
Estimated new distributors	23	U17 (Low DS)
Total number of current distributors	75	C18 (Common)
Promotion for this year	12% off on $2,500 or more	L19 (Low CS)
Forecast demand for 2006	*2100*	*T20*

PROBLEM 3

QUESTION: In order to produce DR-2000, drake needs to order FM tuners from outside supplier. How many FM tuners should Drake Radio order for 2006 when it orders FM tuner from Collins Electronics?

Condition 1: High DS + High CS		
About		
Introduction	Drake Radio is a manufacturer of radio stereo systems. The most remarkable stereo system that Drake manufactured is the DR-2000, a sophisticated stereo receiver.	C1 (Common)
Mission	The firm wants to maintain a 95% service level with its customers to minimize losses due to lost orders.	R2 (High DS)
Company address	230 Industrial Drive Franklin, Ohio 45005 U.S.A	C3 (Common)
Contact us	Do you have any questions a question regarding to product purchase price, ordering, please call us at 937-746-4556 or send us an email at info@drakeradio.com	H4 (High CS)
Purchasing		
Safety stock	400	R5 (High DS)
The purchase price for the FM turner (per unit) for Collines Electronics	*$22*	*T6*
The purchase price for the FM turner (per unit) Nitobitso Electronics	$21	H7 (High CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ground shipping	C9 (Common)
Delivery time	3 weeks	R10 (High DS)
Inventory cost for Collins Electronics	*25% per year*	*T11*
Inventory cost for Nitobitso Electronics	24% per year	H12 (High CS)
Finance		
Cost of communication and paperwork (per order) for Collins Electronics	$50	*T13*
Cost of communication and paperwork (per order) for Nitobitso Electronics	$75	H14 (High CS)
The cost of products manufactured	$575	R15 (High DS)
Salary/employee/yr	$48,000	C16 (Common)
Marketing		
The average selling product price (per unit)	$778	R17 (High DS)
Total number of current distributors	125	C18 (Common)
Total demand in 2005	2045	H19 (High CS)
Forecast demand for 2006	*2100*	*T20*

Condition 2: High DS + Low CS		
About		
Introduction	Drake Radio is a manufacturer of radio stereo systems. The most remarkable stereo system that Drake manufactured is the DR-2000, a sophisticated stereo receiver.	C1 (Common)
Mission	The firm wants to maintain a 95% service level with its customers to minimize losses due to lost orders.	R2 (High DS)
Company address	230 Industrial Drive Franklin, Ohio 45005 U.S.A	C3 (Common)
Future plan	Drake brand products will be utilized and available worldwide.	L4 (Low CS)
Purchasing		
Safety stock	400	R5 (High DS)
The purchase price for the FM turner (per unit) for Collines Electronics	*$22*	*T6*
Collins Electronics contract	3570 E Julie Ann Drive, Midland, MI 48642	L7 (Low CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ground shipping	C9 (Common)
Delivery time	3 weeks	R10 (High DS)
Inventory cost for Collins Electronics	*25% per year*	*T11*
Packaging types	Carton and pallet	L12 (Low CS)
Finance		
Cost of communication and paperwork (per order) for Collins Electronics	$50	*T13*
Building rent (per month)	$12,000	L14 (Low CS)
The cost of products manufactured	$575	R15 (High DS)
Salary/employee/yr	$48,000	C16 (Common)
Marketing		
The average selling product price (per unit)	$778	R17 (High DS)
Total number of current distributors	125	C18 (Common)
Promotion for this year	Promotion for this year is 5% off on $25,000 or more	L19 (Low CS)
Forecast demand for 2006	*2100*	*T20*

Condition 3: Low DS + High CS		
About		
Introduction	Drake Radio is a manufacturer of radio stereo systems. The most remarkable stereo system that Drake manufactured is the DR-2000, a sophisticated stereo receiver.	C1 (Common)
Mission	We want to become known as one of the best producers of radio system.	U2 (Low DS)
Company address	230 Industrial Drive Franklin, Ohio 45005 U.S.A	C3 (Common)
Contact us	Do you have any questions a question regarding to product purchase price, ordering, please call us at 937-746-4556 or send us an email at info@drakeradio.com	H4 (High CS)
Purchasing		
Value of purchasing and using the equipment for this year.	$45,000	U5 (Low DS)
The purchase price for the FM turner (per unit) for Collines Electronics	*$22*	*T6*
The purchase price for the FM turner (per unit) Nitobitso Electronics	$21	H7 (High CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ground shipping	C9 (Common)
Average number of fork trucks	12	U10 (Low DS)
Inventory cost for Collins Electronics	*25% per year*	*T11*
Inventory cost for Nitobitso Electronics	*24% per year*	H12 (High CS)
Finance		
Cost of communication and paperwork (per order) for Collins Electronics	$50	*T13*
Cost of communication and paperwork (per order) for Nitobitso Electronics	$75	H14 (High CS)
MARR of company	11.75%	U15 (Low DS)
Salary/employee/yr	$48,000	C16 (Common)
Marketing		
Estimated new distributors	33	U17 (Low DS)
Total number of current distributors	125	C18 (Common)
Total demand in 2005	2045	H19 (High CS)
Forecast demand for 2006	*2100*	*T20*

Condition 4: Low DS + Low CS		
About		
Introduction	Drake Radio is a manufacturer of radio stereo systems. The most remarkable stereo system that Drake manufactured is the DR-2000, a sophisticated stereo receiver.	C1 (Common)
Mission	We want to become known as one of the best producers of radio system.	U2 (Low DS)
Company address	230 Industrial Drive Franklin, Ohio 45005 U.S.A	C3 (Common)
Future plan	Drake brand products will be utilized and available worldwide.	L4 (Low CS)
Purchasing		
Value of purchasing and using the equipment for this year.	$45,000	U5 (Low DS)
The purchase price for the FM turner (per unit) for Collines Electronics	*$22*	*T6*
Collins Electronics contract	3570 E Julie Ann Drive, Midland, MI 48642	L7 (Low CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ground shipping	C9 (Common)
Average number of fork trucks	12	U10 (Low DS)
Inventory cost for Collins Electronics	*25% per year*	*T11*
Packaging types	Carton and pallet	L12 (Low CS)
Finance		
Cost of communication and paperwork (per order) for Collins Electronics	$50	*T13*
Building rent (per month)	$12,000	L14 (Low CS)
MARR of company	11.75%	U15 (Low DS)
Salary/employee/yr	$48,000	C16 (Common)
Marketing		
Estimated new distributors	33	U17 (Low DS)
Total number of current distributors	125	C18 (Common)
Promotion for this year	Promotion for this year is 5% off on $25,000 or more	L19 (Low CS)
Forecast demand for 2006	*2100*	*T20*

PROBLEM 4

QUESTION: In order to produce a basic video system, PVM need to order videotape from outside supplier. In what quantities should the PVM order the videotape when PVM orders from Toshiki in 2006?

Condition 1: High DS + High CS		
About		
Introduction	Professional Video Management (PVM) contributes unique video systems. The basic system includes a comprehensive control box, videotape system, a videodisk, and a television set.	C1 (Common)
Mission	PVM wants to maintain a 95% service level with its customers to minimize losses due to lost orders.	R2 (High DS)
Company address	One Research Drive Suite 200 B Westborough, MA 0158	C3 (Common)
Contact us	Do you have a question regarding to product purchase price, ordering, please send us an email at info@PVM.com	H4 (High CS)
Purchasing		
Safety stock	1,000	R5 (High DS)
The purchase price (per unit) for Toshiki	*$205*	*T6*
The purchase price (per unit) for Koni	$220	H7 (High CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ship and ground shipping	C9 (Common)
Delivery time	1.5 months	R10 (High DS)
Inventory cost for Toshiki	*2.5% per month*	*T11*
Inventory cost for Koni	*2.5% per month*	H12 (High CS)
Finance		
Cost of communication and paperwork (per order) for Toshiki	*$90*	*T13*
Cost of communication and paperwork (per order) for Koni	$40	H14 (High CS)
The cost of products manufactured	$1,788	R15 (High DS)
Salary/employee/yr	$47,500	C16 (Common)
Marketing		
The average selling product price (per unit)	$2,025	R17 (High DS)
Total number of current distributors	210	C18 (Common)
Total demand in 2005	92,300	H19 (High CS)
Forecast demand for 2006	*96,200*	*T20*

Condition 2: High DS + Low CS		
About		
Introduction	Professional Video Management (PVM) contributes unique video systems. The basic system includes a comprehensive control box, videotape system, a videodisk, and a television set.	C1 (Common)
Mission	PVM wants to maintain a 95% service level with its customers to minimize losses due to lost orders.	R2 (High DS)
Company address	One Research Drive Suite 200 B Westborough, MA 0158	C3 (Common)
Future plan	To develop a smart control box with the ability to coordinate the use and function of the any other devices attached to it.	L4 (Low CS)
Purchasing		
Safety stock	1,000	R5 (High DS)
The purchase price (per unit) for Toshiki	*$205*	*T6*
Toshiki contact	63 Minami-Azabu, NTT-AZABU-Seminar House Minato-ku Tokyo Japan 106-0047	L7 (Low CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ship and ground shipping	C9 (Common)
Delivery time	1.5 months	R10 (High DS)
Inventory cost for Toshiki	*2.5% per month*	*T11*
Packaging types	Carton and Pallet	L12 (Low CS)
Finance		
Cost of communication and paperwork (per order) for Toshiki	*$90*	*T13*
Building rent (per month)	$14,000	L14 (Low CS)
The cost of products manufactured	$1,788	R15 (High DS)
Salary/employee/yr	$47,500	C16 (Common)
Marketing		
The average selling product price (per unit)	$2,025	R17 (High DS)
Total number of current distributors	210	C18 (Common)
Promotion for this year	10% off on 1,000 units or more	L19 (Low CS)
Forecast demand for 2006	*96,200*	*T20*

Condition 3: Low DS + High CS		
About		
Introduction	Professional Video Management (PVM) contributes unique video systems. The basic system includes a comprehensive control box, videotape system, a videodisk, and a television set.	C1 (Common)
Mission	PVM wants to maintain a 95% service level with its customers to minimize losses due to lost orders.	U2 (Low DS)
Company address	One Research Drive Suite 200 B Westborough, MA 0158	C3 (Common)
Contact us	Do you have a question regarding to product purchase price, ordering, please send us an email at info@PVM.com	H4 (High CS)
Purchasing		
Value of purchasing and using the equipment for this year.	$72,000	U5 (Low DS)
The purchase price (per unit) for Toshiki	*$205*	*T6*
The purchase price (per unit) for Koni	$220	H7 (High CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ship and ground shipping	C9 (Common)
Average number of fork trucks	30	U10 (Low DS)
Inventory cost for Toshiki	*2.5% per month*	*T11*
Inventory cost for Koni	*2.5% per month*	H12 (High CS)
Finance		
Cost of communication and paperwork (per order) for Toshiki	*$90*	*T13*
Cost of communication and paperwork (per order) for Koni	$40	H14 (High CS)
MARR of company	11.8%	U15 (Low DS)
Salary/employee/yr	$47,500	C16 (Common)
Marketing		
Estimated new distributors	33	U17 (Low DS)
Total number of current distributors	210	C18 (Common)
Total demand in 2005	92,300	H19 (High CS)
Forecast demand for 2006	*96,200*	*T20*

Condition 4: Low DS + Low CS		
About		
Introduction	Professional Video Management (PVM) contributes unique video systems. The basic system includes a comprehensive control box, videotape system, a videodisk, and a television set.	C1 (Common)
Mission	PVM wants to maintain a 95% service level with its customers to minimize losses due to lost orders.	U2 (Low DS)
Company address	One Research Drive Suite 200 B Westborough, MA 0158	C3 (Common)
Future plan	To develop a smart control box with the ability to coordinate the use and function of the any other devices attached to it.	L4 (Low CS)
Purchasing		
Value of purchasing and using the equipment for this year.	$72,000	U5 (Low DS)
The purchase price (per unit) for Toshiki	*$205*	*T6*
Toshiki contact	63 Minami-Azabu, NTT-AZABU-Semina rHouse Minato-ku Tokyo Japan 106-0047	L7 (Low CS)
Order method	telephone, fax or email	C8 (Common)
Logistics		
Delivery method	ship and ground shipping	C9 (Common)
Average number of fork trucks	30	U10 (Low DS)
Inventory cost for Toshiki	*2.5% per month*	*T11*
Packaging types	Carton and Pallet	L12 (Low CS)
Finance		
Cost of communication and paperwork (per order) for Toshiki	*$90*	*T13*
Building rent (per month)	$14,000	L14 (Low CS)
MARR of company	11.8%	U15 (Low DS)
Salary/employee/yr	$47,500	C16 (Common)
Marketing		
Estimated new distributors	33	U17 (Low DS)
Total number of current distributors	210	C18 (Common)
Promotion for this year	10% off on 1,000 units or more	L19 (Low CS)
Forecast demand for 2006	*96,200*	*T20*

APPENDIX D. SAMPLE SIZE ANALYSIS

The power of a statistical test is the probability that it will yield significant results (Cohen, 1988). Power describes the ability to find a difference when a real difference exists. The power of a study is determined by three factors, namely, sample size, alpha level, and effect size. Power analysis can precede or follow data collection. Before conducting an empirical study, an estimate of sample size is made based on achieving some power level. Low power would indicate a need for a large number of samples.

SIGNIFICANCE CRITERION OR ALPHA LEVEL (α)

A "significance at the Alpha (α) level" is the probability of a Type I error (i.e., probability of rejecting the null hypothesis given that that the null hypothesis is true). A common value for α is 0.05 (e.g., a 95% confidence interval).

SAMPLE SIZE (n)

The accuracy of parameter estimates is proportional to the sample size, n. This suggests that increasing the sample size will increase statistical power.

POWER LEVEL

Power is the probability of not making a Type II error and can be expressed as 1 - β, where β is the probability of a Type II error. As $1-\beta \to 1$, detecting an effect is more likely. A power value of 0.8 is commonly used.

EFFECT SIZE INDEX (d)

Effect size index (ES or d) is the degree of departure of the alternative hypothesis from the null hypothesis (Cohen, 1988). For two different populations under the same condition (t test on the difference between two means), the index is given by,

$$d = \frac{|m_A - m_B|}{\delta} \quad \textbf{(D 1)}$$

where,

d is the index for a t test of the difference between two means,

m_A, m_B are estimates of population means, and

δ is an estimate of the standard deviation for the population.

For one population tested under two conditions (where the same subject appears in both conditions), we have a set of correlated observations (X_i, Y_i). A paired t test is often used for hypothesis testing. The index for this case is

$$d = \frac{\sqrt{2}\, m_z}{\delta_z} \quad \textbf{(D 2)}$$

where,

d is the index for a paired t test of means in standard unit,

m_z is an estimate of the mean difference between the paired observations, and

δ_z is an estimate of the standard deviation of the paired difference.

Sample Size Estimation for the Proposed Experiment

Given values for α, n and d, power can be obtained for many statistical tests by using statistical tables. Using the data from our previous experiment, we can estimate the sample size for independent populations (Experienced, Novice). For dependent samples (i.e., within subjects samples) used in the high/low DS condition and the high/low CS condition, the sample size is estimated based on previous dependent samples (High vs. Low density and Skewed vs. Uniform distribution).

Between Subject - Independent observations

The results from the previous experiment (Tables D.1 and D.2) indicate that the standard deviation for each dependent variable is different for the two groups. Cohen (1977, p. 44; 1968, p.42) suggests using an average of the two standard deviations:

$$\delta = \sqrt{\frac{\delta_A^2 + \delta_B^2}{2}} \qquad \textbf{(D 3)}$$

Table D. 1: Results for the novice group

Dependent Variable	Mean	Std.
	m_A	δ_A
A'	0.72473	0.23872
B''d	0.35414	0.67030
Accuracy	0.36840	0.35443

Table D. 2: Results for experienced subject group

Dependent Variable	Mean	Std.
	m_B	δ_B
A'	0.83402	0.14764
B"d	-0.14102	0.70829
Accuracy	0.54061	0.27851

We can calculate effect size index (d) by using equation D.1 and D.3. Using a power table (Cohen (1968, p.34-35)) with power level =0.8, α =0.05 and two tails test, we find n as shown in Table D.3.

Table D. 3: Results for two populations

	A'	B"	Accuracy
δ'	0.19848	0.68956	0.31874
d	0.55070	0.71800	0.54029
n	53	32	55

With-in Subject – Dependent observations

Based on our experiment, data will be gathered in (X_i , Y_i) pairs for example, A' for high and low DS condition. Therefore, we will be evaluating the equivalent of n paired differences. When conducting a power analysis for the correlated samples design, a paired t test has been used (Cohen 1988, p.45-52).

Using (A 2), we have to set the mean difference (m_z) to the smallest detectable difference. Using the variance sum law, we can estimate for the standard deviation of the paired difference (δ_z) as

$$\delta_z = \delta_{X-Y} = \sqrt{\delta_X^2 + \delta_Y^2 - 2r_{XY}\delta_X\delta_Y} \quad \textbf{(D 4)}$$

where, r is the estimate of correlation between X and Y values.

Although, the conditions in this experiment are different than the previous experiment, we expect to observe similar characteristics in the data. Using the previous results, we can obtain estimates of correlation and the standard deviations for the dependent variables. Setting m_z to 0.1 for A' and Accuracy represents the smallest detectable difference.

Table D. 4: Results for correlated samples

Independent Variable		*A'*	*B"d*	Accuracy
Density	Pearson Correlation	0.2150	0.4313	0.0456
	δ_X for high density	0.1506	0.5423	0.2413
	δ_Y for low density	0.1534	0.5939	0.2419
	δ_z	0.1905	0.6075	0.3338
	Mean difference (m_z)	0.1	0.2	0.1
	d	0.7426	0.4656	0.4236
	n	28.47	72.41	87.48
Distribution	Pearson Correlation	0.3087	0.4300	0.2438
	δ_X for skewed distribution	0.1345	0.6111	0.2145
	δ_Y for uniform distribution	0.1578	0.5249	0.2285
	δ_z	0.1729	0.6018	0.276
	Mean difference (m_z)	0.1	0.2	0.1
	d	0.8180	0.4631	0.5188
	n	23.46	73.20	58.33
	Average *n*	29.30	72.78	72.16

Conclusion

Given that *A'* is the primary dependent variable of interest and the sample size estimates in Tables D.3 and D.4 are in the range of 23 to 53, a sample size of 48 for each group appears to be a reasonable number.

APPENDIX E. THE COMPLETE MARKOV MODEL ANALYSIS RESULTS

This study used a Markov model to personalize subject selecting (*information reduction*) and acquiring (*information acquisition*) information behavior.

INFORMATION REDUCTION

Table E. 1 and Table E. 2 show Markov model result (a highest support) for each expertise level. Based on the first order Markov model, we could see the different behavior in selecting information between novice and experienced subjects. Regarding to confidence value, experienced subjects selected successively relevant information (**quote in bold**). For example, in condition 3, 46.67% of experienced subjects who select “Purchase price from A (T06)” will select “Inventory cost from A (T11)”. On the other hand, novice selecting information behavior trend is based on the structure of information content such as, in condition 3, 39.47% of novice who select “Purchase price from A (T06)” will select “Purchase price from B (H07)”.

In order to achieve high precision in observing subjects’ selecting information behavior, higher-order models can be applied. The 2nd and 3rd order results support that experienced subjects’ selecting information pattern contains more relevant information elements and trend to select relevant information in sequence than novices’ pattern. For instance, in condition 3, 3rd order Markov model shows that 55.56% of experienced subjects who select “Purchase price from A (T06)” followed by “Inventory cost from A (T11)“ and “Order coast from A (T13)“ sequentially would select “Demand in 2006 (T20)”. On the contrary, 60% of novices who select "Value of using equipment(U05)" followed by "Purchase price from A(T06) " and "Purchase price from B(H07) " sequentially would select "Inventory cost from A (T11)"

Table E. 1: The example of 1st ,2nd and 3rd order Markov model result in information reduction behavior for novice group.

First order Markov in selected information (Novice)					
Condition	**Path**	**Support**	**Next information selected**	**Number**	**Confidence**
1	**Purchase price from A(T06)**	0.73	Purchase price from B(H07)	**12**	**33.33%**
			Order method(C08)	6	16.67%
			Inventory cost from A(T11)	5	13.89%
2	**Purchase price from A(T06)**	0.875	Delivery time(R10)	**9**	**19.57%**
			Supplier A address(L07)	7	15.22%
			Inventory cost from A(T11)	6	13.04%
3	**Purchase price from A(T06)**	0.75	Purchase price from B(H07)	**15**	**39.47%**
			Inventory cost from A(T11)	10	26.32%
			Order method(C08)	4	10.53%
4	**Purchase price from A(T06)**	0.67	**Inventory cost from A(T11)**	**8**	**21.62%**
			Value of using equipment(U05)	7	18.92%
			Supplier A address(L07)	5	13.51%

Second order Markov in selected information (Novice)					
Condition	**Path**	**Support**	**Next information selected**	**Number**	**Confidence**
1	Safety stock(R05) -> **Purchase price from A(T06)**	0.29	Purchase price from B(H07)	8	57.14%
			Order method(C08)	3	21.43%
2	Delivery time(R10) -> **Inventory cost from A(T11)**	0.33	Packaging types(L12)	6	37.50%
			Order cost from A(Cid02T13)	6	37.50%
3	Value of using equipment(U05) -> **Purchase price from A(T06)**	0.31	Purchase price from B(H07)	10	66.67%
			Order method(C08)	3	20.00%
			Inventory cost from A(T11)	2	13.33%
4	**Inventory cost from A(T11) -> Order cost from A(T13)**	0.25	Building rents(L14)	7	58.33%
			Estimated new distributors(U17)	2	16.67%

Third order Markov in selected information (Novice)					
Condition	**Path**	**Support**	**Next information selected**	**Number**	**Confidence**
1	Average selling product price(R17)-> Number of distributors(C18) -> Demand in 2005(H19)	0.17	**Demand in 2006(T20)**	8	100%
2	**Purchase price from A(T06) ->** Delivery time(R10) -> Inventory cost from A(T11)	0.15	Packaging types(L12)	3	42.86%
			Order cost from A(Cid02T13)	2	28.57%
			Safety stock(R05)	1	14.29%
3	Value of using equipment(U05) -> **Purchase price from A(T06) ->** Purchase price from B(H07)	0.21	**Inventory cost from A(T11)**	6	60%
			Delivery method(C09)	3	30%
			Average number of fork	1	10%
4	**Inventory cost from A(T11) -> Order cost from A(T13) ->** Building rents(L14)	0.15	MARR of company(U15)	2	28.57%
			Demand in 2006(T20)	2	28.57%
			Salary/employee/yr(C16)	1	14.29%

Table E. 2: The example of 1st ,2nd and 3rd order Markov model result in information reduction behavior for experienced subject group.

First order Markov in selected information (Experienced subject)					
Condition	Path	Support	Next information selected	Number	Confidence
1	**Inventory cost from A(T11)**	0.94	**Order cost from A(T13)**	26	57.78%
			Inventory cost from B(H12)	9	20.00%
			Demand in 2006(T20)	4	8.89%
2	**Purchase price from A(T06)**	0.92	Delivery time(R10)	25	56.82%
			Safety stock(R05)	9	20.45%
			Inventory cost from A(T11)	4	9.09%
3	**Purchase price from A(T06)**	0.92	**Inventory cost from A(T11)**	21	46.67%
			Purchase price from B(H07)	16	35.56%
4	**Inventory cost from A(T11)**	0.88	**Order cost from A(T13)**	34	75.56%
			Demand in 2006(T20)	3	6.67%

Second order Markov in selected information (Experienced subject)					
Condition	Path	Support	Next information selected	Number	Confidence
1	Delivery time(R10) -> **Inventory cost from A(T11)**	0.65	**Order cost from A(T13)**	20	64.52%
			Inventory cost from B(H12)	7	22.58%
2	Delivery time(R10) -> **Inventory cost from A(T11)**	0.71	**Order cost from A(Cid02T13)**	31	91.18%
			Packaging types(L12)	1	2.94%
3	**Inventory cost from A(T11) -> Order cost from A(T13)**	0.54	**Demand in 2006(T20)**	12	46.15%
			MARR of company(U15)	5	19.23%
			Demand in 2005(H19)	3	11.54%
4	**Inventory cost from A(T11) -> Order cost from A(T13)**	0.71	**Demand in 2006(T20)**	14	41.18%
			Building rents(L14)	12	35.29%
			MARR of company(U15)	6	17.65%

Third order Markov in selected information (Experienced subject)					
Condition	Path	Support	Next information selected	Number	Confidence
1	Delivery time(R10) -> **Inventory cost from A(T11) -> Order cost from A(T13)**	0.42	Cost of products	8	40%
			Average selling product	4	20%
			Demand in 2006(T20)	4	20%
			Demand in 2005(H19)	3	15%
2	Delivery time(R10) -> **Inventory cost from A(T11) -> Order cost from A(Cid02T13)**	0.60	Cost of products	12	41.38%
			Demand in 2006(T20)	8	27.59%
			Building rents(L14)	6	20.69%
3	**Purchase price from A(T06) -> Inventory cost from A(T11) -> Order cost from A(T13)**	0.38	**Demand in 2006(T20)**	10	55.56%
			MARR of company(U15)	2	11.11%
			Demand in 2005(H19)	2	11.11%
4	**Purchase price from A(T06) -> Inventory cost from A(T11) -> Order cost from A(T13)**	0.50	**Demand in 2006(T20)**	12	50%
			Building rents(L14)	7	29.17%
			MARR of company(U15)	5	20.83%

INFORMATION ACQUISITION

Similar to information reduction, the 1st, 2nd and 3rd order Markov model were applied to analyze information acquisition behavior in each expertise level (Table E. 3 and E. 4).

Table E. 3: The example of 1st ,2nd and 3rd order Markov model result in information acquisition behavior for novice group.

First order Markov in visited information (Novice)					
Condition	Path	Support	Next information visited	Number	Confidence
1	**Purchase price from A(T06)**	1.02	Purchase price from B(H07)	**23**	**46.00%**
			Order method(C08)	13	26.00%
2	**Purchase price from A(T06)**	1.06	Supplier A address(L07)	**33**	**62.26%**
			Safety stock(R05)	4	7.55%
3	**Purchase price from A(T06)**	1.04	Purchase price from B(H07)	**24**	**47.06%**
			Order method(C08)	13	25.49%
4	Value of using equipment(U05)	1.13	**Purchase price from A(T06)**	**34**	**61.82%**
			Delivery method(C09)	4	7.27%

Second order Markov in visited information (Novice)					
Condition	Path	Support	Next information visited	Number	Confidence
1	Safety stock(R05) -> **Purchase price from A(T06)**	0.52	Purchase price from B(H07)	13	52.00%
			Order method(C08)	8	32.00%
2	**Purchase price from A(T06) ->** Supplier A address(L07)	0.69	Order method(C08)	31	93.94%
			Delivery time(R10)	1	3.03%
3	Value of using equipment(U05) -> **Purchase price from A(T06)**	0.65	Purchase price from B(H07)	18	58.06%
			Order method(C08)	8	25.81%
4	Value of using equipment(U05) -> **Purchase price from A(T06)**	0.71	Supplier A address(L07)	26	76.47%
			Order method(C08)	5	14.71%

Third order Markov in visited information (Novice)					
Condition	Path	Support	Next information visited	Number	Confidence
1	Delivery method(C09) -> Delivery time(R10) -> **Inventory cost from A(T11)**	0.40	Inventory cost from B(H12)	11	57.89%
			Order cost from A(T13)	5	26.32%
2	**Purchase price from A(T06) ->** Supplier A address(L07) -> Order method(C08)	0.63	Delivery method(C09)	11	36.67%
			Delivery time(R10)	7	23.33%
3	Value of using equipment(U05) -> **Purchase price from A(T06) ->** Purchase price from B(H07)	0.38	Order method(C08)	9	50%
			Purchase price from A(T06)	4	22.22%
4	Value of using equipment(U05) -> **Purchase price from A(T06) ->** Supplier A address(L07)	0.54	Order method(C08)	19	73.08%
			Delivery method(C09)	4	15.38%

Table E. 4: The example of 1st ,2nd and 3rd order Markov model result in information acquisition behavior for experienced subject group.

First order Markov in visited information (Experienced subject)					
Condition	Path	Support	Next information visited	Number	Confidence
1	**Inventory cost from A(T11)**	1.13	**Order cost from A(T13)**	**26**	**48.15%**
			Inventory cost from B(H12)	14	25.93%
2	**Purchase price from A(T06)**	1.04	Supplier A address(L07)	**33**	**66.00%**
			Safety stock(R05)	8	16.00%
3	**Purchase price from A(T06)**	1.10	Purchase price from B(H07)	**20**	**37.74%**
			Order method(C08)	15	28.30%
			Inventory cost from A(T11)	8	15.09%
4	**Purchase price from A(T06)**	1.08	Supplier A address(L07)	**34**	**64.15%**
			Delivery method(C09)	5	9.43%
			Inventory cost from A(T11)	5	9.43%

Second order Markov in visited information (Experienced subject)					
Condition	Path	Support	Next information visited	Number	Confidence
1	Delivery time(R10) -> **Inventory cost from A(T11)**	0.81	**Order cost from A(T13)**	22	56.41%
			Inventory cost from B(H12)	10	25.64%
2	Delivery time(R10) -> **Inventory cost from A(T11)**	0.81	Packaging types(L12)	31	79.49%
			Order cost from A(Cid02T13)	7	17.95%
4	Supplier A address(L07) -> Order method(C08)	0.75	Delivery method(C09)	19	52.78%
			Value of using equipment(U05)	5	13.89%
			Purchase price from A(T06)	4	11.11%
3	Value of using equipment(U05) -> **Purchase price from A(T06)**	0.65	Purchase price from B(H07)	15	48.39%
			Order method(C08)	13	41.94%
			Delivery method(C09)	2	6.45%

Third order Markov in visited information (Experienced subject)					
Condition	Path	Support	Next information visited	Number	Confidence
1	Delivery method(C09) -> Delivery time(R10) -> **Inventory cost from A(T11)**	0.60	**Order cost from A(T13)**	15	51.72%
			Inventory cost from B(H12)	9	31.03%
2	Delivery time(R10) -> **Inventory cost from A(T11) ->** Packaging types(L12)	0.65	**Order cost from A(Cid02T13)**	28	90.32%
			Salary/employee/yr(C16)	1	3.23%
3	Delivery method(C09) -> Average number of fork trucks(U10) -> **Inventory cost from A(T11)**	0.52	Inventory cost from B(H12)	14	56%
			Order cost from A(T13)	10	40%
4	**Purchase price from A(T06) ->** Supplier A address(L07) -> Order method(C08)	0.65	Delivery method(C09)	18	58.06%
			Value of using equipment(U05)	5	16.13%
			Inventory cost from A(T11)	3	9.68%

Opposite to information reduction behavior, novice and experienced subjects have relatively similar behavior in acquitting information. Subjects' information acquisition behavior trend is based on the structure of information content. For example, in condition 2, 3rd order Markov model shows that 51.72% of experienced subjects who visit "Delivery time(R10)" followed by "Inventory cost from A (T11)" and "Packaging types(L12) " sequentially would select "Order cost from A(T13)". In the similar way, 50% of novices who select "Value of using equipment(U05)" followed by "Purchase price from A(T06) " and "Purchase price from B(H07) " sequentially would select "Order method (C08)"

APPENDIX F. ADDITIONAL CLUSTERING ANALYSIS RESULTS

CLUSTER QUALITY MEASURE

Information Reduction

Average and variance of compactness (Equation 3.3) along with the separation (Equation 3.4) were used to identify number of clusters. Table F. 1 and Table F. 2 demonstrate the cluster quality measure for simple clustering analysis and Markov clustering analysis respectively.

Table F. 1: Cluster quality measures for simple clustering analysis on information reduction behavior

Number of clusters (n)	Cluster Quality Measure		
	Average of compactness	Variance of compactness	Average of Separation
2	1.527	0.113	1.398
3	1.442	0.120	1.740
4	**1.352**	**0.119**	**1.710**
5	1.334	0.124	1.648

Table F. 2: Cluster quality measures for Markov clustering analysis on information reduction behavior

Number of clusters (n)	Cluster Quality			Number of users in meaningful clusters	
	Average of compactness	Variance of compactness	Average of Separation	Total	Average/Cluster
3	1.091	0.177	2.110	28	14.000
4	0.921	0.151	2.121	31	10.333
5	0.968	0.111	1.980	36	9.000
6	0.791	0.137	1.932	41	8.200
7	**0.799**	**0.111**	**1.914**	**51**	**8.500**
8	0.806	0.107	1.892	53	7.571
9	0.769	0.092	2.021	53	6.625

Regarding to a simple clustering analysis, the quality of the clustering obtained by k-Means (*n*=4) is more satisfactory (small average and variance of compactness). Therefore, we kept number of clusters as 4 across all four conditions for simple clustering analysis.

For Markov clustering analysis, there is one cluster always represents a group of subject whose selecting patterns are in not match with the common patterns obtained from the 3rd order Markov model. In this cluster, subjects appear to randomly select information thus we couldn't find any meaning pattern in selecting information behavior. In order to identify number of clusters, number of users in other clusters (meaningful clusters) also needs to be considered. Result in Table F. 2 shows that the quality of the clustering obtained by k-Means (*n*=7) is more reasonable hence, number of cluster for the Markov clustering analysis was 7.

K-Means with n=7 has the best clustering quality measure show shown in Table F. 2. However, due to s small data set, we might need to consider reducing number of clusters. We applied K-Means with specifying three as number of cluster. When we comparing K-Means with n=3 (Table F. 3) with K-Means with n=7 (Table F. 4), it could be noted that the K-Means with n=3 is a subset of K-Means with n=7. The cluster 1 of K-Means (n=3) is the combination of cluster 2 and 4 in K-Means (n=7). The cluster 2 of K-Means (n=3) is a subset of cluster 3 of K-Means (n=7) and the cluster 3 of K-Means (n=3) is cluster 7 of K-Means (n=7). In addition, cluster 1, 5 and 6 of K-Means (n=7) are not considered as a cluster in K-Means (n=3). To have depth understanding in user behavior and with cluster quality measure result (Table F. 2), K-Means with 7 as number of clusters is an appropriate approach as it provides higher cluster quality and more details in user pattern.

Table F. 3: The Markov clustering result from K-Means (n=3) for High DS + High CS condition

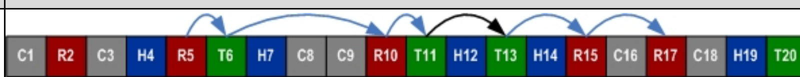
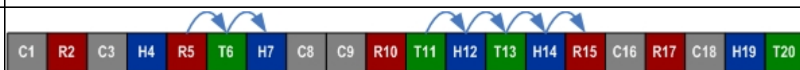
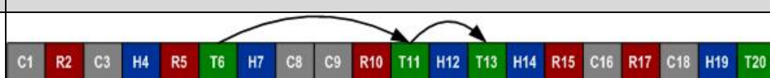
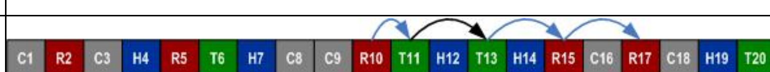
No	Characteristic in information selection	A’	B”d	# of expert	# of novice
1		0.92	-0.87	18	5
2		0.88	-0.94	9	6
3		0.81	0.09	21	37

Table F. 4: The Markov clustering result from K-Means (n=7) for High DS + High CS condition

No	Characteristic in information selection	A’	B”d	H	F	# of expert	# of novice
1		0.97	-0.3	0.96	0.08	6	0
2		0.94	-0.9	0.98	0.21	10	0
3		0.87	-0.9	0.97	0.45	8	0
4		0.91	-0.8	0.94	0.26	7	5
5		0.80	-0.2	0.75	0.29	0	5
6		0.83	-0.9	0.95	0.47	1	9
7	Match in some patterns but none of patterns containing 50% number of subjects	0.80	0.21	0.64	0.17	16	29

Information Acquisition

Similar to clustering analysis in information reduction, average and variance of compactness along with the separation were used to identify number of clusters. The cluster quality measure for simple clustering analysis is shown in Table F. 5.

Table F. 5: Cluster quality measures for simple clustering analysis on information reduction behavior

Number of clusters (n)	Cluster Quality Measure		
	Average of compactness	Variance of compactness	Average of Separation
2	1.501	0.085	1.861
3	1.368	0.077	1.770
4	1.344	0.089	2.020
5	1.038	0.124	2.110

Regarding to a simple clustering analysis, (n=5) is gives the best quality of the clustering. However, with a small data set (24 instances), the more number of clusters the more possibility that we obtains meaningless cluster. Table F. 6 shows there is one member in the last cluster when $n=5$. With our clustering objective to discover a group of subjects sharing common behavior, therefore, we used four as number of cluster for simple clustering analysis.

Table F. 6: Number of subjects in each cluster.

Cluster No	Number of subjects in each cluster			
	N=2	N=3	N=4	N=5
1	13	10	9	9
2	11	3	3	2
3	-	11	3	9
4	-	-	9	3
5	-	-	-	1

THE EXAMPLE OF THE 3RD ORDER MARKOV MODEL RESULT USED IN MARKOV CLUSTERING ANALYSIS (INFORMATION REDUCTION)

Table F. 7: The example of 3rd order Markov model result in condition 1

Experienced subject

Selecting information Pattern	Support
Delivery time(R10) -> Inventory cost from A(T11) -> Order cost from A(T13)	0.42
Purchase price from A(T06) -> Delivery time(R10) -> Inventory cost from A(T11)	0.31
Safety stock(R05) -> Purchase price from A(T06) -> Delivery time(R10)	0.25
Service level(R02) -> Safety stock(R05) -> Purchase price from A(T06)	0.23
Inventory cost from A(T11) -> Order cost from A(T13) -> Cost of products	0.21

Novice

Selecting information Pattern	Support
Average selling product price(R17) -> Number of distributors(C18) -> Demand in 2005(H19)	0.17
Safety stock(R05) -> Purchase price from A(T06) -> Purchase price from B(H07)	0.17
Order cost from A(T13) -> Cost of products manufactured(R15) -> Average selling product price(R17)	0.15
Cost of products manufactured(R15) ->Average selling product price(R17) -> Number of distributors(C18)	0.13
Inventory cost from A(T11) -> Inventory cost from B(H12) -> Order cost from A(T13)	0.13

Table F. 8: The example of 3rd order Markov model result in condition 2

Experienced subject

Selecting information Pattern	Support
Delivery time(R10) -> Inventory cost from A(T11) -> Order cost from A(T13)	0.60
Purchase price from A(T06) -> Delivery time(R10) -> Inventory cost from A(T11)	0.46
Safety stock(R05) -> Purchase price from A(T06) -> Delivery time(R10)	0.42
Inventory cost from A(T11) -> Order cost from A(Cid02T13) -> Cost of products manufactured(R15)	0.29
Service level(R02) -> Safety stock(R05) -> Purchase price from A(T06)	0.23

Novice

Selecting information Pattern	Support
Order cost from A(T13) -> Building rents(H14) -> Cost of products manufactured(R15)	0.15
Purchase price from A(T06) -> Delivery time(R10) -> Inventory cost from A(T11)	0.15
Average selling product price(R17) -> Number of distributors(C18) -> Promotion for this year(H19)	0.13
Delivery time(R10) -> Inventory cost from A(T11) -> Order cost from A(T13)	0.13
Delivery time(R10) -> Inventory cost from A(T11) -> Packaging types(H12)	0.13

Table F. 9: The example of 3rd order Markov model result in condition 3

Experienced subject

Selecting information Pattern	Support
Purchase price from A(T06) -> Inventory cost from A(T11) -> Order cost from A(T13)	0.38
Inventory cost from A(T11) -> Inventory cost from B(H12) -> Order cost from A(T13)	0.27
Purchase price from A(T06) -> Purchase price from B(H07) -> Inventory cost from A(T11)	0.25
Purchase price from B(H07) -> Inventory cost from A(T11) -> Inventory cost from B(H12)	0.25
Inventory cost from B(H12) -> Order cost from A(T13) -> Order cost from B(H14)	0.21

Novice

Selecting information Pattern	Support
Value of using equipment(U05) -> Purchase price from A(T06) -> Purchase price from	0.21
Purchase price from A(T06) -> Purchase price from B(H07) -> Inventory cost from A(T11)	0.19
Inventory cost from A(T11) -> Inventory cost from B(H12) -> Order cost from A(T13)	0.17
Purchase price from B(H07) -> Inventory cost from A(T11) -> Inventory cost from B(H12)	0.17
Inventory cost from B(H12) -> Order cost from A(T13) -> Order cost from B(H14)	0.15

Table F. 10: The example of 3rd order Markov model result in condition 4

Experienced subject

Selecting information Pattern	Support
Purchase price from A(T06) -> Inventory cost from A(T11) -> Order cost from A(T13)	0.50
Value of using equipment(U05) -> Purchase price from A(T06) -> Inventory cost from	0.25
Inventory cost from A(T11) -> Order cost from A(T13) -> Building rents(L14)	0.23
Inventory cost from A(T11) -> Order cost from A(T13) -> MARR of company(U15)	0.13
Purchase price from A(T06) -> Value of using equipment(U05) -> Inventory cost from	0.08

Novice

Selecting information Pattern	Support
Inventory cost from A(T11) -> Order cost from A(T13) -> Building rents(L14)	0.15
Value of using equipment(U05) -> Purchase price from A(T06) -> Inventory cost from	0.08
Purchase price from A(T06) -> Inventory cost from A(T11) -> Order cost from A(T13)	0.06
Order cost from A(T13) -> Building rents(L14) -> MARR of company(U15)	0.06
Estimated new distributors(U17) -> Number of distributors(C18) -> Promotion for this	0.06

SAMPLE MARKOV CLUSTERING ANALYSIS RESULT ON INFORMATION ACQUISITION

Table F.11: The Markov clustering result for information acquisition in condition 1 (First Problem)

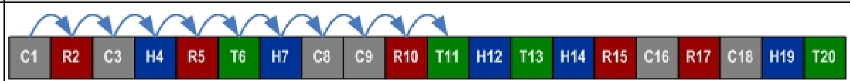
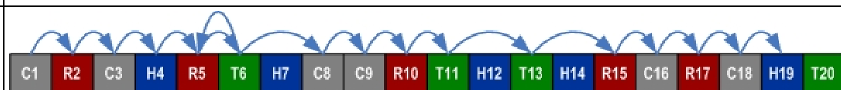
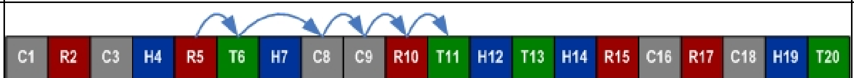
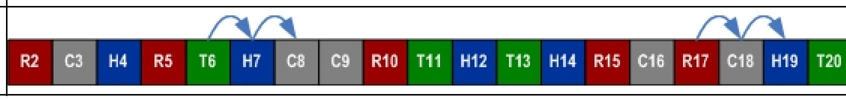
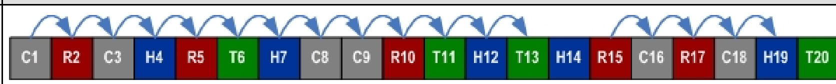
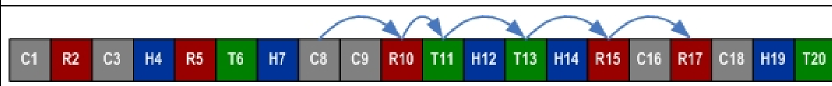
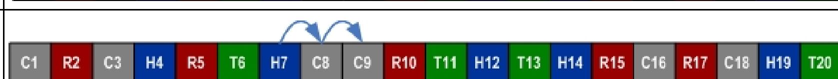
No	Characteristic in information selection	A'	B"d	# of expert	# of novice
1		0.846	-0.05	4	2
2		0.953	-1	2	2
3		0.861	-0.5	3	1
4		0.817	-0.28	3	7

Table F.12: The Markov clustering result for information acquisition in condition 1 (Last Problem)

No	Characteristic in information selection	A'	B"d	# of expert	# of novice
1		0.784	-0.05	0	3
2		0.934	-0.45	6	1
3		0.918	-0.5	4	0
4	Match in some patterns but none of patterns containing 50% number of subjects	0.732	-0.16	2	8

APPENDIX G. PRETEST

There were twelve pretest questions from inventory management domain (3 in Economic Order Quantity and 3 in reorder point) and Engineering Economy domain (6 questions).

PRETEST QUESTIONS

EOQ (Economic Order Quantity)

1. The goal of the basic EOQ model is to:
   a. minimize order size.
   b. minimize order cost.
   c. minimize the sum of purchasing & carrying costs.
   d. minimize the sum of purchasing & ordering costs.
   e. minimize the sum of ordering & carrying costs.

2. In the EOQ model, which assumption is relaxed?
   a. Lead time is constant
   b. Demand is constant
   c. Items are received all at once
   d. Supply is certain
   e. Order costs independent of order quantity

3. A service garage uses 204 boxes of cleaning cloths a year. The boxes cost $12 each. The cost to place one order is $15, and the cost to hold one box in inventory for a year is 20% of box cost. The EOQ is

   a. 40.4 boxes

   b. **50.5 boxes**

   c. 174.9 boxes

   d. 156.5 boxes

   e. 626.7 boxes

. $Q_{Opt} = \sqrt{\frac{2DS}{H}} = \sqrt{\frac{2*204*15}{20\%*12}} = \sqrt{2550} = 50.5$

Questions from the same knowledge domain

4. Which of the following is not generally a determinant of the reorder point?

   a. purchase cost

   b. length of lead time

   c. lead time variability

   d. stockout risk

   e. rate of demand

5. Service level of 95% means that

   a. the service goal is to meet 95% of monthly demand

   b. the service goal is to meet 95% of annual demand

   c. the service goal is to meet 95% of demand during lead time

   d. there is a 95% chance that 95% of demand during lead time will be met

- **e. there is a 95% chance that all of demand during lead time will be met**

6. If average demand for an item is 20 units per day, safety stock is 50 units, and lead time is four days, the ROP will be:

   b. 20

   c. 50

   c. 70

   d. 80

   e. 130 ROP = SS+DL = 50 + 20*4 = 130

Questions from the different knowledge domain (Engineering Economy)

7. Which one of the following problems is best suited for solution by engineering economic analysis?

   a. choosing between a new or used copy of a textbook

   b. deciding to either buy or lease vehicles for a company's sales force

   c. writing a computer simulation model of an automobile assembly plant

   d. selecting the best location for a daily walk

   e. making a decision to select a bus or taxi for travel within a city

8. All of the following are interest rates except:

   a. Return on investment

   b. MARR

   c. MARB

   d. Accrued interest

   e. Rate of return

9. Suppose that the time value of money is represented by an annual interest rate of 6%. How much is $20,000 one year from now worth today, recognizing the time value of money?
    a. $18,077
    b. $18,475
    c. **$18,868**
    d. $19,432
    e. $19,694

10. A distribution center must purchase a new fork truck, and three competing candidates have been identified. The costs of the three alternatives vary as do the benefits (maximum payload, e.g.). What economic criterion should be used in selecting a fork truck for purchase?
    a. Choose the fork truck with the lowest cost
    b. Choose the fork truck with the highest benefits
    c. Choose the fork truck with the highest discount
    d. Choose the fork truck with the highest (cost - benefits)
    e. Choose the fork truck with the highest (benefits - cost)

11. All of the following are examples of cash inflows except:
    a. Income taxes
    b. Asset salvage value
    c. Operating cost reduction
    d. Construction cost savings

e. Sales revenue

12. A continuously compounded loan has what nominal interest rate if the effective interest rate is 25%? Select one of the five choices below.

a. $e^{1.25}$

b. $e^{0.25}$

c. $\log_e (1.25)$

d. $\log_e (0.25)$

e. $e^{.25} - 1$

Pretest scores

Only pretest score on EQO questions (EOQ score) was used in order to categorize expertise level. Threshold values were used to classify the expertise level. In theory, subjects who score above the upper threshold (2 out of 3) on the pretest was classified as experienced subjects. They are likely to understand concepts. Those who score less than the lower threshold (1 out of 3) were classified as novices.

Table G. 1: Pretest scores

Uid	Expertise	IE341	EOQ Score	Low DS Score	High DS score
1	Expert	Yes	2	4	0
100	Expert	No	2	6	3
12	Expert	Yes	3	3	2
2	Expert	Yes	2	4	0
20	Expert	Yes	2	3	2
22	Expert	Yes	2	4	0
24	Expert	Yes	2	3	2
25	Expert	Yes	2	5	1
26	Expert	Yes	2	5	2
27	Expert	No	2	5	1
29	Expert	No	2	5	1
3	Expert	Yes	2	5	2

30	Expert	Yes	2	5	0
31	Expert	Yes	3	5	2
32	Expert	Yes	2	3	1
33	Expert	Yes	2	3	1
35	Expert	Yes	2	4	2
36	Expert	Yes	2	4	0
39	Expert	Yes	2	5	1
40	Expert	Yes	3	2	0
42	Expert	Yes	2	4	0
45	Expert	No	2	3	1
47	Expert	No	2	3	2
48	Expert	Yes	2	4	1
52	Expert	Yes	2	5	3
53	Expert	No	2	4	2
55	Expert	Yes	2	3	1
57	Expert	Yes	2	3	0
60	Expert	Yes	2	3	1
65	Expert	Yes	2	4	1
66	Expert	Yes	2	1	1
67	Expert	Yes	2	6	0
7	Expert	Yes	2	2	2
70	Expert	No	2	0	0
71	Expert	Yes	2	4	0
72	Expert	No	2	4	1
78	Expert	Yes	2	3	1
81	Expert	Yes	2	4	0
83	Expert	Yes	2	3	2
85	Expert	Yes	2	3	2
86	Expert	Yes	3	4	2
87	Expert	Yes	2	4	1
9	Expert	Yes	2	6	0
90	Expert	Yes	3	4	0
94	Expert	Yes	2	5	2
95	Expert	Yes	2	2	1
96	Expert	No	3	5	2
98	Expert	Yes	2	2	1
111	Novice	No	0	1	0
112	Novice	No	0	0	0
113	Novice	No	0	1	0
114	Novice	No	1	4	1
115	Novice	No	0	0	0
117	Novice	No	0	1	0
118	Novice	No	0	0	0
119	Novice	No	0	6	2
121	Novice	No	0	1	0

122	Novice	No	0	0	0
124	Novice	No	1	2	1
125	Novice	No	0	2	0
126	Novice	No	0	3	2
13	Novice	No	0	2	1
15	Novice	No	0	1	0
16	Novice	No	0	3	1
17	Novice	No	0	4	0
18	Novice	Yes	0	6	2
21	Novice	No	0	4	0
23	Novice	Yes	1	5	1
28	Novice	No	0	3	1
34	Novice	No	0	1	0
38	Novice	No	0	5	0
4	Novice	No	0	2	0
43	Novice	No	1	2	1
44	Novice	No	0	4	0
49	Novice	No	0	4	0
50	Novice	No	0	2	2
5	Novice	No	0	2	0
51	Novice	No	0	0	0
54	Novice	No	0	1	1
59	Novice	No	0	2	0
61	Novice	No	1	3	0
62	Novice	No	0	1	0
63	Novice	Yes	0	3	1
64	Novice	No	0	5	1
68	Novice	No	1	4	3
69	Novice	No	0	1	2
74	Novice	No	0	4	2
75	Novice	No	0	2	1
77	Novice	Yes	1	2	0
80	Novice	Yes	1	5	2
84	Novice	No	0	2	0
88	Novice	No	0	2	1
91	Novice	No	0	2	1
92	Novice	Yes	0	1	0
93	Novice	No	0	1	0
99	Novice	Yes	0	2	1

APPENDIX H. RAW DATA

INFORMATION REDUCTION

Performance measures

Table H. 1: Information reduction raw data for experienced subject group.

Experienced subjects										
uid	session	Problem ID	Condition ID	Sequence No	H	F	A'	B"d	D'	C
2	TaskRelevant	1	1	1	1	0.25	0.9375	-1	4.9394	-1.795
2	TaskRelevant	2	2	2	1	0.1875	0.9531	-1	5.152	-1.689
2	TaskRelevant	3	3	3	1	0.1875	0.9531	-1	5.152	-1.689
2	TaskRelevant	4	4	4	1	0.125	0.9688	-1	5.4152	-1.557
2	Revise TaskRelevant	4	4		1	0.0625	0.9844	-1	5.799	-1.365
1	TaskRelevant	3	1	1	1	0.3125	0.9219	-1	4.7537	-1.888
1	TaskRelevant	1	2	2	1	0.3125	0.9219	-1	4.7537	-1.888
1	TaskRelevant	4	4	3	1	0.1875	0.9531	-1	5.152	-1.689
1	TaskRelevant	2	3	4	1	0.125	0.9688	-1	5.4152	-1.557
1	Revise TaskRelevant	2	3		0.75	0	0.9375	1	4.9394	1.7952
9	TaskRelevant	4	1	1	1	0.1875	0.9531	-1	5.152	-1.689
9	TaskRelevant	3	3	2	1	0	1	0	8.5298	0
9	TaskRelevant	2	2	3	0.75	0.1875	0.8606	0.1818	1.5616	0.1063
9	TaskRelevant	1	4	4	1	0	1	0	8.5298	0
9	Revise TaskRelevant	1	4		1	0	1	0	8.5298	0
3	TaskRelevant	2	1	1	1	0.25	0.9375	-1	4.9394	-1.795
3	TaskRelevant	3	3	2	1	0.3125	0.9219	-1	4.7537	-1.888
3	TaskRelevant	4	4	3	1	0.125	0.9688	-1	5.4152	-1.557
3	TaskRelevant	1	2	4	1	0.375	0.9063	-1	4.5835	-1.973
3	Revise TaskRelevant	1	2		1	0.125	0.9688	-1	5.4152	-1.557
57	TaskRelevant	2	1	1	1	0.1875	0.9531	-1	5.152	-1.689
57	TaskRelevant	3	4	2	1	0	1	0	8.5298	0
57	TaskRelevant	1	2	3	1	0.25	0.9375	-1	4.9394	-1.795
57	TaskRelevant	4	3	4	1	0	1	0	8.5298	0
57	Revise TaskRelevant	4	3		1	0	1	0	8.5298	0
7	TaskRelevant	4	1	1	0.5	0.0625	0.8354	0.875	1.5341	0.7671
7	TaskRelevant	1	4	2	0.5	0.0625	0.8354	0.875	1.5341	0.7671
7	TaskRelevant	2	3	3	0.5	0	0.875	1	4.2649	2.1324
7	TaskRelevant	3	2	4	0.5	0.0625	0.8354	0.875	1.5341	0.7671
7	Revise TaskRelevant	3	2		1	0	1	0	8.5298	0
12	TaskRelevant	1	2	1	0.75	0.1875	0.8606	0.1818	1.5616	0.1063

12	TaskRelevant	4	1	2	0.75	0.1875	0.8606	0.1818	1.5616	0.1063
12	TaskRelevant	2	4	3	0.5	0	0.875	1	4.2649	2.1324
12	TaskRelevant	3	3	4	0.75	0.0625	0.9125	0.6667	2.2086	0.4298
12	Revise TaskRelevant	3	3		1	0	1	0	8.5298	0
20	TaskRelevant	4	2	1	0.75	0.25	0.8333	0	1.349	0
20	TaskRelevant	1	3	2	1	0	1	0	8.5298	0
20	TaskRelevant	3	4	3	0.75	0.0625	0.9125	0.6667	2.2086	0.4298
20	TaskRelevant	2	1	4	0.75	0.0625	0.9125	0.6667	2.2086	0.4298
20	Revise TaskRelevant	2	1		0.75	0	0.9375	1	4.9394	1.7952
27	TaskRelevant	1	2	1	1	0.1875	0.9531	-1	5.152	-1.689
27	TaskRelevant	3	4	2	1	0.0625	0.9844	-1	5.799	-1.365
27	TaskRelevant	2	1	3	1	0.375	0.9063	-1	4.5835	-1.973
27	TaskRelevant	4	3	4	1	0.25	0.9375	-1	4.9394	-1.795
27	Revise TaskRelevant	4	3		1	0.1875	0.9531	-1	5.152	-1.689
24	TaskRelevant	3	2	1	1	0.125	0.9688	-1	5.4152	-1.557
24	TaskRelevant	2	4	2	1	0.1875	0.9531	-1	5.152	-1.689
24	TaskRelevant	1	3	3	1	0	1	0	8.5298	0
24	TaskRelevant	4	1	4	1	0.125	0.9688	-1	5.4152	-1.557
24	Revise TaskRelevant	4	1		1	0.125	0.9688	-1	5.4152	-1.557
29	TaskRelevant	2	3	1	1	0.25	0.9375	-1	4.9394	-1.795
29	TaskRelevant	3	1	2	1	0.4375	0.8906	-1	4.4222	-2.054
29	TaskRelevant	1	2	3	1	0.1875	0.9531	-1	5.152	-1.689
29	TaskRelevant	4	4	4	1	0	1	0	8.5298	0
29	Revise TaskRelevant	4	4		1	0	1	0	8.5298	0
22	TaskRelevant	1	3	1	1	0.125	0.9688	-1	5.4152	-1.557
22	TaskRelevant	4	1	2	1	0.3125	0.9219	-1	4.7537	-1.888
22	TaskRelevant	3	4	3	1	0.0625	0.9844	-1	5.799	-1.365
22	TaskRelevant	2	2	4	1	0.1875	0.9531	-1	5.152	-1.689
22	Revise TaskRelevant	2	2		1	0.1875	0.9531	-1	5.152	-1.689
25	TaskRelevant	4	3	1	0.75	0	0.9375	1	4.9394	1.7952
25	TaskRelevant	3	2	2	0.25	0.0625	0.7375	0.9565	0.8596	1.1043
25	TaskRelevant	1	1	3	1	0.1875	0.9531	-1	5.152	-1.689
25	TaskRelevant	2	4	4	0.75	0.0625	0.9125	0.6667	2.2086	0.4298
25	Revise TaskRelevant	2	4		1	0.0625	0.9844	-1	5.799	-1.365
26	TaskRelevant	3	3	1	1	0.125	0.9688	-1	5.4152	-1.557
26	TaskRelevant	4	2	2	1	0.3125	0.9219	-1	4.7537	-1.888
26	TaskRelevant	1	4	3	1	0.1875	0.9531	-1	5.152	-1.689
26	TaskRelevant	2	1	4	1	0.3125	0.9219	-1	4.7537	-1.888
26	Revise TaskRelevant	2	1		1	0.25	0.9375	-1	4.9394	-1.795
33	TaskRelevant	3	3	1	1	0.1875	0.9531	-1	5.152	-1.689
33	TaskRelevant	2	4	2	1	0.0625	0.9844	-1	5.799	-1.365
33	TaskRelevant	4	1	3	0.75	0.25	0.8333	0	1.349	0

33	TaskRelevant	1	2	4	1	0.25	0.9375	-1	4.9394	-1.795
33	Revise TaskRelevant	1	2		1	0.1875	0.9531	-1	5.152	-1.689
35	TaskRelevant	4	3	1	1	0.125	0.9688	-1	5.4152	-1.557
35	TaskRelevant	2	4	2	1	0.0625	0.9844	-1	5.799	-1.365
35	TaskRelevant	3	2	3	1	0.3125	0.9219	-1	4.7537	-1.888
35	TaskRelevant	1	1	4	1	0.3125	0.9219	-1	4.7537	-1.888
35	Revise TaskRelevant	1	1		1	0.3125	0.9219	-1	4.7537	-1.888
31	TaskRelevant	1	4	1	1	0.0625	0.9844	-1	5.799	-1.365
31	TaskRelevant	2	1	2	1	0.1875	0.9531	-1	5.152	-1.689
31	TaskRelevant	4	2	3	1	0.1875	0.9531	-1	5.152	-1.689
31	TaskRelevant	3	3	4	1	0.25	0.9375	-1	4.9394	-1.795
31	Revise TaskRelevant	3	3		1	0	1	0	8.5298	0
30	TaskRelevant	2	4	1	0.75	0.125	0.8869	0.4	1.8248	0.2379
30	TaskRelevant	1	1	2	1	0.125	0.9688	-1	5.4152	-1.557
30	TaskRelevant	3	3	3	0.25	0	0.8125	1	3.5904	2.4697
30	TaskRelevant	4	2	4	1	0.1875	0.9531	-1	5.152	-1.689
30	Revise TaskRelevant	4	2		1	0.1875	0.9531	-1	5.152	-1.689
36	TaskRelevant	2	4	1	1	0.1875	0.9531	-1	5.152	-1.689
36	TaskRelevant	4	2	2	1	0.1875	0.9531	-1	5.152	-1.689
36	TaskRelevant	3	1	3	1	0.25	0.9375	-1	4.9394	-1.795
36	TaskRelevant	1	3	4	1	0.1875	0.9531	-1	5.152	-1.689
36	Revise TaskRelevant	1	3		1	0.0625	0.9844	-1	5.799	-1.365
32	TaskRelevant	3	4	1	1	0.0625	0.9844	-1	5.799	-1.365
32	TaskRelevant	1	2	2	1	0.1875	0.9531	-1	5.152	-1.689
32	TaskRelevant	2	3	3	0.75	0.1875	0.8606	0.1818	1.5616	0.1063
32	TaskRelevant	4	1	4	1	0.25	0.9375	-1	4.9394	-1.795
32	Revise TaskRelevant	4	1		0.75	0	0.9375	1	4.9394	1.7952
39	TaskRelevant	3	4	1	1	0.25	0.9375	-1	4.9394	-1.795
39	TaskRelevant	4	3	2	1	0	1	0	8.5298	0
39	TaskRelevant	2	1	3	1	0	1	0	8.5298	0
39	TaskRelevant	1	2	4	0.75	0.0625	0.9125	0.6667	2.2086	0.4298
39	Revise TaskRelevant	1	2		0.75	0.0625	0.9125	0.6667	2.2086	0.4298
40	TaskRelevant	4	4	1	1	0.375	0.9063	-1	4.5835	-1.973
40	TaskRelevant	2	3	2	0.75	0.375	0.775	-0.286	0.9931	-0.178
40	TaskRelevant	1	2	3	1	0.5	0.875	-1	4.2649	-2.132
40	TaskRelevant	3	1	4	1	0.375	0.9063	-1	4.5835	-1.973
40	Revise TaskRelevant	3	1		1	0.0625	0.9844	-1	5.799	-1.365
55	TaskRelevant	3	1	1	1	0.125	0.9688	-1	5.4152	-1.557
55	TaskRelevant	4	2	2	1	0.1875	0.9531	-1	5.152	-1.689
55	TaskRelevant	1	4	3	1	0.125	0.9688	-1	5.4152	-1.557
55	TaskRelevant	2	3	4	1	0.0625	0.9844	-1	5.799	-1.365
55	Revise TaskRelevant	2	3		1	0	1	0	8.5298	0

42	TaskRelevant	3	1	1	0.75	0.1875	0.8606	0.1818	1.5616	0.1063
42	TaskRelevant	2	3	2	0.5	0	0.875	1	4.2649	2.1324
42	TaskRelevant	4	2	3	0.5	0.125	0.7946	0.75	1.1503	0.5752
42	TaskRelevant	1	4	4	0.75	0	0.9375	1	4.9394	1.7952
42	Revise TaskRelevant	1	4		0.75	0.0625	0.9125	0.6667	2.2086	0.4298
45	TaskRelevant	4	1	1	0.75	0.25	0.8333	0	1.349	0
45	TaskRelevant	3	3	2	1	0.25	0.9375	-1	4.9394	-1.795
45	TaskRelevant	1	4	3	1	0.3125	0.9219	-1	4.7537	-1.888
45	TaskRelevant	2	2	4	1	0.3125	0.9219	-1	4.7537	-1.888
45	Revise TaskRelevant	2	2		1	0.375	0.9063	-1	4.5835	-1.973
48	TaskRelevant	2	1	1	1	0.125	0.9688	-1	5.4152	-1.557
48	TaskRelevant	3	4	2	0.75	0.0625	0.9125	0.6667	2.2086	0.4298
48	TaskRelevant	1	2	3	0.75	0.125	0.8869	0.4	1.8248	0.2379
48	TaskRelevant	4	3	4	0.75	0	0.9375	1	4.9394	1.7952
48	Revise TaskRelevant	4	3		1	0.25	0.9375	-1	4.9394	-1.795
47	TaskRelevant	4	1	1	0.75	0.0625	0.9125	0.6667	2.2086	0.4298
47	TaskRelevant	2	4	2	1	0.0625	0.9844	-1	5.799	-1.365
47	TaskRelevant	1	3	3	0.75	0	0.9375	1	4.9394	1.7952
47	TaskRelevant	3	2	4	1	0.125	0.9688	-1	5.4152	-1.557
47	Revise TaskRelevant	3	2		0.75	0.0625	0.9125	0.6667	2.2086	0.4298
52	TaskRelevant	1	2	1	1	0.25	0.9375	-1	4.9394	-1.795
52	TaskRelevant	2	1	2	1	0.4375	0.8906	-1	4.4222	-2.054
52	TaskRelevant	4	3	3	1	0.1875	0.9531	-1	5.152	-1.689
52	TaskRelevant	3	4	4	1	0	1	0	8.5298	0
52	Revise TaskRelevant	3	4		1	0	1	0	8.5298	0
53	TaskRelevant	2	2	1	1	0.5	0.875	-1	4.2649	-2.132
53	TaskRelevant	1	1	2	1	0.5	0.875	-1	4.2649	-2.132
53	TaskRelevant	3	4	3	1	0.4375	0.8906	-1	4.4222	-2.054
53	TaskRelevant	4	3	4	1	0.375	0.9063	-1	4.5835	-1.973
53	Revise TaskRelevant	4	3		1	0.3125	0.9219	-1	4.7537	-1.888
60	TaskRelevant	4	2	1	1	0.125	0.9688	-1	5.4152	-1.557
60	TaskRelevant	2	3	2	1	0.0625	0.9844	-1	5.799	-1.365
60	TaskRelevant	3	1	3	0.75	0	0.9375	1	4.9394	1.7952
60	TaskRelevant	1	4	4	0.75	0	0.9375	1	4.9394	1.7952
60	Revise TaskRelevant	1	4		0.75	0	0.9375	1	4.9394	1.7952
70	TaskRelevant	3	2	1	1	0.125	0.9688	-1	5.4152	-1.557
70	TaskRelevant	4	3	2	1	0.3125	0.9219	-1	4.7537	-1.888
70	TaskRelevant	2	4	3	0.75	0	0.9375	1	4.9394	1.7952
70	TaskRelevant	1	1	4	1	0.3125	0.9219	-1	4.7537	-1.888
70	Revise TaskRelevant	1	1		1	0.25	0.9375	-1	4.9394	-1.795
78	TaskRelevant	2	2	1	1	0.375	0.9063	-1	4.5835	-1.973
78	TaskRelevant	4	4	2	1	0.0625	0.9844	-1	5.799	-1.365

78	TaskRelevant	3	1	3	1	0.375	0.9063	-1	4.5835	-1.973
78	TaskRelevant	1	3	4	1	0.1875	0.9531	-1	5.152	-1.689
78	Revise TaskRelevant	1	3		1	0.125	0.9688	-1	5.4152	-1.557
66	TaskRelevant	3	2	1	0.75	0.0625	0.9125	0.6667	2.2086	0.4298
66	TaskRelevant	1	4	2	0.75	0	0.9375	1	4.9394	1.7952
66	TaskRelevant	2	3	3	0.75	0	0.9375	1	4.9394	1.7952
66	TaskRelevant	4	1	4	0.75	0	0.9375	1	4.9394	1.7952
66	Revise TaskRelevant	4	1		0.75	0	0.9375	1	4.9394	1.7952
65	TaskRelevant	1	3	1	0.75	0.25	0.8333	0	1.349	0
65	TaskRelevant	4	1	2	1	0.5	0.875	-1	4.2649	-2.132
65	TaskRelevant	3	2	3	1	0.25	0.9375	-1	4.9394	-1.795
65	TaskRelevant	2	4	4	1	0.25	0.9375	-1	4.9394	-1.795
65	Revise TaskRelevant	2	4		0.75	0.0625	0.9125	0.6667	2.2086	0.4298
67	TaskRelevant	3	3	1	1	0	1	0	8.5298	0
67	TaskRelevant	1	1	2	1	0.0625	0.9844	-1	5.799	-1.365
67	TaskRelevant	4	4	3	1	0	1	0	8.5298	0
67	TaskRelevant	2	2	4	1	0	1	0	8.5298	0
67	Revise TaskRelevant	2	2		1	0	1	0	8.5298	0
81	TaskRelevant	2	3	1	1	0.375	0.9063	-1	4.5835	-1.973
81	TaskRelevant	4	2	2	0.75	0.125	0.8869	0.4	1.8248	0.2379
81	TaskRelevant	1	4	3	0.75	0.125	0.8869	0.4	1.8248	0.2379
81	TaskRelevant	3	1	4	0.75	0.1875	0.8606	0.1818	1.5616	0.1063
81	Revise TaskRelevant	3	1		0.75	0.375	0.775	-0.286	0.9931	-0.178
71	TaskRelevant	2	3	1	1	0.0625	0.9844	-1	5.799	-1.365
71	TaskRelevant	3	4	2	1	0.0625	0.9844	-1	5.799	-1.365
71	TaskRelevant	4	1	3	1	0.25	0.9375	-1	4.9394	-1.795
71	TaskRelevant	1	2	4	1	0.125	0.9688	-1	5.4152	-1.557
71	Revise TaskRelevant	1	2		1	0	1	0	8.5298	0
85	TaskRelevant	4	3	1	1	0	1	0	8.5298	0
85	TaskRelevant	1	4	2	0.5	0.0625	0.8354	0.875	1.5341	0.7671
85	TaskRelevant	2	2	3	0.75	0.0625	0.9125	0.6667	2.2086	0.4298
85	TaskRelevant	3	1	4	1	0	1	0	8.5298	0
85	Revise TaskRelevant	3	1		0.25	0	0.8125	1	3.5904	2.4697
72	TaskRelevant	1	4	1	1	0.25	0.9375	-1	4.9394	-1.795
72	TaskRelevant	4	1	2	1	0.5625	0.8594	-1	4.1076	-2.211
72	TaskRelevant	2	2	3	1	0.375	0.9063	-1	4.5835	-1.973
72	TaskRelevant	3	3	4	1	0.4375	0.8906	-1	4.4222	-2.054
72	Revise TaskRelevant	3	3		1	0.25	0.9375	-1	4.9394	-1.795
83	TaskRelevant	2	4	1	1	0.125	0.9688	-1	5.4152	-1.557
83	TaskRelevant	1	1	2	1	0.1875	0.9531	-1	5.152	-1.689
83	TaskRelevant	4	3	3	1	0.0625	0.9844	-1	5.799	-1.365
83	TaskRelevant	3	2	4	0.75	0.125	0.8869	0.4	1.8248	0.2379

83	Revise TaskRelevant	3	2		1	0	1	0	8.5298	0
86	TaskRelevant	1	4	1	0.25	0	0.8125	1	3.5904	2.4697
86	TaskRelevant	3	2	2	0.25	0	0.8125	1	3.5904	2.4697
86	TaskRelevant	4	1	3	0.5	0.1875	0.7524	0.625	0.8871	0.4436
86	TaskRelevant	2	3	4	1	0.0625	0.9844	-1	5.799	-1.365
86	Revise TaskRelevant	2	3		1	0	1	0	8.5298	0
87	TaskRelevant	1	4	1	1	0.3125	0.9219	-1	4.7537	-1.888
87	TaskRelevant	3	2	2	1	0.1875	0.9531	-1	5.152	-1.689
87	TaskRelevant	2	3	3	1	0.3125	0.9219	-1	4.7537	-1.888
87	TaskRelevant	4	1	4	1	0.5	0.875	-1	4.2649	-2.132
87	Revise TaskRelevant	4	1		1	0.1875	0.9531	-1	5.152	-1.689
90	TaskRelevant	3	4	1	1	0.125	0.9688	-1	5.4152	-1.557
90	TaskRelevant	2	3	2	1	0.125	0.9688	-1	5.4152	-1.557
90	TaskRelevant	1	1	3	1	0.25	0.9375	-1	4.9394	-1.795
90	TaskRelevant	4	2	4	1	0.25	0.9375	-1	4.9394	-1.795
90	Revise TaskRelevant	4	2		1	0.0625	0.9844	-1	5.799	-1.365
94	TaskRelevant	4	4	1	0.75	0	0.9375	1	4.9394	1.7952
94	TaskRelevant	1	3	2	0.75	0	0.9375	1	4.9394	1.7952
94	TaskRelevant	3	2	3	0.75	0.125	0.8869	0.4	1.8248	0.2379
94	TaskRelevant	2	1	4	0.75	0.1875	0.8606	0.1818	1.5616	0.1063
94	Revise TaskRelevant	2	1		0.75	0.25	0.8333	0	1.349	0
95	TaskRelevant	4	3	1	1	0.1875	0.9531	-1	5.152	-1.689
95	TaskRelevant	3	2	2	1	0.125	0.9688	-1	5.4152	-1.557
95	TaskRelevant	2	1	3	0.75	0.3125	0.8049	-0.154	1.1633	-0.093
95	TaskRelevant	1	4	4	1	0	1	0	8.5298	0
95	Revise TaskRelevant	1	4		1	0	1	0	8.5298	0
96	TaskRelevant	2	2	1	1	0.25	0.9375	-1	4.9394	-1.795
96	TaskRelevant	1	3	2	1	0	1	0	8.5298	0
96	TaskRelevant	4	1	3	1	0.125	0.9688	-1	5.4152	-1.557
96	TaskRelevant	3	4	4	1	0.0625	0.9844	-1	5.799	-1.365
96	Revise TaskRelevant	3	4		1	0	1	0	8.5298	0
98	TaskRelevant	1	2	1	1	0.1875	0.9531	-1	5.152	-1.689
98	TaskRelevant	3	1	2	1	0.25	0.9375	-1	4.9394	-1.795
98	TaskRelevant	4	3	3	1	0	1	0	8.5298	0
98	TaskRelevant	2	4	4	0.75	0	0.9375	1	4.9394	1.7952
98	Revise TaskRelevant	2	4		0.75	0	0.9375	1	4.9394	1.7952
100	TaskRelevant	1	1	1	1	0.125	0.9688	-1	5.4152	-1.557
100	TaskRelevant	2	2	2	1	0.0625	0.9844	-1	5.799	-1.365
100	TaskRelevant	3	3	3	1	0	1	0	8.5298	0
100	TaskRelevant	4	4	4	1	0	1	0	8.5298	0
100	Revise TaskRelevant	4	4		1	0	1	0	8.5298	0

Table H. 2: Information reduction raw data for novice group.

Novice										
uid	session	Problem ID	Condition ID	Sequence No	H	F	A'	B"d	D'	C
13	TaskRelevant	3	1	1	0.25	0.188	0.582	0.857	0.213	0.781
13	TaskRelevant	1	2	2	0.75	0.063	0.913	0.667	2.209	0.43
13	TaskRelevant	4	4	3	0.75	0.188	0.861	0.182	1.562	0.106
13	TaskRelevant	2	3	4	0.75	0.25	0.833	0	1.349	0
13	Revise TaskRelevant	2	3	4	0.5	0.188	0.752	0.625	0.887	0.444
4	TaskRelevant	4	1	1	0.25	0.125	0.661	0.909	0.476	0.912
4	TaskRelevant	3	3	2	0.25	0.063	0.738	0.957	0.86	1.104
4	TaskRelevant	2	2	3	0.5	0.125	0.795	0.75	1.15	0.575
4	TaskRelevant	1	4	4	0.5	0	0.875	1	4.265	2.132
4	Revise TaskRelevant	1	4	4	0.25	0.063	0.738	0.957	0.86	1.104
17	TaskRelevant	2	1	1	1	0.625	0.844	-1	3.946	-2.29
17	TaskRelevant	3	3	2	1	0.375	0.906	-1	4.584	-1.97
17	TaskRelevant	4	4	3	1	0.438	0.891	-1	4.422	-2.05
17	TaskRelevant	1	2	4	1	0.563	0.859	-1	4.108	-2.21
17	Revise TaskRelevant	1	2	4	1	0.438	0.891	-1	4.422	-2.05
5	TaskRelevant	2	1	1	0.5	0.188	0.752	0.625	0.887	0.444
5	TaskRelevant	4	4	2	0.5	0.25	0.708	0.5	0.675	0.337
5	TaskRelevant	1	2	3	0.5	0.375	0.613	0.25	0.319	0.159
5	TaskRelevant	3	3	4	0.5	0.188	0.752	0.625	0.887	0.444
5	Revise TaskRelevant	3	3	4	0.75	0.188	0.861	0.182	1.562	0.106
15	TaskRelevant	4	1	1	0.25	0.188	0.582	0.857	0.213	0.781
15	TaskRelevant	1	4	2	0.25	0.063	0.738	0.957	0.86	1.104
15	TaskRelevant	2	3	3	0.5	0.125	0.795	0.75	1.15	0.575
15	TaskRelevant	3	2	4	0.5	0.25	0.708	0.5	0.675	0.337
15	Revise TaskRelevant	3	2	4	0.5	0.25	0.708	0.5	0.675	0.337
18	TaskRelevant	1	2	1	0.5	0.688	0.338	-0.38	-0.49	-0.24
18	TaskRelevant	3	1	2	0.5	0.688	0.338	-0.38	-0.49	-0.24
18	TaskRelevant	4	3	3	0.75	0.625	0.625	-0.67	0.356	-0.5
18	TaskRelevant	2	4	4	0.75	0.563	0.67	-0.59	0.517	-0.42
18	Revise TaskRelevant	2	4	4	0.75	0.563	0.67	-0.59	0.517	-0.42
16	TaskRelevant	2	2	1	0.25	0.063	0.738	0.957	0.86	1.104
16	TaskRelevant	1	3	2	0.25	0.188	0.582	0.857	0.213	0.781
16	TaskRelevant	4	1	3	0.25	0.063	0.738	0.957	0.86	1.104
16	TaskRelevant	3	4	4	0.25	0	0.813	1	3.59	2.47
16	Revise TaskRelevant	3	4	4	0.25	0	0.813	1	3.59	2.47
21	TaskRelevant	4	2	1	0.25	0	0.813	1	3.59	2.47
21	TaskRelevant	1	3	2	0.25	0	0.813	1	3.59	2.47

21	TaskRelevant	3	4	3	0.25	0	0.813	1	3.59	2.47
21	TaskRelevant	2	1	4	0	0.063	0.234	1	-2.73	2.9
21	Revise TaskRelevant	2	1		0	0.063	0.234	1	-2.73	2.9
28	TaskRelevant	3	2	1	0.5	0.125	0.795	0.75	1.15	0.575
28	TaskRelevant	2	4	2	0.25	0.125	0.661	0.909	0.476	0.912
28	TaskRelevant	1	3	3	0.5	0.188	0.752	0.625	0.887	0.444
28	TaskRelevant	4	1	4	0.75	0.063	0.913	0.667	2.209	0.43
28	Revise TaskRelevant	4	1		0.75	0.063	0.913	0.667	2.209	0.43
23	TaskRelevant	2	3	1	0.25	0.125	0.661	0.909	0.476	0.912
23	TaskRelevant	3	1	2	0.5	0.188	0.752	0.625	0.887	0.444
23	TaskRelevant	1	2	3	0.75	0.125	0.887	0.4	1.825	0.238
23	TaskRelevant	4	4	4	1	0.188	0.953	-1	5.152	-1.69
23	Revise TaskRelevant	4	4		1	0	1	NaN	8.53	0
34	TaskRelevant	1	3	1	0.75	0.125	0.887	0.4	1.825	0.238
34	TaskRelevant	4	1	2	0.75	0.25	0.833	0	1.349	0
34	TaskRelevant	3	4	3	1	0.25	0.938	-1	4.939	-1.8
34	TaskRelevant	2	2	4	0.75	0.313	0.805	-0.15	1.163	-0.09
34	Revise TaskRelevant	2	2		0.75	0.313	0.805	-0.15	1.163	-0.09
38	TaskRelevant	3	3	1	1	0.438	0.891	-1	4.422	-2.05
38	TaskRelevant	4	2	2	1	0.438	0.891	-1	4.422	-2.05
38	TaskRelevant	1	4	3	0.25	0	0.813	1	3.59	2.47
38	TaskRelevant	2	1	4	0.25	0.188	0.582	0.857	0.213	0.781
38	Revise TaskRelevant	2	1		0.25	0.125	0.661	0.909	0.476	0.912
44	TaskRelevant	4	3	1	1	0.313	0.922	-1	4.754	-1.89
44	TaskRelevant	2	4	2	1	0.313	0.922	-1	4.754	-1.89
44	TaskRelevant	3	2	3	1	0.438	0.891	-1	4.422	-2.05
44	TaskRelevant	1	1	4	1	0.625	0.844	-1	3.946	-2.29
44	Revise TaskRelevant	1	1		1	0.563	0.859	-1	4.108	-2.21
75	TaskRelevant	2	4	1	1	0.25	0.938	-1	4.939	-1.8
75	TaskRelevant	1	1	2	1	0.375	0.906	-1	4.584	-1.97
75	TaskRelevant	3	3	3	1	0.25	0.938	-1	4.939	-1.8
75	TaskRelevant	4	2	4	1	0.563	0.859	-1	4.108	-2.21
75	Revise TaskRelevant	4	2		0.75	0.375	0.775	-0.29	0.993	-0.18
74	TaskRelevant	2	4	1	0.75	0.125	0.887	0.4	1.825	0.238
74	TaskRelevant	4	2	2	1	0.188	0.953	-1	5.152	-1.69
74	TaskRelevant	3	1	3	0.75	0.25	0.833	0	1.349	0
74	TaskRelevant	1	3	4	0.75	0.188	0.861	0.182	1.562	0.106
74	Revise TaskRelevant	1	3		0.25	0.063	0.738	0.957	0.86	1.104
50	TaskRelevant	3	4	1	0.75	0.313	0.805	-0.15	1.163	-0.09
50	TaskRelevant	1	2	2	1	0.375	0.906	-1	4.584	-1.97
50	TaskRelevant	2	3	3	0.75	0.063	0.913	0.667	2.209	0.43

50	TaskRelevant	4	1	4	1	0.25	0.938	-1	4.939	-1.8
50	Revise TaskRelevant	4	1		1	0.063	0.984	-1	5.799	-1.37
49	TaskRelevant	3	4	1	0.25	0.063	0.738	0.957	0.86	1.104
49	TaskRelevant	4	3	2	0.25	0.125	0.661	0.909	0.476	0.912
49	TaskRelevant	2	1	3	0.5	0.063	0.835	0.875	1.534	0.767
49	TaskRelevant	1	2	4	0.25	0.125	0.661	0.909	0.476	0.912
49	Revise TaskRelevant	1	2		0.75	0.188	0.861	0.182	1.562	0.106
51	TaskRelevant	4	4	1	1	0.375	0.906	-1	4.584	-1.97
51	TaskRelevant	2	3	2	1	0.375	0.906	-1	4.584	-1.97
51	TaskRelevant	1	2	3	0.75	0.375	0.775	-0.29	0.993	-0.18
51	TaskRelevant	3	1	4	1	0.438	0.891	-1	4.422	-2.05
51	Revise TaskRelevant	3	1		1	0.5	0.875	-1	4.265	-2.13
54	TaskRelevant	1	1	1	1	0.188	0.953	-1	5.152	-1.69
54	TaskRelevant	2	2	2	1	0.313	0.922	-1	4.754	-1.89
54	TaskRelevant	3	3	3	1	0.063	0.984	-1	5.799	-1.37
54	TaskRelevant	4	4	4	0.75	0.25	0.833	0	1.349	0
54	Revise TaskRelevant	4	4		0.5	0.188	0.752	0.625	0.887	0.444
43	TaskRelevant	3	1	1	1	0.25	0.938	-1	4.939	-1.8
43	TaskRelevant	4	2	2	0.5	0.188	0.752	0.625	0.887	0.444
43	TaskRelevant	1	4	3	0.75	0.188	0.861	0.182	1.562	0.106
43	TaskRelevant	2	3	4	1	0.313	0.922	-1	4.754	-1.89
43	Revise TaskRelevant	2	3		1	0.375	0.906	-1	4.584	-1.97
59	TaskRelevant	4	1	1	1	0.313	0.922	-1	4.754	-1.89
59	TaskRelevant	3	3	2	1	0.188	0.953	-1	5.152	-1.69
59	TaskRelevant	1	4	3	1	0.188	0.953	-1	5.152	-1.69
59	TaskRelevant	2	2	4	0.75	0.438	0.743	-0.4	0.832	-0.26
59	Revise TaskRelevant	2	2		0.75	0.438	0.743	-0.4	0.832	-0.26
62	TaskRelevant	4	1	1	1	0.375	0.906	-1	4.584	-1.97
62	TaskRelevant	2	4	2	0.75	0.125	0.887	0.4	1.825	0.238
62	TaskRelevant	1	3	3	0.75	0.063	0.913	0.667	2.209	0.43
62	TaskRelevant	3	2	4	0.75	0.313	0.805	-0.15	1.163	-0.09
62	Revise TaskRelevant	3	2		0.75	0.5	0.708	-0.5	0.675	-0.34
64	TaskRelevant	1	2	1	0.5	0.063	0.835	0.875	1.534	0.767
64	TaskRelevant	2	1	2	0.5	0.125	0.795	0.75	1.15	0.575
64	TaskRelevant	4	3	3	0.75	0.188	0.861	0.182	1.562	0.106
64	TaskRelevant	3	4	4	0.5	0.125	0.795	0.75	1.15	0.575
64	Revise TaskRelevant	3	4		0.5	0.125	0.795	0.75	1.15	0.575
63	TaskRelevant	2	2	1	0.25	0.063	0.738	0.957	0.86	1.104
63	TaskRelevant	1	1	2	0.5	0.063	0.835	0.875	1.534	0.767
63	TaskRelevant	3	4	3	0.5	0.063	0.835	0.875	1.534	0.767
63	TaskRelevant	4	3	4	0.5	0	0.875	1	4.265	2.132

63	Revise TaskRelevant	4	3		0.5	0	0.875	1	4.265	2.132
69	TaskRelevant	4	2	1	1	0.625	0.844	-1	3.946	-2.29
69	TaskRelevant	2	3	2	0.75	0.5	0.708	-0.5	0.675	-0.34
69	TaskRelevant	3	1	3	1	0.625	0.844	-1	3.946	-2.29
69	TaskRelevant	1	4	4	1	0.688	0.828	-1	3.776	-2.38
69	Revise TaskRelevant	1	4		1	0.688	0.828	-1	3.776	-2.38
61	TaskRelevant	2	2	1	0	0.375	0.156	1	-3.95	2.292
61	TaskRelevant	4	4	2	1	0.313	0.922	-1	4.754	-1.89
61	TaskRelevant	3	1	3	0.5	0.313	0.662	0.375	0.489	0.244
61	TaskRelevant	1	3	4	1	0.5	0.875	-1	4.265	-2.13
61	Revise TaskRelevant	1	3		1	0.438	0.891	-1	4.422	-2.05
84	TaskRelevant	1	3	1	1	0	1	NaN	8.53	0
84	TaskRelevant	4	1	2	0.25	0.125	0.661	0.909	0.476	0.912
84	TaskRelevant	3	2	3	0.25	0.125	0.661	0.909	0.476	0.912
84	TaskRelevant	2	4	4	0.25	0.125	0.661	0.909	0.476	0.912
84	Revise TaskRelevant	2	4		0.25	0.188	0.582	0.857	0.213	0.781
88	TaskRelevant	3	3	1	0.75	0.188	0.861	0.182	1.562	0.106
88	TaskRelevant	1	1	2	1	0.125	0.969	-1	5.415	-1.56
88	TaskRelevant	4	4	3	1	0.125	0.969	-1	5.415	-1.56
88	TaskRelevant	2	2	4	0.75	0.125	0.887	0.4	1.825	0.238
88	Revise TaskRelevant	2	2		0.75	0.125	0.887	0.4	1.825	0.238
68	TaskRelevant	4	3	1	0.75	0.063	0.913	0.667	2.209	0.43
68	TaskRelevant	3	2	2	0.75	0.063	0.913	0.667	2.209	0.43
68	TaskRelevant	2	1	3	0.5	0.063	0.835	0.875	1.534	0.767
68	TaskRelevant	1	4	4	0.5	0.125	0.795	0.75	1.15	0.575
68	Revise TaskRelevant	1	4		0.75	0.188	0.861	0.182	1.562	0.106
77	TaskRelevant	2	3	1	0.25	0.25	NaN	0.8	0	0.675
77	TaskRelevant	4	2	2	0.25	0.063	0.738	0.957	0.86	1.104
77	TaskRelevant	1	4	3	0.25	0.063	0.738	0.957	0.86	1.104
77	TaskRelevant	3	1	4	0	0.125	0.219	1	-3.11	2.708
77	Revise TaskRelevant	3	1		0	0.125	0.219	1	-3.11	2.708
91	TaskRelevant	2	3	1	0.75	0.063	0.913	0.667	2.209	0.43
91	TaskRelevant	3	4	2	0.75	0.188	0.861	0.182	1.562	0.106
91	TaskRelevant	4	1	3	1	0.5	0.875	-1	4.265	-2.13
91	TaskRelevant	1	2	4	1	0.313	0.922	-1	4.754	-1.89
91	Revise TaskRelevant	1	2		1	0.313	0.922	-1	4.754	-1.89
113	TaskRelevant	1	4	1	0.75	0.125	0.887	0.4	1.825	0.238
113	TaskRelevant	4	1	2	1	0.125	0.969	-1	5.415	-1.56
113	TaskRelevant	2	2	3	1	0.188	0.953	-1	5.152	-1.69
113	TaskRelevant	3	3	4	1	0.5	0.875	-1	4.265	-2.13
113	Revise TaskRelevant	3	3		1	0.25	0.938	-1	4.939	-1.8

92	TaskRelevant	2	4	1	0.25	0.063	0.738	0.957	0.86	1.104
92	TaskRelevant	1	1	2	0.5	0	0.875	1	4.265	2.132
92	TaskRelevant	4	3	3	0.5	0.063	0.835	0.875	1.534	0.767
92	TaskRelevant	3	2	4	0.5	0.063	0.835	0.875	1.534	0.767
92	Revise TaskRelevant	3	2	4	0.5	0.063	0.835	0.875	1.534	0.767
93	TaskRelevant	1	4	1	0	0.063	0.234	1	-2.73	2.9
93	TaskRelevant	3	2	2	0.25	0.063	0.738	0.957	0.86	1.104
93	TaskRelevant	4	1	3	0.25	0	0.813	1	3.59	2.47
93	TaskRelevant	2	3	4	0.25	0.063	0.738	0.957	0.86	1.104
93	Revise TaskRelevant	2	3	4	0.25	0.063	0.738	0.957	0.86	1.104
112	TaskRelevant	1	4	1	0.5	0	0.875	1	4.265	2.132
112	TaskRelevant	3	2	2	0.75	0.125	0.887	0.4	1.825	0.238
112	TaskRelevant	2	3	3	1	0.063	0.984	-1	5.799	-1.37
112	TaskRelevant	4	1	4	1	0.188	0.953	-1	5.152	-1.69
112	Revise TaskRelevant	4	1	4	0.5	0.188	0.752	0.625	0.887	0.444
80	TaskRelevant	3	4	1	0.5	0	0.875	1	4.265	2.132
80	TaskRelevant	2	3	2	0.5	0	0.875	1	4.265	2.132
80	TaskRelevant	1	1	3	0.25	0.125	0.661	0.909	0.476	0.912
80	TaskRelevant	4	2	4	0.25	0.125	0.661	0.909	0.476	0.912
80	Revise TaskRelevant	4	2	4	0.75	0.063	0.913	0.667	2.209	0.43
111	TaskRelevant	3	2	1	0.75	0.188	0.861	0.182	1.562	0.106
111	TaskRelevant	4	4	2	0.75	0.125	0.887	0.4	1.825	0.238
111	TaskRelevant	2	3	3	0.75	0.125	0.887	0.4	1.825	0.238
111	TaskRelevant	1	1	4	0.75	0.375	0.775	-0.29	0.993	-0.18
111	Revise TaskRelevant	1	1	4	0.5	0.313	0.662	0.375	0.489	0.244
114	TaskRelevant	1	1	1	0.5	0.188	0.752	0.625	0.887	0.444
114	TaskRelevant	4	3	2	1	0.25	0.938	-1	4.939	-1.8
114	TaskRelevant	3	2	3	0.75	0.25	0.833	0	1.349	0
114	TaskRelevant	2	4	4	1	0.25	0.938	-1	4.939	-1.8
114	Revise TaskRelevant	2	4	4	1	0.25	0.938	-1	4.939	-1.8
115	TaskRelevant	3	3	1	0.75	0	0.938	1	4.939	1.795
115	TaskRelevant	2	4	2	0.75	0.063	0.913	0.667	2.209	0.43
115	TaskRelevant	4	1	3	0.75	0.063	0.913	0.667	2.209	0.43
115	TaskRelevant	1	2	4	0.75	0.125	0.887	0.4	1.825	0.238
115	Revise TaskRelevant	1	2	4	0.75	0.125	0.887	0.4	1.825	0.238
117	TaskRelevant	1	4	1	1	0.25	0.938	-1	4.939	-1.8
117	TaskRelevant	2	1	2	1	0.5	0.875	-1	4.265	-2.13
117	TaskRelevant	4	2	3	1	0.375	0.906	-1	4.584	-1.97
117	TaskRelevant	3	3	4	0.75	0.375	0.775	-0.29	0.993	-0.18
117	Revise TaskRelevant	3	3	4	0.75	0.375	0.775	-0.29	0.993	-0.18
118	TaskRelevant	4	3	1	1	0.313	0.922	-1	4.754	-1.89

118	TaskRelevant	3	2	2	1	0.5	0.875	-1	4.265	-2.13
118	TaskRelevant	1	1	3	1	0.375	0.906	-1	4.584	-1.97
118	TaskRelevant	2	4	4	1	0.375	0.906	-1	4.584	-1.97
118	Revise TaskRelevant	2	4		1	0.438	0.891	-1	4.422	-2.05
119	TaskRelevant	1	2	1	0.75	0.25	0.833	0	1.349	0
119	TaskRelevant	4	1	2	0.75	0.25	0.833	0	1.349	0
119	TaskRelevant	2	4	3	0.75	0.125	0.887	0.4	1.825	0.238
119	TaskRelevant	3	3	4	0.5	0.063	0.835	0.875	1.534	0.767
119	Revise TaskRelevant	3	3		0.75	0.063	0.913	0.667	2.209	0.43
99	TaskRelevant	1	1	1	0.75	0.625	0.625	-0.67	0.356	-0.5
99	TaskRelevant	2	2	2	0.75	0.563	0.67	-0.59	0.517	-0.42
99	TaskRelevant	3	3	3	0.75	0.563	0.67	-0.59	0.517	-0.42
99	TaskRelevant	4	4	4	0.75	0.375	0.775	-0.29	0.993	-0.18
99	Revise TaskRelevant	4	4		0.75	0.375	0.775	-0.29	0.993	-0.18
121	TaskRelevant	4	3	1	1	0.063	0.984	-1	5.799	-1.37
121	TaskRelevant	1	4	2	0.5	0.25	0.708	0.5	0.675	0.337
121	TaskRelevant	2	2	3	1	0.438	0.891	-1	4.422	-2.05
121	TaskRelevant	3	1	4	0.75	0.25	0.833	0	1.349	0
121	Revise TaskRelevant	3	1		0.75	0.313	0.805	-0.15	1.163	-0.09
122	TaskRelevant	4	4	1	0.5	0.125	0.795	0.75	1.15	0.575
122	TaskRelevant	1	3	2	1	0.25	0.938	-1	4.939	-1.8
122	TaskRelevant	3	2	3	0.75	0.313	0.805	-0.15	1.163	-0.09
122	TaskRelevant	2	1	4	1	0.5	0.875	-1	4.265	-2.13
122	Revise TaskRelevant	2	1		1	0.5	0.875	-1	4.265	-2.13
124	TaskRelevant	3	1	1	1	0.25	0.938	-1	4.939	-1.8
124	TaskRelevant	4	4	2	0.5	0.313	0.662	0.375	0.489	0.244
124	TaskRelevant	1	2	3	0.75	0.313	0.805	-0.15	1.163	-0.09
124	TaskRelevant	2	3	4	0.75	0.313	0.805	-0.15	1.163	-0.09
124	Revise TaskRelevant	2	3		0.75	0.313	0.805	-0.15	1.163	-0.09
125	TaskRelevant	3	2	1	0.5	0.125	0.795	0.75	1.15	0.575
125	TaskRelevant	1	3	2	0.5	0.188	0.752	0.625	0.887	0.444
125	TaskRelevant	2	4	3	0.75	0.125	0.887	0.4	1.825	0.238
125	TaskRelevant	4	1	4	0.75	0.313	0.805	-0.15	1.163	-0.09
125	Revise TaskRelevant	4	1		0.75	0.313	0.805	-0.15	1.163	-0.09
126	TaskRelevant	1	2	1	0.5	0	0.875	1	4.265	2.132
126	TaskRelevant	3	4	2	0.5	0	0.875	1	4.265	2.132
126	TaskRelevant	2	1	3	0.5	0.063	0.835	0.875	1.534	0.767
126	TaskRelevant	4	3	4	0.5	0	0.875	1	4.265	2.132
126	Revise TaskRelevant	4	3		0.5	0	0.875	1	4.265	2.132

Selected information elements

The following tables show selected information elements in each condition. “1” represents subject has selected individual information element.

Table H. 3: Selected information elements in condition 1

Condition 1 (High DS + High CS)																							
UID	Expertise	Problem ID	Sequence No	C1	R2	C3	H4	R5	T6	H7	C8	C9	R10	T11	H12	T13	H14	R15	C16	R17	C18	H19	T20
1	Expert	3	1	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	1	1	0	0	1
100	Expert	1	1	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	1
12	Expert	4	2	0	0	0	0	0	1	0	0	0	1	1	1	0	0	1	0	0	0	0	1
2	Expert	1	1	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	0	1	1
20	Expert	2	4	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1
22	Expert	4	2	0	1	0	0	1	1	0	0	0	0	1	0	1	0	1	0	1	0	1	1
24	Expert	4	4	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	1
25	Expert	1	3	0	0	0	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0	0	1
26	Expert	2	4	0	1	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	0	1
27	Expert	2	3	0	0	0	0	1	1	1	0	0	1	1	1	1	1	0	0	1	0	0	1
29	Expert	3	2	0	0	0	0	1	1	1	0	0	0	1	1	1	1	1	0	1	0	1	1
3	Expert	2	1	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	0	1
30	Expert	1	2	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	1
31	Expert	2	2	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	0	0	1
32	Expert	4	4	0	0	0	0	0	1	0	0	0	1	1	0	1	0	1	0	1	0	1	1
33	Expert	4	3	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	0	0
35	Expert	1	4	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	1	1
36	Expert	3	3	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	0	1	1
39	Expert	2	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
40	Expert	3	4	0	1	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	1	1	1
42	Expert	3	1	0	1	0	0	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	1
45	Expert	4	1	0	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	1	1	1
47	Expert	4	1	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1
48	Expert	2	1	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	1
52	Expert	2	2	0	1	0	0	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0	1
53	Expert	1	2	0	1	0	0	1	1	0	0	1	1	1	0	1	0	1	0	1	1	1	1
55	Expert	3	1	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	1
57	Expert	2	1	0	0	0	0	0	1	0	0	0	1	1	0	1	0	1	0	1	0	0	1
60	Expert	3	3	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1
65	Expert	4	2	0	1	0	0	1	1	1	0	0	1	1	1	1	1	1	0	1	0	0	1
66	Expert	4	4	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1
67	Expert	1	2	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	0	0	0	1
7	Expert	4	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1

70	Expert	1	4	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	1	1
71	Expert	4	3	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	0	1
72	Expert	4	2	0	1	0	0	0	1	1	0	0	1	1	1	1	1	1	0	1	1	1	1
78	Expert	3	3	0	1	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	1	1
81	Expert	3	4	0	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	1	1
83	Expert	1	2	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	0	0	0	1
85	Expert	3	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
86	Expert	4	3	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	1
87	Expert	4	4	0	1	0	0	1	1	1	0	0	1	1	1	1	1	1	0	0	0	1	1
9	Expert	4	1	0	1	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	1
90	Expert	1	3	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	0	1
94	Expert	2	4	0	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	1	1
95	Expert	2	3	0	0	0	0	1	1	1	0	0	1	1	1	1	1	0	0	0	0	0	0
96	Expert	4	3	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0	0	1
98	Expert	3	2	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	0	1
111	Novice	1	4	0	1	0	0	0	1	0	0	0	1	1	0	0	0	1	0	1	1	1	1
112	Novice	4	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	1	0	1	1
113	Novice	4	2	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	1	0	0	1
114	Novice	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1
115	Novice	4	3	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0
117	Novice	2	2	0	0	0	0	1	1	1	0	0	0	1	1	1	1	1	0	1	1	1	1
118	Novice	1	3	0	1	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	1	0	1
119	Novice	4	2	0	0	0	0	1	1	0	0	0	1	1	0	0	0	0	0	1	1	0	1
121	Novice	3	4	0	0	0	0	0	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0
122	Novice	2	4	0	0	0	0	0	1	1	1	1	0	1	1	1	1	0	1	1	0	1	1
124	Novice	3	1	0	0	0	0	1	1	0	1	0	1	1	0	1	0	1	0	0	0	0	1
125	Novice	4	4	0	0	0	0	1	1	0	1	0	0	0	0	1	0	1	0	1	0	1	1
126	Novice	2	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1
13	Novice	3	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	1
15	Novice	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	1
16	Novice	4	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
17	Novice	2	1	0	1	0	0	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1
18	Novice	3	2	1	1	0	1	1	1	1	0	1	1	0	0	0	0	1	0	1	1	1	1
21	Novice	2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
23	Novice	3	2	0	0	0	0	1	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0
28	Novice	4	4	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1	1
34	Novice	4	2	0	1	0	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	1	1
38	Novice	2	4	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
4	Novice	4	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1
43	Novice	3	1	0	0	0	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0	1	1
44	Novice	1	4	0	0	0	0	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1
49	Novice	2	3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1

50	Novice	4	4	0	0	0	0	0	1	0	1	1	1	1	0	1	0	0	0	1	0	0	1
5	Novice	2	1	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	1	1
51	Novice	3	4	0	1	0	0	1	1	0	0	0	0	1	0	1	0	1	1	1	1	1	1
54	Novice	1	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	1	1	1	1
59	Novice	4	1	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	1	1	1	1
61	Novice	3	3	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1
62	Novice	4	1	0	0	0	0	0	1	0	1	1	1	1	0	1	0	1	0	1	0	1	1
63	Novice	1	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1
64	Novice	2	2	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1
68	Novice	2	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1
69	Novice	3	3	0	1	0	0	1	1	1	0	0	1	1	1	1	1	1	0	1	1	1	1
74	Novice	3	3	0	0	0	0	1	0	0	0	1	1	1	0	1	0	0	0	0	1	0	1
75	Novice	1	2	0	1	0	0	1	1	1	0	0	1	1	1	1	1	0	0	0	0	0	1
77	Novice	3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0
80	Novice	1	3	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
84	Novice	4	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
88	Novice	1	2	0	0	0	0	0	1	0	0	1	1	1	0	1	0	0	0	0	0	0	1
91	Novice	4	3	0	0	1	0	1	1	1	0	0	1	1	1	1	1	0	0	0	1	1	1
92	Novice	1	2	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
93	Novice	4	3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
99	Novice	1	1	1	1	0	0	1	1	0	1	1	1	1	1	0	0	0	0	1	1	1	1

Table H. 4: Selected information elements in condition 2

Condition 2 (High DS + Low CS)																							
UID	Expertise	Problem ID	Sequence No	C1	U2	C3	L4	U5	T6	L7	C8	C9	U10	T11	L12	T13	L14	U15	C16	U17	C18	L19	T20
1	Expert	1	2	0	0	0	0	1	1	0	0	0	1	1	0	1	1	1	0	1	0	0	1
100	Expert	2	2	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
12	Expert	1	1	0	0	0	0	0	1	0	0	0	1	1	0	0	0	1	0	1	0	0	1
20	Expert	4	1	0	1	0	0	1	1	0	0	0	1	1	0	0	0	0	0	0	0	1	1
2	Expert	2	2	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	0	0	1
22	Expert	2	4	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	1	0	0	1
24	Expert	3	1	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	1
25	Expert	3	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
26	Expert	4	2	0	1	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	0	1
27	Expert	1	1	0	0	0	0	1	1	0	0	0	1	1	0	1	1	0	0	0	0	0	1
29	Expert	1	3	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	1	0	0	1
3	Expert	1	4	0	1	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	1	1
30	Expert	4	4	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	1	1
31	Expert	4	3	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	0	0	1
32	Expert	1	2	0	0	0	0	0	1	0	0	0	1	1	0	1	0	1	0	1	0	0	1

33	Expert	1	4	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	0	1
35	Expert	3	3	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	1	1
36	Expert	4	2	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	0	0	1
39	Expert	1	4	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1
40	Expert	1	3	1	1	0	0	1	1	0	0	0	1	1	0	1	1	1	0	1	1	0	1
42	Expert	4	3	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1
45	Expert	2	4	0	0	0	0	1	1	0	0	0	1	1	0	1	1	0	0	0	1	1	1
47	Expert	3	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	0	0	1	1
48	Expert	1	3	0	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1
52	Expert	1	1	0	1	0	0	1	1	0	0	0	1	1	0	1	0	1	0	0	0	0	1
53	Expert	2	1	1	0	1	0	1	1	1	0	1	1	1	0	1	1	1	0	0	0	0	1
55	Expert	4	2	0	0	0	0	1	1	0	0	0	1	1	0	1	1	0	0	0	0	0	1
57	Expert	1	3	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	0	1
60	Expert	4	1	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	1
65	Expert	3	3	0	1	0	0	1	1	0	0	0	1	1	0	1	0	1	0	0	0	0	1
66	Expert	3	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	1
67	Expert	2	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
7	Expert	3	4	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1
70	Expert	3	1	0	0	0	0	0	1	0	0	0	1	1	0	1	0	0	0	0	1	0	1
71	Expert	1	4	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	1
72	Expert	2	3	0	1	0	0	0	1	0	0	0	1	1	0	1	1	1	0	1	1	0	1
78	Expert	2	1	0	1	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	1	1
81	Expert	4	2	0	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1
83	Expert	3	4	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	0
85	Expert	2	3	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	1
86	Expert	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
87	Expert	3	2	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	0	0	1
9	Expert	2	3	0	0	0	0	1	1	0	0	0	1	1	0	0	0	1	0	0	0	0	1
90	Expert	4	4	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	0	1
94	Expert	3	3	0	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1
95	Expert	3	2	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	1
96	Expert	2	1	0	1	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	1	1
98	Expert	1	1	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	0	0	1
111	Novice	3	1	0	1	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	1	0	1
112	Novice	3	2	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	1	0	0	1
113	Novice	2	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	1	0	1	1
114	Novice	3	3	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	1	1	1	1
115	Novice	1	4	0	0	0	0	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	1
117	Novice	4	3	0	0	0	1	1	1	0	0	1	0	1	0	1	1	1	0	1	0	0	1
118	Novice	3	2	0	1	0	0	1	1	1	1	1	0	1	0	1	0	1	0	1	1	0	1
119	Novice	1	1	0	0	0	1	1	1	0	0	0	0	1	0	0	0	0	0	1	1	0	1
121	Novice	2	3	0	0	0	0	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1

122	Novice	3	3	0	0	0	0	0	1	1	1	1	0	1	1	0	0	0	0	1	0	0	1
124	Novice	1	3	0	0	0	0	1	1	0	0	0	1	0	0	1	0	1	0	1	1	0	1
125	Novice	3	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1
126	Novice	1	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
13	Novice	1	2	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1	1
15	Novice	3	4	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	1	1	0	1
16	Novice	2	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
17	Novice	1	4	0	1	0	0	1	1	0	0	0	1	1	0	1	1	1	1	1	1	1	1
18	Novice	1	1	1	1	0	1	0	1	1	0	1	1	0	1	0	0	1	0	1	1	1	1
21	Novice	4	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	Novice	1	3	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	1
28	Novice	3	1	0	0	0	0	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0
34	Novice	2	4	0	1	0	0	1	1	0	0	0	1	1	1	0	0	0	0	0	1	0	1
38	Novice	4	2	0	1	0	0	1	1	0	0	0	1	1	0	1	1	1	1	1	0	0	1
4	Novice	2	3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	1
43	Novice	4	2	0	0	0	0	0	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0
44	Novice	3	3	0	0	0	0	1	1	0	0	0	1	1	0	1	1	1	1	1	0	1	1
49	Novice	1	4	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
50	Novice	1	2	0	0	0	0	0	1	0	1	1	1	1	1	1	0	1	0	1	0	0	1
51	Novice	1	3	0	0	0	0	1	1	0	0	0	0	1	0	0	1	1	0	1	1	1	1
5	Novice	1	3	0	0	0	0	1	1	0	0	0	1	0	0	0	1	1	0	1	0	1	1
54	Novice	2	2	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	1	1	1	1
59	Novice	2	4	0	0	0	0	0	1	1	0	1	1	1	1	0	1	1	0	0	1	0	1
61	Novice	2	1	0	1	0	0	1	0	1	1	0	1	0	0	0	0	0	0	0	1	0	0
62	Novice	3	4	0	0	0	0	0	1	0	0	0	1	1	1	0	0	1	0	1	0	1	1
63	Novice	2	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
64	Novice	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
68	Novice	3	2	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	1
69	Novice	4	1	0	1	0	0	1	1	0	0	1	1	1	1	1	1	1	0	1	1	1	1
74	Novice	4	2	0	0	0	0	1	1	0	0	1	1	1	0	1	0	0	0	0	0	0	1
75	Novice	4	4	0	1	0	1	1	1	0	0	0	1	1	1	1	1	1	0	1	0	1	1
77	Novice	4	2	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0
80	Novice	4	4	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
84	Novice	3	3	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
88	Novice	2	4	0	1	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1
91	Novice	1	4	0	0	1	0	1	1	1	0	0	1	1	0	1	0	0	0	0	1	0	1
92	Novice	3	4	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0
93	Novice	3	2	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
99	Novice	2	2	0	1	0	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1

Table H. 5: Selected information elements in condition 3

Condition 3 (Low DS + High CS)																							
UID	Expertise	Problem ID	Sequence No	C1	U2	C3	H4	U5	T6	H7	C8	C9	U10	T11	H12	T13	H14	U15	C16	U17	C18	H19	T20
1	Expert	2	4	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	1	0	0	0	1
100	Expert	3	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
12	Expert	3	4	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1
20	Expert	1	2	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
22	Expert	1	1	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1
2	Expert	3	3	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	0	0	1	1
24	Expert	1	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
25	Expert	4	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1
26	Expert	3	1	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	0	0	0	1
27	Expert	4	4	0	0	0	0	0	1	1	0	0	0	1	1	1	1	1	0	0	0	0	1
29	Expert	2	1	0	0	0	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0	1	1
3	Expert	3	2	0	0	0	0	0	1	1	0	0	0	1	1	1	1	1	0	0	0	1	1
30	Expert	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
31	Expert	3	4	0	0	0	0	1	1	1	0	0	0	1	1	1	1	0	0	0	0	0	1
32	Expert	2	3	0	0	0	0	0	1	1	0	0	0	1	1	0	0	0	0	0	0	1	1
33	Expert	3	1	0	0	0	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0	0	1
35	Expert	4	1	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1
36	Expert	1	4	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	0	0	1	1
39	Expert	4	2	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
40	Expert	2	2	1	0	0	0	1	1	1	0	0	1	1	1	1	1	0	0	0	0	0	0
42	Expert	2	2	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1
45	Expert	3	2	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1	1	1	1
47	Expert	1	3	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1
48	Expert	4	4	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1
52	Expert	4	3	0	0	0	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0	0	1
53	Expert	4	4	0	0	1	0	1	1	0	0	1	0	1	0	1	0	0	0	1	1	1	1
55	Expert	2	4	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
57	Expert	4	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
60	Expert	2	2	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1
65	Expert	1	1	0	0	0	0	1	1	1	0	0	0	0	0	1	1	1	0	0	0	0	1
66	Expert	2	3	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1
67	Expert	3	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
7	Expert	2	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
70	Expert	4	2	0	0	0	0	0	1	0	0	0	0	1	1	1	1	0	0	1	1	1	1
71	Expert	2	1	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
72	Expert	3	4	0	0	0	0	1	1	1	0	0	0	1	1	1	1	0	0	1	1	1	1
78	Expert	1	4	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	1	1
81	Expert	2	1	0	0	0	0	1	1	1	0	1	0	1	1	1	1	0	0	0	0	1	1

83	Expert	4	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	0	0	0	1
85	Expert	4	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
86	Expert	2	4	0	0	0	0	0	1	0	0	1	0	1	0	1	0	0	0	0	0	0	1
87	Expert	2	3	0	0	0	0	1	1	1	0	0	0	1	1	1	1	0	0	0	0	1	1
9	Expert	3	2	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
90	Expert	2	2	0	0	0	0	0	1	0	0	1	0	1	0	1	0	1	0	0	0	0	1
94	Expert	1	2	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1
95	Expert	4	1	0	0	0	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0	0	1
96	Expert	1	2	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
98	Expert	4	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
111	Novice	2	3	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	0	1	1
112	Novice	2	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1
113	Novice	3	4	0	0	0	0	0	1	1	0	0	1	1	1	1	1	1	0	1	1	1	1
114	Novice	4	2	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1	1	1	1
115	Novice	3	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0
117	Novice	3	4	0	1	0	0	1	1	1	0	0	0	1	1	1	1	1	0	0	0	0	0
118	Novice	4	1	0	0	0	0	1	1	0	0	1	1	1	0	1	0	0	0	1	1	0	1
119	Novice	3	4	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1
121	Novice	4	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1
122	Novice	1	2	0	0	0	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0	1	1
124	Novice	2	4	0	0	0	0	1	1	0	1	0	1	1	0	0	0	0	0	1	1	0	1
125	Novice	1	2	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	0	1	1
126	Novice	4	4	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
13	Novice	2	4	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	1	1	1	1
15	Novice	2	3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	1
16	Novice	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
17	Novice	3	2	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	1	1	1	1	1
18	Novice	4	3	1	1	0	1	1	1	1	0	1	0	0	0	1	1	1	0	1	0	1	1
21	Novice	1	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
23	Novice	2	1	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0
28	Novice	1	3	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1
34	Novice	1	1	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1	1
38	Novice	3	1	0	0	0	0	1	1	1	0	0	0	1	1	1	1	1	1	0	0	1	1
4	Novice	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
43	Novice	2	4	0	0	0	0	0	1	1	0	0	0	1	1	1	1	1	0	0	0	1	1
44	Novice	4	1	0	1	0	0	0	1	0	0	1	1	1	0	1	0	0	1	0	0	1	1
49	Novice	4	2	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
50	Novice	2	3	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0
51	Novice	2	2	0	0	0	0	1	1	1	0	0	0	1	1	1	0	0	0	1	1	1	1
5	Novice	3	4	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1
54	Novice	3	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1
59	Novice	3	2	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	0	0	1	1

61	Novice	1	4	0	0	0	0	1	1	1	0	1	0	1	1	1	1	0	0	1	1	1	1
62	Novice	1	3	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1	1
63	Novice	4	4	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
64	Novice	4	3	0	0	0	0	0	1	1	0	0	0	1	1	0	0	1	0	0	0	0	1
68	Novice	4	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1
69	Novice	2	2	0	1	0	0	1	1	1	0	1	1	1	1	0	0	1	0	0	0	1	1
74	Novice	1	4	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0	0	1	0	1
75	Novice	3	3	0	0	0	0	1	1	1	0	0	0	1	1	1	1	0	0	0	0	0	1
77	Novice	2	1	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	0	0	1	0
80	Novice	2	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
84	Novice	1	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
88	Novice	3	1	0	0	0	1	0	1	0	1	1	0	1	0	1	0	0	0	0	0	0	0
91	Novice	2	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	1
92	Novice	4	3	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
93	Novice	2	4	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0
99	Novice	3	3	0	0	0	0	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0

Table H. 6: Selected information elements in condition 4

Condition 4 (Low DS + Low CS)																							
UID	expertise	Problem ID	Sequence No	C1	R2	C3	H4	R5	T6	H7	C8	C9	R10	T11	H12	T13	H14	R15	C16	R17	C18	H19	T20
1	Expert	4	3	0	0	0	0	1	1	0	0	0	0	1	0	1	1	0	1	0	0	0	1
100	Expert	4	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
12	Expert	2	3	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
2	Expert	4	4	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	0	0	0	1
20	Expert	3	3	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	1
22	Expert	3	3	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
24	Expert	2	2	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	0	0	1	1
25	Expert	2	4	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	1
26	Expert	1	3	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	0	0	1	1
27	Expert	3	2	0	0	0	0	1	1	0	0	0	1	1	0	1	1	1	1	0	0	0	1
29	Expert	4	4	0	0	0	0	-1	1	0	0	0	-1	1	0	1	0	-1	-1	0	0	0	1
30	Expert	2	1	0	0	0	0	1	1	0	0	0	0	1	0	1	1	0	0	0	0	0	0
31	Expert	1	1	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
32	Expert	3	1	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
33	Expert	2	2	0	0	0	0	0	1	0	0	0	0	1	0	1	1	0	0	0	0	0	1
3	Expert	4	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	0	0	1	1
35	Expert	2	2	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1
36	Expert	2	1	0	0	0	0	1	1	0	0	0	0	1	0	1	1	1	0	0	0	0	1
39	Expert	3	1	0	0	1	0	1	1	1	0	0	0	1	0	1	0	0	0	0	0	1	1
40	Expert	4	1	1	0	0	0	1	1	0	0	0	1	1	0	1	1	0	0	1	1	0	1

42	Expert	1	4	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1
45	Expert	1	3	0	0	0	0	0	1	0	0	0	0	1	1	1	1	0	0	1	1	1	1
47	Expert	2	2	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1
48	Expert	3	2	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	1
52	Expert	3	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
53	Expert	3	3	0	0	1	0	1	1	1	0	1	0	1	0	1	1	0	0	1	1	0	1
55	Expert	1	3	0	0	0	0	1	1	0	0	0	0	1	0	1	1	0	0	0	0	0	1
57	Expert	3	2	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
60	Expert	1	4	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1
65	Expert	2	4	0	0	0	0	1	1	0	0	0	0	1	0	1	1	1	0	0	0	1	1
66	Expert	1	2	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1
67	Expert	4	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
7	Expert	1	2	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
70	Expert	2	3	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1
71	Expert	3	2	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
72	Expert	1	1	0	0	0	0	1	1	0	0	0	0	1	0	1	1	0	0	1	1	0	1
78	Expert	4	2	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
81	Expert	1	3	0	0	0	1	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	1
83	Expert	2	1	0	0	0	0	0	1	0	0	0	0	1	0	1	1	1	0	0	0	0	1
85	Expert	1	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1
86	Expert	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
87	Expert	1	1	0	0	0	0	1	1	0	0	1	0	1	1	1	0	0	0	1	0	1	1
90	Expert	3	1	0	0	0	0	0	1	0	0	1	0	1	0	1	0	1	0	0	0	0	1
94	Expert	4	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1
9	Expert	1	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
95	Expert	1	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
96	Expert	3	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1
98	Expert	2	4	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1
111	Novice	4	2	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	1
112	Novice	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
113	Novice	1	1	0	0	0	0	1	1	0	0	0	0	0	0	1	0	1	0	0	0	0	1
114	Novice	2	4	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1	1	1	1
115	Novice	2	2	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0
117	Novice	1	1	0	0	0	0	1	1	0	0	1	1	1	1	1	0	0	0	0	0	0	1
118	Novice	2	4	0	0	0	0	1	1	1	0	0	0	1	0	1	1	0	0	1	1	1	1
119	Novice	2	3	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	1
121	Novice	1	2	0	0	0	0	1	0	1	1	0	0	0	0	1	1	0	0	0	0	0	1
122	Novice	4	1	0	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0
124	Novice	4	2	0	0	0	0	1	0	0	1	0	1	0	0	1	0	0	0	1	1	0	1
125	Novice	2	3	0	0	0	0	1	1	0	1	0	0	0	0	1	0	0	0	0	0	0	1
126	Novice	3	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
13	Novice	4	3	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	1	1	1

15	Novice	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
16	Novice	3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
17	Novice	4	3	0	0	0	0	1	1	0	0	0	0	1	0	1	1	1	1	1	1	1	1
18	Novice	2	4	1	1	0	1	1	1	1	0	0	0	0	1	1	0	0	0	1	1	1	1
21	Novice	3	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	Novice	4	4	0	0	0	0	1	1	0	0	1	1	1	0	1	0	0	0	0	0	0	1
28	Novice	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1
34	Novice	3	3	0	0	0	0	0	1	0	0	0	0	1	1	1	1	0	0	1	1	0	1
38	Novice	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
43	Novice	1	3	0	0	0	0	1	1	0	0	0	0	0	0	1	0	1	0	0	0	1	1
44	Novice	2	2	0	1	0	0	1	1	0	0	0	0	1	0	1	1	0	1	0	0	1	1
4	Novice	1	4	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
49	Novice	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
50	Novice	3	1	0	0	0	0	1	1	0	1	1	0	1	1	1	1	0	0	0	0	0	0
51	Novice	4	1	0	0	0	0	1	1	0	0	0	0	1	0	1	1	1	0	1	1	1	1
5	Novice	4	2	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	1	0	0	1	1
54	Novice	4	4	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	1	1	1	1
59	Novice	1	3	0	0	0	0	1	1	1	0	0	0	1	0	1	1	0	0	0	0	0	1
61	Novice	4	2	0	1	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1	1	1	1
62	Novice	2	2	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	1	1
63	Novice	3	3	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
64	Novice	3	4	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1
68	Novice	1	4	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1
69	Novice	1	4	0	1	0	1	1	1	0	0	1	1	1	1	1	1	1	0	1	1	1	1
74	Novice	2	1	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0	0	0	0	1
75	Novice	2	1	0	0	0	0	0	1	0	0	0	0	1	0	1	1	0	0	1	1	1	1
77	Novice	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
80	Novice	3	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
84	Novice	2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1
88	Novice	4	3	0	0	0	0	0	1	0	1	1	0	1	0	1	0	0	0	0	0	0	1
91	Novice	3	2	0	0	1	0	0	0	1	0	1	0	1	0	1	0	0	0	0	0	0	1
92	Novice	2	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	Novice	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
99	Novice	4	4	0	0	0	0	1	1	0	0	0	1	1	0	1	1	1	0	1	1	0	0

INFORMATION ACQUISITIONS

Acquisition measure

Table H. 7: Information acquisition raw data for experienced subject group.

Experienced subjects															
uid	session	Problem ID	Condition ID	Sequence No	Time			Number of clicks				Number of visited items			
					Total	Relevant	Irrelevant	Relevant	Common	CS	DS	Relevant	Common	CS	DS
2	TaskRelevant	1	1	1	132	29	58	9	5	1	7	4	4	1	5
2	TaskRelevant	2	2	2	95	14	44	5	2	7	4	4	2	4	4
2	TaskRelevant	3	3	3	103	35	30	6	5	1	5	4	5	1	4
2	TaskRelevant	4	4	4	102	25	58	4	2	4	4	4	2	3	4
2	Revise TaskRelevant	4	4		102	0	93	4	2	4	4	4	2	3	4
1	TaskRelevant	3	1	1	270	41	142	4	5	2	4	4	5	2	4
1	TaskRelevant	1	2	2	132	24	91	4	6	6	5	4	6	5	5
1	TaskRelevant	4	4	3	93	16	53	4	6	5	5	4	6	5	5
1	TaskRelevant	2	3	4	77	14	46	4	6	5	5	4	6	5	5
1	Revise TaskRelevant	2	3		370	12	199	4	6	5	5	4	6	5	5
9	TaskRelevant	4	1	1	218	49	115	4	5	2	6	4	4	2	4
9	TaskRelevant	3	3	2	193	66	82	4	3	0	4	4	3	0	3
9	TaskRelevant	2	2	3	115	34	59	4	0	4	5	4	0	4	4
9	TaskRelevant	1	4	4	83	44	20	4	1	1	3	4	1	1	3
9	Revise TaskRelevant	1	4		122	37	43	8	3	4	7	4	3	3	5
3	TaskRelevant	2	1	1	158	36	80	5	4	2	5	4	4	2	4
3	TaskRelevant	3	3	2	165	34	80	5	5	6	7	4	5	5	5
3	TaskRelevant	4	4	3	157	22	80	6	6	7	6	4	5	5	4
3	TaskRelevant	1	2	4	112	25	54	7	6	4	5	4	5	3	5
3	Revise TaskRelevant	1	2		949	0	616	7	6	4	5	4	5	3	5
57	TaskRelevant	2	1	1	225	57	123	4	6	3	5	4	6	3	5
57	TaskRelevant	3	4	2	131	23	65	4	6	5	5	4	6	5	5
57	TaskRelevant	1	2	3	106	22	58	4	5	5	5	4	5	5	5
57	TaskRelevant	4	3	4	135	21	9	4	1	0	2	4	1	0	2
57	Revise TaskRelevant	4	3		786	0	0	4	1	0	2	4	1	0	2
7	TaskRelevant	4	1	1	157	52	61	3	4	3	6	3	4	3	5
7	TaskRelevant	1	4	2	87	11	34	2	1	2	1	2	1	2	1
7	TaskRelevant	2	3	3	52	22	0	2	1	2	1	2	1	2	1
7	TaskRelevant	3	2	4	70	16	5	2	0	0	1	2	0	0	1
7	Revise TaskRelevant	3	2		61	30	4	4	0	0	1	4	0	0	1
12	TaskRelevant	1	2	1	187	27	121	4	6	5	5	4	6	5	5

12	TaskRelevant	4	1	2	156	76	19	3	1	1	4	3	1	1	4
12	TaskRelevant	2	4	3	67	10	11	3	1	0	1	3	1	0	1
12	TaskRelevant	3	3	4	74	18	11	3	1	0	1	3	1	0	1
12	Revise TaskRelevant	3	3		31	13	11	6	1	0	1	4	1	0	1
20	TaskRelevant	4	2	1	361	151	127	6	7	5	5	4	6	5	5
20	TaskRelevant	1	3	2	111	29	42	4	4	2	6	4	4	2	5
20	TaskRelevant	3	4	3	55	13	19	3	1	2	1	3	1	2	1
20	TaskRelevant	2	1	4	96	18	47	3	2	2	3	3	2	2	3
20	Revise TaskRelevant	2	1		177	122	44	4	2	2	3	4	2	2	3
27	TaskRelevant	1	2	1	196	22	152	4	7	5	6	4	6	5	5
27	TaskRelevant	3	4	2	226	31	157	5	8	6	6	4	6	5	5
27	TaskRelevant	2	1	3	142	13	116	4	6	6	5	4	6	5	5
27	TaskRelevant	4	3	4	139	32	49	4	9	5	7	4	6	5	5
27	Revise TaskRelevant	4	3		1383	0	25	4	9	5	7	4	6	5	5
24	TaskRelevant	3	2	1	144	34	86	4	5	5	4	4	5	5	4
24	TaskRelevant	2	4	2	95	15	53	5	6	6	5	4	6	5	5
24	TaskRelevant	1	3	3	65	22	25	4	2	1	3	4	2	1	3
24	TaskRelevant	4	1	4	62	15	23	4	2	0	4	4	2	0	4
24	Revise TaskRelevant	4	1		370	0	0	4	2	0	4	4	2	0	4
29	TaskRelevant	2	3	1	178	52	82	4	4	5	4	4	4	5	4
29	TaskRelevant	3	1	2	175	13	109	4	1	4	5	4	1	4	4
29	TaskRelevant	1	2	3	93	17	40	4	1	5	4	4	1	5	4
29	TaskRelevant	4	4	4	68	26	7	4	0	0	1	4	0	0	1
29	Revise TaskRelevant	4	4		11	0	0	4	0	0	1	4	0	0	1
22	TaskRelevant	1	3	1	255	35	177	4	7	4	5	4	6	4	5
22	TaskRelevant	4	1	2	162	21	104	4	5	1	6	4	4	1	5
22	TaskRelevant	3	4	3	106	18	38	4	3	4	3	4	3	4	3
22	TaskRelevant	2	2	4	89	18	42	4	2	3	5	4	2	2	5
22	Revise TaskRelevant	2	2		416	0	0	4	2	3	5	4	2	2	5
25	TaskRelevant	4	3	1	359	247	67	6	5	6	4	4	5	5	4
25	TaskRelevant	3	2	2	489	138	190	6	9	8	9	4	6	5	5
25	TaskRelevant	1	1	3	154	31	66	4	5	5	4	4	5	5	4
25	TaskRelevant	2	4	4	148	40	38	8	4	4	2	4	4	3	1
25	Revise TaskRelevant	2	4		10	5	0	10	4	4	2	4	4	3	1
26	TaskRelevant	3	3	1	323	130	100	4	6	3	6	4	6	3	5
26	TaskRelevant	4	2	2	205	16	147	4	6	6	5	4	6	5	5
26	TaskRelevant	1	4	3	169	16	111	5	5	7	5	4	5	5	5
26	TaskRelevant	2	1	4	96	20	48	5	6	5	5	4	6	5	5
26	Revise TaskRelevant	2	1		7	0	0	5	6	5	5	4	6	5	5
33	TaskRelevant	3	3	1	98	17	30	4	1	3	2	4	1	3	2
33	TaskRelevant	2	4	2	79	18	30	5	2	3	2	4	2	3	2
33	TaskRelevant	4	1	3	66	15	28	4	2	1	4	4	2	1	4

33	TaskRelevant	1	2	4	84	15	29	4	2	3	4	4	2	3	4
33	Revise TaskRelevant	1	2		259	0	77	4	2	3	4	4	2	3	4
35	TaskRelevant	4	3	1	102	25	35	4	2	2	3	4	2	2	3
35	TaskRelevant	2	4	2	60	13	27	4	1	4	0	4	1	4	0
35	TaskRelevant	3	2	3	74	14	22	4	1	1	4	4	1	1	4
35	TaskRelevant	1	1	4	42	10	20	4	0	1	4	4	0	1	4
35	Revise TaskRelevant	1	1		44	0	39	4	0	1	5	4	0	1	5
31	TaskRelevant	1	4	1	239	45	134	8	10	8	11	4	6	5	5
31	TaskRelevant	2	1	2	206	35	86	5	3	3	6	4	2	3	5
31	TaskRelevant	4	2	3	122	50	33	4	1	1	3	4	1	1	3
31	TaskRelevant	3	3	4	148	33	55	4	1	3	2	4	1	3	2
31	Revise TaskRelevant	3	3		32	0	373	4	1	3	2	4	1	3	2
30	TaskRelevant	2	4	1	125	18	79	4	6	5	5	4	6	5	5
30	TaskRelevant	1	1	2	99	18	59	4	2	1	3	4	2	1	3
30	TaskRelevant	3	3	3	116	33	13	3	1	2	2	3	1	2	2
30	TaskRelevant	4	2	4	91	19	41	4	1	4	2	4	1	4	2
30	Revise TaskRelevant	4	2		161	0	0	4	1	4	2	4	1	4	2
36	TaskRelevant	2	4	1	147	41	65	4	4	4	4	4	4	4	4
36	TaskRelevant	4	2	2	101	17	36	4	1	3	4	4	1	3	4
36	TaskRelevant	3	1	3	92	38	29	5	0	2	3	4	0	1	3
36	TaskRelevant	1	3	4	75	24	14	4	0	1	2	4	0	1	2
36	Revise TaskRelevant	1	3		687	0	164	4	0	1	2	4	0	1	2
32	TaskRelevant	3	4	1	315	66	182	5	9	9	5	4	6	5	5
32	TaskRelevant	1	2	2	115	40	43	4	4	5	4	4	4	5	4
32	TaskRelevant	2	3	3	114	25	47	4	2	3	3	4	2	3	3
32	TaskRelevant	4	1	4	85	15	37	4	1	2	4	4	1	2	4
32	Revise TaskRelevant	4	1		438	91	271	4	1	2	4	4	1	2	4
39	TaskRelevant	3	4	1	132	28	60	4	6	5	5	4	6	5	5
39	TaskRelevant	4	3	2	93	28	0	4	6	5	5	4	6	5	5
39	TaskRelevant	2	1	3	67	26	0	4	6	5	5	4	6	5	5
39	TaskRelevant	1	2	4	79	36	10	3	0	0	1	3	0	0	1
39	Revise TaskRelevant	1	2		132	0	0	3	0	0	1	3	0	0	1
40	TaskRelevant	4	4	1	220	43	134	6	8	8	8	4	6	5	5
40	TaskRelevant	2	3	2	120	12	77	3	7	4	4	3	5	4	4
40	TaskRelevant	1	2	3	120	15	81	4	6	5	5	4	6	5	5
40	TaskRelevant	3	1	4	179	33	111	4	5	3	5	4	5	3	5
40	Revise TaskRelevant	3	1		123	0	117	4	5	3	5	4	5	3	5
55	TaskRelevant	3	1	1	201	29	114	4	6	1	4	4	6	1	4
55	TaskRelevant	4	2	2	325	18	59	4	6	5	4	4	6	5	4
55	TaskRelevant	1	4	3	105	23	59	4	5	5	6	4	5	5	5
55	TaskRelevant	2	3	4	68	16	28	4	3	3	2	4	3	3	2
55	Revise TaskRelevant	2	3		548	0	116	4	3	3	2	4	3	3	2

42	TaskRelevant	3	1	1	222	44	107	7	7	4	6	4	5	4	4
42	TaskRelevant	2	3	2	157	47	52	5	4	3	6	4	3	3	5
42	TaskRelevant	4	2	3	213	68	76	5	3	3	3	4	2	3	2
42	TaskRelevant	1	4	4	77	13	30	3	1	2	3	3	1	2	3
42	Revise TaskRelevant	1	4		108	0	96	3	1	2	4	3	1	2	3
45	TaskRelevant	4	1	1	151	49	72	5	5	5	3	4	5	4	3
45	TaskRelevant	3	3	2	83	16	32	4	4	2	4	4	4	2	4
45	TaskRelevant	1	4	3	76	18	30	4	2	4	3	4	2	4	3
45	TaskRelevant	2	2	4	72	12	34	4	1	4	4	4	1	4	4
45	Revise TaskRelevant	2	2		1379	9	1131	9	6	10	12	4	4	5	5
48	TaskRelevant	2	1	1	163	38	91	4	0	0	5	4	0	0	4
48	TaskRelevant	3	4	2	170	34	31	4	0	1	2	4	0	1	2
48	TaskRelevant	1	2	3	133	28	40	5	0	3	2	4	0	3	2
48	TaskRelevant	4	3	4	128	34	37	7	2	2	2	4	1	2	2
48	Revise TaskRelevant	4	3		54	8	24	8	3	5	3	4	1	3	2
47	TaskRelevant	4	1	1	435	138	141	6	7	4	8	4	5	3	5
47	TaskRelevant	2	4	2	246	82	88	7	3	4	5	4	3	4	5
47	TaskRelevant	1	3	3	192	42	3	6	0	0	1	4	0	0	1
47	TaskRelevant	3	2	4	223	36	130	4	1	1	5	4	1	1	3
47	Revise TaskRelevant	3	2		474	7	93	4	1	1	5	4	1	1	3
52	TaskRelevant	1	2	1	86	17	50	4	6	5	5	4	6	5	5
52	TaskRelevant	2	1	2	92	18	55	4	5	6	5	4	5	5	5
52	TaskRelevant	4	3	3	68	13	34	4	5	4	3	4	4	4	3
52	TaskRelevant	3	4	4	71	16	22	4	5	4	3	4	5	4	3
52	Revise TaskRelevant	3	4		227	0	0	4	5	4	3	4	5	4	3
53	TaskRelevant	2	2	1	339	43	196	6	11	8	8	4	6	5	5
53	TaskRelevant	1	1	2	197	30	110	5	5	6	5	4	5	5	5
53	TaskRelevant	3	4	3	180	28	97	4	8	5	5	4	6	5	5
53	TaskRelevant	4	3	4	150	23	58	4	7	2	5	4	6	2	5
53	Revise TaskRelevant	4	3		521	0	372	4	7	2	5	4	6	2	5
60	TaskRelevant	4	2	1	144	34	50	4	4	2	3	4	3	2	2
60	TaskRelevant	2	3	2	90	23	32	4	3	1	1	4	3	1	1
60	TaskRelevant	3	1	3	102	31	25	4	0	0	2	4	0	0	2
60	TaskRelevant	1	4	4	26	13	0	3	0	0	2	3	0	0	2
60	Revise TaskRelevant	1	4		212	0	0	3	0	0	2	3	0	0	2
70	TaskRelevant	3	2	1	370	44	201	5	7	9	12	4	6	5	5
70	TaskRelevant	4	3	2	185	27	113	5	6	6	5	4	6	4	5
70	TaskRelevant	2	4	3	205	12	116	5	6	7	7	4	3	5	4
70	TaskRelevant	1	1	4	120	16	65	5	3	2	9	4	3	2	5
70	Revise TaskRelevant	1	1		769	0	713	5	3	2	9	4	3	2	5
78	TaskRelevant	2	2	1	183	37	125	4	6	6	5	4	6	5	5
78	TaskRelevant	4	4	2	162	30	102	4	5	5	6	4	5	5	5

78	TaskRelevant	3	1	3	137	49	56	4	5	2	5	4	5	2	5
78	TaskRelevant	1	3	4	98	34	34	4	5	2	5	4	5	2	4
78	Revise TaskRelevant	1	3		361	0	194	4	5	2	5	4	5	2	4
66	TaskRelevant	3	2	1	72	17	35	3	4	3	3	3	4	3	3
66	TaskRelevant	1	4	2	122	16	41	4	6	6	6	4	4	5	4
66	TaskRelevant	2	3	3	42	12	0	3	6	6	6	3	4	5	4
66	TaskRelevant	4	1	4	58	13	20	5	0	1	2	4	0	1	2
66	Revise TaskRelevant	4	1		349	0	0	5	0	1	2	4	0	1	2
65	TaskRelevant	1	3	1	183	36	123	8	11	14	10	4	6	5	5
65	TaskRelevant	4	1	2	126	13	90	4	6	5	5	4	6	5	5
65	TaskRelevant	3	2	3	150	14	99	4	6	6	6	4	6	5	5
65	TaskRelevant	2	4	4	77	13	46	4	5	5	5	4	5	5	5
65	Revise TaskRelevant	2	4		91	6	83	4	5	5	5	4	5	5	5
67	TaskRelevant	3	3	1	175	48	86	4	5	1	5	4	4	1	4
67	TaskRelevant	1	1	2	66	31	11	4	1	0	2	4	1	0	2
67	TaskRelevant	4	4	3	81	48	0	4	1	0	2	4	1	0	2
67	TaskRelevant	2	2	4	120	43	50	4	0	0	2	4	0	0	1
67	Revise TaskRelevant	2	2		462	0	0	4	0	0	2	4	0	0	1
81	TaskRelevant	2	3	1	240	88	127	4	5	5	6	4	5	5	5
81	TaskRelevant	4	2	2	192	47	105	4	5	5	5	4	5	5	5
81	TaskRelevant	1	4	3	123	23	52	3	4	6	4	3	4	5	4
81	TaskRelevant	3	1	4	135	30	52	3	3	1	4	3	3	1	4
81	Revise TaskRelevant	3	1		32	0	19	3	3	4	4	3	3	4	4
71	TaskRelevant	2	3	1	158	28	101	4	7	2	6	4	6	2	5
71	TaskRelevant	3	4	2	112	23	45	4	5	5	4	4	5	5	4
71	TaskRelevant	4	1	3	116	14	60	4	3	0	4	4	3	0	4
71	TaskRelevant	1	2	4	83	15	52	4	2	3	4	4	2	3	4
71	Revise TaskRelevant	1	2		5	0	18	4	2	3	4	4	2	3	4
85	TaskRelevant	4	3	1	84	29	0	4	0	0	0	4	0	0	0
85	TaskRelevant	1	4	2	92	13	38	2	1	3	2	2	1	3	2
85	TaskRelevant	2	2	3	80	19	32	4	3	2	2	4	3	2	2
85	TaskRelevant	3	1	4	84	12	8	4	1	0	0	4	1	0	0
85	Revise TaskRelevant	3	1		4	45	0	4	1	0	0	4	1	0	0
72	TaskRelevant	1	4	1	225	41	139	4	6	5	8	4	6	5	5
72	TaskRelevant	4	1	2	336	73	201	4	5	6	5	4	5	5	5
72	TaskRelevant	2	2	3	173	28	97	4	5	6	4	4	5	5	4
72	TaskRelevant	3	3	4	140	23	76	4	3	4	5	4	3	4	5
72	Revise TaskRelevant	3	3		1847	0	705	4	3	4	5	4	3	4	5
83	TaskRelevant	2	4	1	252	103	121	5	5	4	5	4	5	4	4
83	TaskRelevant	1	1	2	103	35	42	4	3	1	4	4	3	1	4
83	TaskRelevant	4	3	3	117	43	40	4	3	0	3	4	3	0	3
83	TaskRelevant	3	2	4	89	16	49	3	2	2	4	3	2	2	3

83	Revise TaskRelevant	3	2		135	87	47	4	3	2	5	4	2	2	3
86	TaskRelevant	1	4	1	63	11	17	1	2	2	1	1	2	2	1
86	TaskRelevant	3	2	2	19	5	0	1	2	2	1	1	2	2	1
86	TaskRelevant	4	1	3	58	9	25	2	1	2	3	2	1	2	3
86	TaskRelevant	2	3	4	60	18	22	4	3	1	0	4	3	1	0
86	Revise TaskRelevant	2	3		12	0	10	4	3	1	0	4	3	1	0
87	TaskRelevant	1	4	1	170	32	104	6	11	10	10	4	6	5	5
87	TaskRelevant	3	2	2	103	18	63	4	4	4	5	4	4	4	5
87	TaskRelevant	2	3	3	72	12	41	4	4	5	3	4	4	5	3
87	TaskRelevant	4	1	4	67	14	32	4	2	4	5	4	2	4	4
87	Revise TaskRelevant	4	1		35	0	20	4	2	4	5	4	2	4	4
90	TaskRelevant	3	4	1	249	39	132	4	8	6	5	4	5	5	5
90	TaskRelevant	2	3	2	146	41	69	4	4	4	3	4	4	4	3
90	TaskRelevant	1	1	3	81	29	27	5	2	0	4	4	2	0	4
90	TaskRelevant	4	2	4	75	22	22	4	1	2	4	4	1	2	4
90	Revise TaskRelevant	4	2		23	0	15	4	1	2	4	4	1	2	4
94	TaskRelevant	4	4	1	179	35	78	4	3	2	3	4	3	2	3
94	TaskRelevant	1	3	2	59	16	0	3	3	2	3	3	3	2	3
94	TaskRelevant	3	2	3	74	17	13	3	0	0	2	3	0	0	2
94	TaskRelevant	2	1	4	65	14	20	3	1	1	2	3	1	1	2
94	Revise TaskRelevant	2	1		13	0	7	3	1	1	3	3	1	1	3
95	TaskRelevant	4	3	1	283	45	116	5	5	4	6	4	5	4	5
95	TaskRelevant	3	2	2	233	45	129	5	6	6	5	4	5	5	4
95	TaskRelevant	2	1	3	336	53	220	6	5	6	5	4	4	4	4
95	TaskRelevant	1	4	4	231	60	135	5	4	6	2	4	4	4	2
95	Revise TaskRelevant	1	4		148	0	0	5	4	6	2	4	4	4	2
96	TaskRelevant	2	2	1	189	54	93	4	6	4	5	4	6	4	5
96	TaskRelevant	1	3	2	152	37	86	4	5	5	4	4	5	5	3
96	TaskRelevant	4	1	3	206	31	125	4	0	0	3	4	0	0	3
96	TaskRelevant	3	4	4	75	21	19	4	0	1	1	4	0	1	1
96	Revise TaskRelevant	3	4		410	0	16	4	0	1	1	4	0	1	1
98	TaskRelevant	1	2	1	183	60	55	4	0	0	3	4	0	0	3
98	TaskRelevant	3	1	2	279	50	151	5	0	3	5	4	0	3	4
98	TaskRelevant	4	3	3	130	49	7	4	0	0	1	4	0	0	1
98	TaskRelevant	2	4	4	101	44	15	5	0	1	0	4	0	1	0
98	Revise TaskRelevant	2	4		188	0	0	5	0	1	0	4	0	1	0
100	TaskRelevant	1	1	1	350	111	46	5	2	0	2	4	2	0	2
100	TaskRelevant	2	2	2	279	96	55	4	1	1	2	4	1	1	1
100	TaskRelevant	3	3	3	244	62	33	4	0	1	0	4	0	1	0
100	TaskRelevant	4	4	4	208	83	6	5	1	0	0	4	1	0	0
100	Revise TaskRelevant	4	4		575	0	0	5	1	0	0	4	1	0	0

Table H. 8: Information acquisition raw data for novice group.

Novice															
uid	session	Problem ID	Condition ID	Sequence No	Time			Number of clicks				Number of visited items			
					Total	Relevant	Irrelevant	Relevant	Common	CS	DS	Relevant	Common	CS	DS
13	TaskRelevant	3	1	1	167	15	74	5	2	4	4	4	2	3	4
13	TaskRelevant	1	2	2	66	20	9	3	0	2	0	3	0	2	0
13	TaskRelevant	4	4	3	134	43	43	5	1	2	3	4	1	2	2
13	TaskRelevant	2	3	4	89	17	29	4	1	1	2	4	1	1	2
13	Revise TaskRelevant	2	3		536	99	76	4	1	1	2	4	1	1	2
4	TaskRelevant	4	1	1	93	11	62	1	3	2	4	1	3	2	4
4	TaskRelevant	3	3	2	24	10	2	1	0	1	0	1	0	1	0
4	TaskRelevant	2	2	3	77	21	14	3	0	2	2	3	0	2	2
4	TaskRelevant	1	4	4	50	8	10	2	0	1	1	2	0	1	1
4	Revise TaskRelevant	1	4		22	2	5	2	0	1	2	2	0	1	2
17	TaskRelevant	2	1	1	163	27	103	4	6	5	5	4	6	5	5
17	TaskRelevant	3	3	2	190	82	54	4	6	2	5	4	6	2	5
17	TaskRelevant	4	4	3	133	19	87	4	6	6	6	4	6	5	5
17	TaskRelevant	1	2	4	98	22	65	5	6	5	6	4	6	5	5
17	Revise TaskRelevant	1	2		35	0	28	5	6	5	6	4	6	5	5
5	TaskRelevant	2	1	1	143	23	100	4	5	4	6	4	5	4	5
5	TaskRelevant	4	4	2	221	30	159	5	7	4	7	4	5	4	5
5	TaskRelevant	1	2	3	93	20	53	3	2	3	5	3	2	3	4
5	TaskRelevant	3	3	4	132	32	61	4	2	3	4	4	2	3	4
5	Revise TaskRelevant	3	3		47	18	165	6	2	6	6	4	2	3	4
15	TaskRelevant	4	1	1	135	5	42	1	3	1	2	1	3	1	2
15	TaskRelevant	1	4	2	281	23	96	4	6	4	5	4	4	4	4
15	TaskRelevant	2	3	3	159	13	81	2	5	3	4	2	4	3	4
15	TaskRelevant	3	2	4	186	18	135	2	3	1	4	2	2	1	4
15	Revise TaskRelevant	3	2		854	0	0	2	3	1	4	2	2	1	4
18	TaskRelevant	1	2	1	294	42	204	4	7	6	7	4	6	5	5
18	TaskRelevant	3	1	2	174	35	88	5	5	4	5	4	5	3	5
18	TaskRelevant	4	3	3	174	40	96	5	5	6	5	4	5	4	4
18	TaskRelevant	2	4	4	118	20	62	4	5	4	4	4	4	4	4
18	Revise TaskRelevant	2	4		791	0	0	4	5	4	4	4	4	4	4
16	TaskRelevant	2	2	1	217	49	114	5	6	5	5	4	6	5	4
16	TaskRelevant	1	3	2	130	20	76	4	5	4	4	3	4	3	3
16	TaskRelevant	4	1	3	80	12	48	3	2	2	1	2	1	1	1
16	TaskRelevant	3	4	4	75	13	11	3	1	1	1	2	1	1	1
16	Revise TaskRelevant	3	4		303	0	0	3	1	1	1	2	1	1	1
21	TaskRelevant	4	2	1	51	7	3	1	1	0	0	1	1	0	0

21	TaskRelevant	1	3	2	29	5	0	1	1	0	0	1	1	0	0
21	TaskRelevant	3	4	3	32	3	0	1	1	0	0	1	1	0	0
21	TaskRelevant	2	1	4	20	0	4	0	0	0	1	0	0	0	1
21	Revise TaskRelevant	2	1		282	0	0	0	0	0	1	0	0	0	1
28	TaskRelevant	3	2	1	137	17	70	2	4	4	4	2	3	3	3
28	TaskRelevant	2	4	2	67	7	38	1	2	2	3	1	2	2	3
28	TaskRelevant	1	3	3	73	17	32	4	2	3	2	3	2	2	2
28	TaskRelevant	4	1	4	57	13	14	3	1	1	0	3	1	1	0
28	Revise TaskRelevant	4	1		239	0	0	3	1	1	0	3	1	1	0
23	TaskRelevant	2	3	1	151	32	40	2	1	2	1	2	1	2	1
23	TaskRelevant	3	1	2	132	45	26	2	2	1	2	2	2	1	2
23	TaskRelevant	1	2	3	83	26	30	3	2	2	1	3	2	2	1
23	TaskRelevant	4	4	4	134	26	61	4	2	3	3	4	2	3	2
23	Revise TaskRelevant	4	4		37	8	19	5	2	3	3	4	2	3	2
34	TaskRelevant	1	3	1	142	38	44	4	3	1	0	4	3	1	0
34	TaskRelevant	4	1	2	194	41	93	3	4	2	3	3	3	2	3
34	TaskRelevant	3	4	3	153	15	89	4	2	5	2	4	1	5	2
34	TaskRelevant	2	2	4	128	47	34	4	1	1	3	4	1	1	3
34	Revise TaskRelevant	2	2		246	0	0	4	1	1	3	4	1	1	3
38	TaskRelevant	3	3	1	128	31	59	5	6	6	5	4	6	5	5
38	TaskRelevant	4	2	2	95	12	63	4	6	6	6	4	6	5	5
38	TaskRelevant	1	4	3	82	20	36	4	4	3	3	4	4	3	3
38	TaskRelevant	2	1	4	58	7	20	1	2	2	2	1	2	2	2
38	Revise TaskRelevant	2	1		411	0	6	1	2	2	2	1	2	2	2
44	TaskRelevant	4	3	1	143	23	78	5	6	3	4	4	6	2	4
44	TaskRelevant	2	4	2	154	19	71	4	5	5	5	4	5	5	4
44	TaskRelevant	3	2	3	101	14	58	4	5	5	5	4	5	4	5
44	TaskRelevant	1	1	4	113	13	73	4	5	5	5	4	5	5	5
44	Revise TaskRelevant	1	1		809	0	82	4	5	5	5	4	5	5	5
75	TaskRelevant	2	4	1	345	69	236	8	11	8	9	4	6	5	5
75	TaskRelevant	1	1	2	134	26	68	6	6	7	6	4	5	5	4
75	TaskRelevant	3	3	3	87	12	46	4	3	5	2	4	3	5	2
75	TaskRelevant	4	2	4	103	18	62	4	3	5	5	4	3	5	5
75	Revise TaskRelevant	4	2		6	235	130	4	3	5	5	4	3	5	5
74	TaskRelevant	2	4	1	150	36	73	5	6	6	5	4	6	5	5
74	TaskRelevant	4	2	2	97	16	44	4	6	5	5	4	6	5	5
74	TaskRelevant	3	1	3	113	22	57	14	6	3	5	4	6	3	5
74	TaskRelevant	1	3	4	76	19	35	4	5	1	4	4	5	1	4
74	Revise TaskRelevant	1	3		450	161	10	4	5	1	4	4	5	1	4
50	TaskRelevant	3	4	1	154	20	91	6	8	4	8	4	5	3	5
50	TaskRelevant	1	2	2	58	21	19	4	2	2	3	4	2	2	3
50	TaskRelevant	2	3	3	95	8	11	3	0	1	1	3	0	1	1

50	TaskRelevant	4	1	4	58	17	13	4	2	0	2	4	2	0	2
50	Revise TaskRelevant	4	1		541	0	24	4	2	0	2	4	2	0	2
49	TaskRelevant	3	4	1	67	14	7	1	0	0	1	1	0	0	1
49	TaskRelevant	4	3	2	52	7	12	1	1	0	1	1	1	0	1
49	TaskRelevant	2	1	3	87	9	10	2	0	1	1	2	0	1	1
49	TaskRelevant	1	2	4	49	12	10	1	1	1	0	1	1	1	0
49	Revise TaskRelevant	1	2		10	12	7	3	1	1	1	3	1	1	1
51	TaskRelevant	4	4	1	276	27	153	4	6	6	6	4	5	5	4
51	TaskRelevant	2	3	2	186	97	47	4	4	4	4	4	4	4	4
51	TaskRelevant	1	2	3	179	14	115	3	4	5	5	3	4	5	5
51	TaskRelevant	3	1	4	175	38	86	5	6	4	5	4	6	4	5
51	Revise TaskRelevant	3	1		385	0	369	5	7	4	5	4	6	4	5
54	TaskRelevant	1	1	1	270	62	147	6	9	5	8	4	6	4	5
54	TaskRelevant	2	2	2	191	20	136	4	7	5	7	4	6	5	5
54	TaskRelevant	3	3	3	190	50	89	4	7	4	6	4	6	3	5
54	TaskRelevant	4	4	4	162	34	89	5	9	5	8	4	6	5	5
54	Revise TaskRelevant	4	4		449	161	189	10	16	10	14	4	6	5	5
43	TaskRelevant	3	1	1	167	40	87	6	5	6	1	4	5	4	1
43	TaskRelevant	4	2	2	76	16	30	2	2	2	1	2	2	2	1
43	TaskRelevant	1	4	3	73	18	33	3	1	2	3	3	1	2	3
43	TaskRelevant	2	3	4	70	17	38	4	1	4	3	4	1	4	3
43	Revise TaskRelevant	2	3		299	0	292	4	1	4	4	4	1	4	4
59	TaskRelevant	4	1	1	208	37	112	4	4	1	5	4	4	1	4
59	TaskRelevant	3	3	2	154	28	40	5	1	2	3	4	1	2	3
59	TaskRelevant	1	4	3	136	14	90	4	3	5	4	4	3	4	3
59	TaskRelevant	2	2	4	86	17	36	3	3	3	3	3	3	3	3
59	Revise TaskRelevant	2	2		511	0	0	3	3	3	3	3	3	3	3
62	TaskRelevant	4	1	1	307	40	208	8	11	5	6	4	5	3	4
62	TaskRelevant	2	4	2	179	34	86	5	5	6	7	4	5	4	4
62	TaskRelevant	1	3	3	137	28	64	8	3	5	7	4	2	3	4
62	TaskRelevant	3	2	4	89	21	39	5	1	4	4	4	1	4	3
62	Revise TaskRelevant	3	2		123	26	73	11	8	11	11	4	5	5	5
64	TaskRelevant	1	2	1	182	43	61	3	3	2	3	3	3	2	3
64	TaskRelevant	2	1	2	375	79	173	10	8	8	9	4	5	4	5
64	TaskRelevant	4	3	3	163	18	31	5	1	3	2	4	1	2	2
64	TaskRelevant	3	4	4	184	15	110	2	2	3	4	2	2	2	3
64	Revise TaskRelevant	3	4		46	6	13	5	3	4	5	4	2	2	3
63	TaskRelevant	2	2	1	139	65	25	1	1	2	1	1	1	2	1
63	TaskRelevant	1	1	2	74	21	30	2	0	0	2	2	0	0	2
63	TaskRelevant	3	4	3	72	8	10	2	0	0	1	2	0	0	1
63	TaskRelevant	4	3	4	54	15	13	2	0	0	2	2	0	0	2
63	Revise TaskRelevant	4	3		40	20	0	3	0	0	2	3	0	0	2

69	TaskRelevant	4	2	1	153	22	90	7	6	5	7	4	6	5	5
69	TaskRelevant	2	3	2	115	25	66	5	4	3	6	4	4	3	5
69	TaskRelevant	3	1	3	125	24	38	5	3	4	5	4	3	4	5
69	TaskRelevant	1	4	4	94	12	54	4	3	5	5	4	2	5	5
69	Revise TaskRelevant	1	4		1153	0	0	4	3	5	5	4	2	5	5
61	TaskRelevant	2	2	1	364	50	251	8	10	6	10	4	6	4	5
61	TaskRelevant	4	4	2	200	26	81	4	3	3	4	4	3	3	3
61	TaskRelevant	3	1	3	192	27	101	2	3	2	4	2	3	2	2
61	TaskRelevant	1	3	4	116	12	73	4	4	5	4	4	4	5	3
61	Revise TaskRelevant	1	3		268	0	10	4	4	5	4	4	4	5	3
84	TaskRelevant	1	3	1	388	46	202	9	11	8	9	4	6	5	5
84	TaskRelevant	4	1	2	150	31	91	4	5	2	5	4	5	2	5
84	TaskRelevant	3	2	3	88	25	36	4	3	2	2	3	3	2	2
84	TaskRelevant	2	4	4	54	5	17	1	1	1	1	1	1	1	1
84	Revise TaskRelevant	2	4		273	0	4	1	1	2	1	1	1	2	1
88	TaskRelevant	3	3	1	255	61	106	4	6	4	5	4	6	3	5
88	TaskRelevant	1	1	2	143	35	64	4	5	1	4	4	4	1	4
88	TaskRelevant	4	4	3	174	28	85	4	5	5	4	4	5	4	4
88	TaskRelevant	2	2	4	144	27	66	4	3	4	2	4	3	4	2
88	Revise TaskRelevant	2	2		529	0	0	4	3	4	2	4	3	4	2
68	TaskRelevant	4	3	1	148	41	9	4	0	0	1	4	0	0	1
68	TaskRelevant	3	2	2	123	21	39	3	2	2	1	3	2	2	1
68	TaskRelevant	2	1	3	129	34	13	4	0	0	2	3	0	0	1
68	TaskRelevant	1	4	4	81	13	22	2	0	1	1	2	0	1	1
68	Revise TaskRelevant	1	4		201	74	113	3	1	1	1	3	1	1	1
77	TaskRelevant	2	3	1	67	10	27	4	1	3	3	3	1	3	3
77	TaskRelevant	4	2	2	24	8	4	1	0	1	0	1	0	1	0
77	TaskRelevant	1	4	3	14	3	5	1	1	0	0	1	1	0	0
77	TaskRelevant	3	1	4	12	0	6	0	1	1	0	0	1	1	0
77	Revise TaskRelevant	3	1		261	0	0	0	1	1	0	0	1	1	0
91	TaskRelevant	2	3	1	152	39	54	5	4	3	3	4	4	3	3
91	TaskRelevant	3	4	2	188	33	91	5	6	6	2	4	5	5	2
91	TaskRelevant	4	1	3	208	23	124	7	10	8	5	4	6	5	5
91	TaskRelevant	1	2	4	116	28	60	5	4	5	4	4	4	4	4
91	Revise TaskRelevant	1	2		427	0	0	5	4	5	4	4	4	4	4
113	TaskRelevant	1	4	1	133	22	71	7	8	6	8	4	5	4	4
113	TaskRelevant	4	1	2	72	23	18	4	2	0	3	4	2	0	3
113	TaskRelevant	2	2	3	67	17	23	4	2	2	3	4	2	2	3
113	TaskRelevant	3	3	4	148	9	29	4	3	4	3	4	3	4	3
113	Revise TaskRelevant	3	3		16	0	297	4	3	4	4	4	3	4	3
92	TaskRelevant	2	4	1	100	6	33	1	1	1	1	1	1	1	1
92	TaskRelevant	1	1	2	80	16	42	2	2	0	2	2	2	0	2

92	TaskRelevant	4	3	3	110	32	23	2	0	0	2	2	0	0	2
92	TaskRelevant	3	2	4	57	21	14	2	0	0	2	2	0	0	2
92	Revise TaskRelevant	3	2		615	0	0	2	0	0	2	2	0	0	2
93	TaskRelevant	1	4	1	81	0	70	0	3	1	2	0	2	1	1
93	TaskRelevant	3	2	2	115	24	41	3	1	2	2	2	1	1	1
93	TaskRelevant	4	1	3	104	8	51	3	2	2	3	2	1	1	1
93	TaskRelevant	2	3	4	56	18	27	3	1	1	2	2	1	1	1
93	Revise TaskRelevant	2	3		9	0	0	3	1	1	2	2	1	1	1
112	TaskRelevant	1	4	1	206	19	67	3	4	3	4	3	3	3	4
112	TaskRelevant	3	2	2	258	64	105	5	3	4	4	4	3	4	3
112	TaskRelevant	2	3	3	67	15	25	4	0	2	1	4	0	1	1
112	TaskRelevant	4	1	4	59	17	9	4	0	1	2	4	0	1	2
112	Revise TaskRelevant	4	1		630	45	0	4	0	1	2	4	0	1	2
80	TaskRelevant	3	4	1	114	30	45	3	3	1	3	3	3	1	3
80	TaskRelevant	2	3	2	117	51	15	3	0	1	0	3	0	1	0
80	TaskRelevant	1	1	3	77	5	30	1	1	0	2	1	1	0	2
80	TaskRelevant	4	2	4	95	32	18	1	0	0	2	1	0	0	2
80	Revise TaskRelevant	4	2		36	15	2	3	0	0	2	3	0	0	2
111	TaskRelevant	3	2	1	355	30	239	6	8	7	8	4	6	4	4
111	TaskRelevant	4	4	2	138	16	74	3	5	4	5	3	4	4	4
111	TaskRelevant	2	3	3	100	22	44	3	4	2	2	3	4	2	2
111	TaskRelevant	1	1	4	78	12	42	3	3	1	5	3	3	1	5
111	Revise TaskRelevant	1	1		564	6	5	3	3	1	5	3	3	1	5
114	TaskRelevant	1	1	1	128	44	20	5	1	2	1	4	1	1	1
114	TaskRelevant	4	3	2	91	29	22	4	2	1	2	4	1	1	2
114	TaskRelevant	3	2	3	74	9	35	3	2	2	2	3	2	2	2
114	TaskRelevant	2	4	4	56	17	19	4	2	1	2	4	2	1	2
114	Revise TaskRelevant	2	4		13	0	253	4	3	1	3	4	2	1	2
115	TaskRelevant	3	3	1	105	29	36	5	2	1	3	4	2	1	3
115	TaskRelevant	2	4	2	98	18	48	3	2	4	3	3	2	4	3
115	TaskRelevant	4	1	3	128	53	43	3	1	1	4	3	1	1	4
115	TaskRelevant	1	2	4	67	16	21	4	0	3	2	4	0	3	2
115	Revise TaskRelevant	1	2		290	0	0	4	0	3	2	4	0	3	2
117	TaskRelevant	1	4	1	188	21	82	4	6	4	6	4	5	4	4
117	TaskRelevant	2	1	2	90	15	41	4	3	4	4	4	3	4	4
117	TaskRelevant	4	2	3	88	11	44	4	3	3	4	4	3	3	4
117	TaskRelevant	3	3	4	124	9	44	3	2	3	3	3	2	3	3
117	Revise TaskRelevant	3	3		390	0	0	3	2	3	3	3	2	3	3
118	TaskRelevant	4	3	1	259	30	169	4	9	3	8	4	6	3	5
118	TaskRelevant	3	2	2	210	24	131	4	5	6	5	4	4	5	5
118	TaskRelevant	1	1	3	91	16	56	4	6	1	5	4	6	1	5
118	TaskRelevant	2	4	4	113	17	62	4	3	7	5	4	3	5	5

118	Revise TaskRelevant	2	4		78	8	47	8	7	11	9	4	4	5	5
119	TaskRelevant	1	2	1	132	21	72	4	6	3	5	4	5	3	5
119	TaskRelevant	4	1	2	78	17	28	3	3	1	4	3	3	1	4
119	TaskRelevant	2	4	3	85	21	37	4	6	4	4	4	5	4	4
119	TaskRelevant	3	3	4	110	32	31	3	5	0	2	3	5	0	2
119	Revise TaskRelevant	3	3		61	39	3	5	5	1	2	4	5	1	2
99	TaskRelevant	1	1	1	103	11	61	3	6	2	5	3	4	2	4
99	TaskRelevant	2	2	2	103	11	58	3	5	4	4	3	5	4	4
99	TaskRelevant	3	3	3	87	13	53	5	4	4	5	4	4	4	4
99	TaskRelevant	4	4	4	68	11	43	3	3	3	4	3	3	3	4
99	Revise TaskRelevant	4	4		17	0	0	3	3	3	4	3	3	3	4
121	TaskRelevant	4	3	1	235	30	136	5	5	5	3	4	5	3	3
121	TaskRelevant	1	4	2	147	12	84	2	4	6	3	2	4	5	3
121	TaskRelevant	2	2	3	110	14	64	4	4	3	5	4	4	3	4
121	TaskRelevant	3	1	4	72	16	31	3	3	0	2	3	3	0	2
121	Revise TaskRelevant	3	1		489	0	477	3	3	0	3	3	3	0	3
122	TaskRelevant	4	4	1	209	28	121	6	5	7	5	4	5	4	4
122	TaskRelevant	1	3	2	139	21	87	5	4	8	4	4	4	5	4
122	TaskRelevant	3	2	3	168	19	123	3	5	6	4	3	4	4	4
122	TaskRelevant	2	1	4	161	20	98	5	6	5	5	4	6	5	5
122	Revise TaskRelevant	2	1		739	0	0	5	6	5	5	4	6	5	5
124	TaskRelevant	3	1	1	350	90	153	8	8	3	9	4	6	3	5
124	TaskRelevant	4	4	2	182	62	76	4	4	4	4	4	4	4	4
124	TaskRelevant	1	2	3	117	27	43	3	2	2	4	3	2	2	4
124	TaskRelevant	2	3	4	87	19	49	5	3	2	3	4	3	1	3
124	Revise TaskRelevant	2	3		1071	0	0	5	3	2	3	4	3	1	3
125	TaskRelevant	3	2	1	191	18	65	3	2	3	4	3	2	3	3
125	TaskRelevant	1	3	2	72	14	34	3	2	2	1	3	2	2	1
125	TaskRelevant	2	4	3	74	19	23	3	2	1	2	3	2	1	2
125	TaskRelevant	4	1	4	59	14	21	3	1	1	3	3	1	1	3
125	Revise TaskRelevant	4	1		337	0	0	3	1	1	3	3	1	1	3
126	TaskRelevant	1	2	1	50	20	0	2	0	0	0	2	0	0	0
126	TaskRelevant	3	4	2	39	17	0	2	0	0	0	2	0	0	0
126	TaskRelevant	2	1	3	42	12	7	2	0	0	1	2	0	0	1
126	TaskRelevant	4	3	4	47	16	0	2	0	0	1	2	0	0	1
126	Revise TaskRelevant	4	3		321	0	0	2	0	0	1	2	0	0	1

Visited information elements

The following tables show visited information elements in each condition. Number in cell represents number of visitations that subject has made in individual information element.

Table H. 9: Visited information elements in condition 1

Condition 1 (High DS + High CS)																							
UID	expertise	Problem ID	Sequence No	C1	R2	C3	H4	R5	T6	H7	C8	C9	R10	T11	H12	T13	H14	R15	C16	R17	C18	H19	T20
100	Expert	1	1	0	0	0	0	1	1	0	1	1	1	2	0	1	0	0	0	0	0	0	1
1	Expert	3	1	1	0	0	0	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1
12	Expert	4	2	1	1	0	0	1	1	0	0	0	1	1	1	0	0	1	0	0	0	0	1
20	Expert	2	4	1	1	1	1	1	1	0	0	0	0	0	1	1	0	1	0	0	0	0	1
2	Expert	1	1	1	1	0	0	2	3	0	2	1	2	2	0	2	0	1	0	1	1	1	1
22	Expert	4	2	2	2	0	0	1	1	0	1	1	1	1	0	1	0	1	0	1	1	1	1
24	Expert	4	4	0	0	0	0	1	1	0	1	1	1	1	0	1	0	1	0	1	0	0	1
25	Expert	1	3	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
26	Expert	2	4	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1
27	Expert	2	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1
29	Expert	3	2	0	0	0	0	2	1	1	1	0	1	1	1	1	1	1	0	1	0	1	1
30	Expert	1	2	0	0	0	0	1	1	0	1	1	1	1	0	1	0	1	0	0	0	1	1
3	Expert	2	1	0	0	0	0	1	1	1	1	1	1	1	0	2	0	2	1	1	1	1	1
31	Expert	2	2	2	2	0	1	1	1	1	1	0	1	1	0	1	0	1	0	1	0	1	2
32	Expert	4	4	0	1	0	0	0	1	1	1	0	1	1	0	1	0	1	0	1	0	1	1
33	Expert	4	3	0	0	0	0	1	1	0	1	1	1	1	0	1	1	1	0	1	0	0	1
35	Expert	1	4	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	0	1	1
36	Expert	3	3	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	0	2	2
39	Expert	2	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
40	Expert	3	4	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	1	1	1	1
42	Expert	3	1	2	2	1	1	2	2	1	2	1	1	2	1	2	1	1	0	0	1	0	1
45	Expert	4	1	1	1	1	1	1	1	1	1	1	1	2	1	1	0	0	0	0	1	2	2
47	Expert	4	1	2	2	1	2	2	2	1	2	1	2	1	0	2	1	1	1	1	0	0	1
48	Expert	2	1	0	0	0	0	1	1	0	0	0	1	1	0	1	0	2	0	1	0	0	1
52	Expert	2	2	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	0	1	1	1	1
53	Expert	1	2	1	1	1	1	1	1	1	1	1	1	2	2	1	1	1	0	1	1	1	1
55	Expert	3	1	1	1	1	1	1	1	0	1	1	1	1	0	1	0	1	1	0	1	0	1
57	Expert	2	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	2
60	Expert	3	3	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	0	0	0	1
65	Expert	4	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
66	Expert	4	4	0	0	0	0	1	1	0	0	0	0	2	1	0	0	1	0	0	0	0	1
67	Expert	1	2	0	0	0	0	1	1	0	1	0	0	1	0	1	0	1	0	0	0	0	1
70	Expert	1	4	1	1	1	1	1	1	0	1	0	2	2	0	1	0	3	0	2	0	1	1
7	Expert	4	1	1	1	1	1	1	1	1	1	1	2	1	0	0	0	1	0	1	0	1	1
71	Expert	4	3	1	0	0	0	1	1	0	1	1	1	1	0	1	0	1	0	1	0	0	1
72	Expert	4	2	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	0	1	1	1	1
78	Expert	3	3	1	1	0	1	1	1	0	1	1	1	1	0	1	0	1	1	1	1	1	1
81	Expert	3	4	1	1	0	0	1	0	0	1	1	1	1	0	1	0	1	0	0	0	1	1
83	Expert	1	2	1	0	0	0	1	1	0	1	1	1	1	0	1	0	1	0	1	0	1	1
85	Expert	3	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	1	0	0	0	1

86	Expert	4	3	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	1	1	1	1
87	Expert	4	4	0	2	1	0	1	1	1	0	1	1	1	1	1	1	1	0	0	0	1	1
90	Expert	1	3	0	0	0	0	1	1	0	1	1	1	1	0	2	0	1	0	1	0	0	1
9	Expert	4	1	1	2	2	1	1	1	0	0	1	1	1	0	1	0	2	1	0	0	1	1
94	Expert	2	4	0	0	0	0	1	0	0	1	0	1	1	0	1	0	0	0	0	0	1	1
95	Expert	2	3	2	0	0	0	1	1	1	1	1	1	2	2	1	1	1	0	2	1	2	2
96	Expert	4	3	0	1	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0	0	1
98	Expert	3	2	0	0	0	0	2	1	1	0	0	1	1	0	1	1	1	0	1	0	1	1
111	Novice	1	4	0	1	0	0	1	1	0	1	1	1	1	0	0	0	1	0	1	1	1	1
112	Novice	4	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	1	0	1	1
113	Novice	4	2	1	1	0	0	0	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1
114	Novice	1	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	1	1	2	2
115	Novice	4	3	0	0	0	0	1	1	1	1	0	1	1	0	1	0	1	0	1	0	0	0
117	Novice	2	2	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
118	Novice	1	3	1	1	1	1	1	1	0	1	1	1	1	0	1	0	1	1	1	1	0	1
119	Novice	4	2	0	1	1	0	1	1	1	1	0	1	1	0	0	0	0	0	1	1	0	1
121	Novice	3	4	1	0	0	0	0	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0
122	Novice	2	4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
124	Novice	3	1	1	1	1	1	3	3	0	1	1	2	2	1	1	0	1	1	2	2	1	2
125	Novice	4	4	0	0	0	0	1	1	0	1	0	0	0	0	1	0	1	0	1	0	1	1
126	Novice	2	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1
13	Novice	3	1	0	0	0	0	1	2	2	1	0	1	0	1	1	0	1	0	1	1	1	1
15	Novice	4	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	1	1	1	1
16	Novice	4	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	2	2
17	Novice	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
18	Novice	3	2	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	1	1	2	2
21	Novice	2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
23	Novice	3	2	0	0	0	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0
28	Novice	4	4	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	1	1
34	Novice	4	2	1	1	0	0	1	1	1	1	2	1	1	0	0	0	0	0	0	0	1	1
38	Novice	2	4	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
4	Novice	4	1	0	1	0	0	1	0	1	1	1	1	0	0	0	0	0	0	1	1	1	1
43	Novice	3	1	1	0	0	0	0	1	1	1	1	0	2	2	2	2	1	1	0	1	1	1
44	Novice	1	4	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
49	Novice	2	3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	1
50	Novice	4	4	0	0	0	0	0	1	0	1	1	1	1	0	1	0	0	0	1	0	0	1
5	Novice	2	1	1	1	1	1	2	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1
51	Novice	3	4	1	1	1	1	1	1	1	1	1	1	2	1	1	0	1	1	1	1	1	1
54	Novice	1	1	2	2	1	1	3	2	2	1	2	1	2	1	1	0	1	1	1	2	1	1
59	Novice	4	1	1	1	0	0	2	1	0	1	1	0	1	0	1	0	1	0	1	1	1	1
61	Novice	3	3	1	3	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1
62	Novice	4	1	2	0	0	0	1	3	2	3	3	2	2	1	1	0	1	1	2	2	2	2
63	Novice	1	2	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1
64	Novice	2	2	3	1	1	0	2	4	3	0	2	2	4	3	1	1	1	1	3	1	1	2

68	Novice	2	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	2	0	0	2
69	Novice	3	3	0	1	0	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	2
74	Novice	3	3	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1
75	Novice	1	2	1	2	1	1	2	2	2	2	1	1	2	2	1	1	1	1	0	0	1	1
77	Novice	3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0
80	Novice	1	3	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1
84	Novice	4	2	1	1	1	1	1	1	0	1	1	1	1	0	1	0	1	0	1	1	1	1
88	Novice	1	2	2	1	1	1	0	1	0	1	1	1	1	0	1	0	1	0	1	0	0	1
91	Novice	4	3	1	1	3	1	1	2	2	1	2	1	2	2	2	2	1	1	1	2	1	1
92	Novice	1	2	0	0	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0
93	Novice	4	3	0	0	0	0	0	0	0	0	2	3	2	2	0	0	0	0	0	0	0	0
99	Novice	1	1	3	2	0	0	1	1	0	1	1	1	1	1	0	0	0	0	1	1	1	1

Table H. 10: Visited information elements in condition 2

Condition 2 (High DS + Low CS)																							
UID	expertise	Problem ID	Sequence No	C1	R2	C3	L4	R5	T6	L7	C8	C9	R10	T11	L12	T13	L14	R15	C16	R17	C18	L19	T20
100	Expert	2	2	0	0	0	0	2	1	1	1	0	0	1	0	1	0	0	0	0	0	0	1
12	Expert	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	Expert	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1
20	Expert	4	1	1	1	1	1	1	2	1	1	1	1	2	1	0	1	1	1	1	2	1	1
2	Expert	2	2	0	0	0	0	1	1	1	1	1	1	1	1	1	3	1	0	1	0	2	2
22	Expert	2	4	0	1	0	0	1	1	2	1	1	1	1	1	1	0	1	0	1	0	0	1
24	Expert	3	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
25	Expert	3	2	1	2	2	2	3	3	2	2	1	1	1	1	1	1	2	2	1	1	2	1
26	Expert	4	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1
27	Expert	1	1	1	1	2	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
29	Expert	1	3	0	0	0	1	1	1	1	1	0	1	1	1	1	1	1	0	1	0	1	1
30	Expert	4	4	0	0	0	0	1	1	1	1	0	1	1	1	1	1	0	0	0	0	1	1
31	Expert	4	3	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	1	1	1
32	Expert	1	2	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1
33	Expert	1	4	0	0	0	0	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	1
3	Expert	1	4	1	1	1	1	1	1	2	2	1	1	1	0	3	0	1	1	1	0	1	1
35	Expert	3	3	0	0	0	0	1	1	0	1	0	1	1	0	1	0	1	0	1	0	1	1
36	Expert	4	2	0	0	0	0	1	1	1	1	0	1	1	1	1	1	1	0	1	0	0	1
39	Expert	1	4	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1
40	Expert	1	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
42	Expert	4	3	1	0	0	1	2	2	0	2	0	1	1	1	0	0	0	0	0	0	1	1
45	Expert	2	4	0	0	0	0	1	1	1	0	0	1	1	1	1	1	1	0	1	1	1	1
47	Expert	3	4	0	0	0	0	1	1	0	0	0	0	1	0	1	0	3	0	1	1	1	1
48	Expert	1	3	0	0	0	0	1	0	1	0	0	1	2	1	1	1	0	0	0	0	0	1
52	Expert	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
53	Expert	2	1	3	3	2	2	1	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1

55	Expert	4	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1
57	Expert	1	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
60	Expert	4	1	0	0	0	0	2	1	1	1	1	1	1	0	1	0	0	0	0	1	1	1
65	Expert	3	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	2	1
66	Expert	3	1	1	1	1	1	1	1	1	1	0	0	1	0	0	0	0	0	1	1	1	1
67	Expert	2	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	2	0	0	0	0	1
70	Expert	3	1	1	2	1	1	1	1	1	1	2	3	2	2	1	2	4	1	2	1	3	1
71	Expert	1	4	1	0	0	1	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	1
72	Expert	2	3	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	1	2	1
7	Expert	3	4	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1
78	Expert	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1
81	Expert	4	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
83	Expert	3	4	0	0	0	0	2	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0
85	Expert	2	3	0	0	0	0	0	1	1	1	1	1	1	0	1	0	1	0	0	1	1	1
86	Expert	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
87	Expert	3	2	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1
90	Expert	4	4	0	0	0	0	1	1	1	1	0	1	1	0	1	1	1	0	1	0	0	1
9	Expert	2	3	0	1	0	1	2	1	1	0	0	1	1	1	1	1	1	0	0	0	0	1
94	Expert	3	3	0	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1
95	Expert	3	2	0	0	1	1	1	1	1	1	1	1	1	1	2	2	2	2	1	1	1	1
96	Expert	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
98	Expert	1	1	0	0	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	0	0	1
111	Novice	3	1	2	3	1	2	0	1	1	1	2	2	2	2	1	0	2	1	1	1	2	2
112	Novice	3	2	0	0	0	0	0	1	1	1	1	1	1	1	2	1	1	1	2	0	1	1
113	Novice	2	3	0	0	0	0	1	1	0	1	1	0	1	1	1	0	1	0	1	0	1	1
114	Novice	3	3	0	0	0	0	1	1	1	1	0	0	0	0	1	0	0	0	1	1	1	1
115	Novice	1	4	0	0	0	0	1	1	1	0	0	1	1	1	1	1	0	0	0	0	0	1
117	Novice	4	3	0	0	0	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1
118	Novice	3	2	0	1	0	1	1	1	2	2	1	1	1	1	1	1	1	1	1	1	1	1
119	Novice	1	1	2	1	1	1	1	1	1	1	0	1	1	0	1	0	1	1	1	1	1	1
121	Novice	2	3	1	0	1	0	1	1	1	1	0	1	1	1	1	1	1	0	2	1	0	1
122	Novice	3	3	1	1	1	1	1	1	3	2	1	1	1	1	0	0	0	0	1	0	1	1
124	Novice	1	3	0	0	0	0	1	1	1	1	0	1	0	0	1	1	1	0	1	1	0	1
125	Novice	3	1	1	1	0	1	2	1	1	1	0	0	0	0	1	0	1	0	0	0	1	1
126	Novice	1	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
13	Novice	1	2	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	1	1
15	Novice	3	4	1	0	0	0	1	1	0	0	0	1	0	0	0	0	1	0	1	2	1	1
16	Novice	2	1	1	1	1	1	1	1	1	1	1	2	2	1	1	1	1	1	0	1	1	1
17	Novice	1	4	1	1	1	1	1	1	1	1	1	2	2	1	1	1	1	1	1	1	1	1
18	Novice	1	1	2	2	1	2	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1
21	Novice	4	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
23	Novice	1	3	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1
28	Novice	3	1	1	1	0	1	2	1	2	2	1	1	1	1	0	0	0	0	0	0	0	0
34	Novice	2	4	0	1	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0	1	0	1

38	Novice	4	2	1	1	1	1	2	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1
4	Novice	2	3	0	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	1	0	1	1
43	Novice	4	2	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
44	Novice	3	3	1	1	1	2	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1
49	Novice	1	4	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
50	Novice	1	2	0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	0	1	0	0	1
51	Novice	1	3	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1
5	Novice	1	3	0	0	0	0	1	1	0	0	1	1	1	1	0	1	1	1	2	0	1	1
54	Novice	2	2	1	1	1	1	2	1	1	1	2	1	1	1	1	1	2	1	1	1	1	1
59	Novice	2	4	0	0	0	0	1	1	1	1	1	1	1	1	0	1	1	0	0	1	0	1
61	Novice	2	1	2	2	2	2	3	3	2	2	2	3	2	1	0	0	1	1	1	1	1	1
62	Novice	3	4	0	0	0	0	0	1	1	0	0	2	2	1	1	1	1	0	1	1	1	1
63	Novice	2	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1	0	1	0
64	Novice	1	1	1	1	0	0	1	1	1	1	0	0	1	0	0	0	1	0	0	1	1	1
68	Novice	3	2	0	0	0	0	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	1
69	Novice	4	1	1	2	1	1	2	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1
74	Novice	4	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1
75	Novice	4	4	1	1	0	1	1	1	1	1	1	1	2	1	0	1	1	1	1	2	1	1
77	Novice	4	2	0	0	0	0	0	1	0	0	0	0	1	1	1	3	1	0	1	0	2	2
80	Novice	4	4	0	0	0	0	1	0	0	0	0	1	1	1	1	0	1	0	1	0	0	1
84	Novice	3	3	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1
88	Novice	2	4	1	1	1	1	0	1	1	1	0	0	1	1	1	1	2	2	1	1	2	1
91	Novice	1	4	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	2	1
92	Novice	3	4	0	0	0	0	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1
93	Novice	3	2	0	0	0	0	2	2	2	1	0	0	1	1	1	1	1	0	1	0	1	1
99	Novice	2	2	1	1	0	1	1	1	1	1	1	0	1	1	1	1	0	0	0	0	1	1

Table H. 11: Visited information elements in condition 3

Condition 3 (Low DS + High CS)																							
UID	expertise	Problem ID	Sequence No	C1	U2	C3	H4	U5	T6	H7	C8	C9	U10	T11	H12	T13	H14	U15	C16	U17	C18	H19	T20
100	Expert	3	3	0	0	0	0	0	1	1	0	0	0	1	0	1	0	0	0	0	0	0	1
12	Expert	3	4	1	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1
1	Expert	2	4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
20	Expert	1	2	1	1	1	1	2	1	0	1	0	1	1	0	1	0	1	0	1	1	1	1
22	Expert	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
2	Expert	3	3	1	0	0	0	2	2	0	1	1	1	2	0	1	0	1	1	1	1	1	1
24	Expert	1	3	0	0	0	0	1	1	0	1	1	1	1	0	1	0	1	0	0	0	1	1
25	Expert	4	1	1	1	1	1	1	2	1	1	1	1	1	1	2	1	1	1	0	0	2	2
26	Expert	3	1	1	1	1	1	2	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1
27	Expert	4	4	3	3	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
29	Expert	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	0	1	1
30	Expert	3	3	0	0	0	0	0	1	0	0	0	1	1	1	0	0	0	0	1	1	1	1

31	Expert	3	4	1	1	0	0	1	1	1	0	0	0	1	1	1	1	0	0	0	0	0	1
3	Expert	3	2	0	2	1	1	1	2	2	1	1	2	1	1	1	1	1	1	1	1	1	1
32	Expert	2	3	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	0	0	0	1	1
33	Expert	3	1	0	0	0	0	1	1	1	1	0	0	1	1	1	1	1	0	0	0	0	1
35	Expert	4	1	0	0	0	0	1	1	1	1	1	1	1	0	1	0	1	0	0	0	1	1
36	Expert	1	4	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0	0	0	1	1
39	Expert	4	2	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
40	Expert	2	2	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
42	Expert	2	2	1	1	1	1	1	1	0	0	2	2	2	1	1	0	1	0	1	0	1	1
45	Expert	3	2	0	0	0	0	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1
47	Expert	1	3	0	1	0	0	0	2	0	0	0	0	1	0	2	0	0	0	0	0	0	1
48	Expert	4	4	0	0	0	0	1	1	1	0	2	1	3	1	1	0	0	0	0	0	0	1
52	Expert	4	3	2	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1
53	Expert	4	4	1	1	2	1	1	1	0	1	1	1	1	0	1	0	1	1	1	1	1	1
55	Expert	2	4	1	1	1	1	1	1	1	1	0	0	1	0	1	0	0	0	0	0	1	1
57	Expert	4	4	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	1	0	0	0	1
60	Expert	2	2	0	0	0	0	0	1	0	1	1	1	1	0	1	0	0	0	0	1	1	1
65	Expert	1	1	2	2	2	2	2	3	3	2	1	1	2	2	2	2	2	1	3	3	5	4
66	Expert	2	3	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1
67	Expert	3	1	1	1	1	1	1	1	0	0	2	2	1	0	1	0	1	1	0	0	0	1
70	Expert	4	2	1	1	1	1	1	1	0	1	1	1	1	1	2	2	1	1	1	1	2	2
71	Expert	2	1	2	1	1	1	2	1	0	1	1	1	1	0	1	0	1	1	1	1	1	1
72	Expert	3	4	1	1	0	0	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1	1
7	Expert	2	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
78	Expert	1	4	1	1	1	1	1	1	0	1	1	2	1	0	1	0	0	0	1	1	1	1
81	Expert	2	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
83	Expert	4	3	1	0	0	0	1	1	0	1	1	1	1	0	1	0	1	0	0	0	0	1
85	Expert	4	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
86	Expert	2	4	0	0	0	0	0	1	0	1	1	0	1	0	1	1	0	1	0	0	0	1
87	Expert	2	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1
90	Expert	2	2	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	0	0	0	1	1
9	Expert	3	2	1	1	0	0	2	1	0	1	0	1	1	0	1	0	0	1	0	0	0	1
94	Expert	1	2	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1
95	Expert	4	1	1	1	0	0	2	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1
96	Expert	1	2	1	1	1	1	2	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1
98	Expert	4	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	0	0	0	1

111	Novice	2	3	1	1	1	1	0	1	0	1	1	0	1	0	0	0	0	0	1	0	1	1
112	Novice	2	3	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	2	1
113	Novice	3	4	1	0	0	0	0	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1
114	Novice	4	2	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1	2	1	1
115	Novice	3	1	0	0	0	0	1	1	0	1	1	1	1	0	2	1	1	0	0	0	0	0
117	Novice	3	4	0	1	0	0	1	1	1	1	1	0	1	1	1	1	1	0	0	0	0	0
118	Novice	4	1	1	2	1	1	3	1	1	2	3	1	1	0	1	0	1	1	1	1	1	1
119	Novice	3	4	1	1	1	0	0	1	0	1	1	1	1	0	0	0	0	0	0	1	0	1
121	Novice	4	1	1	1	1	2	0	1	0	1	1	0	1	1	1	0	1	1	1	0	2	2
122	Novice	1	2	1	1	1	1	1	2	2	1	1	1	1	1	1	1	1	0	0	0	3	2
124	Novice	2	4	0	0	0	0	1	1	0	1	1	1	1	0	0	0	0	0	1	1	2	2
125	Novice	1	2	0	0	0	0	1	1	0	1	0	0	0	0	1	1	0	0	0	1	1	1
126	Novice	4	4	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
13	Novice	2	4	0	0	0	0	0	1	0	0	0	1	1	0	1	0	0	0	1	1	1	1
15	Novice	2	3	1	1	1	1	1	0	0	0	1	0	1	1	0	0	1	0	1	2	1	1
16	Novice	1	2	1	1	1	1	1	2	2	1	0	0	0	0	0	0	0	0	2	2	1	1
17	Novice	3	2	1	1	1	1	1	1	0	1	1	1	1	0	1	0	1	1	1	1	1	1
18	Novice	4	3	1	1	1	1	1	1	1	1	1	0	1	0	2	2	1	1	2	0	2	1
21	Novice	1	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
23	Novice	2	1	0	1	0	1	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0
28	Novice	1	3	0	0	0	0	0	0	0	0	0	0	0	0	2	2	1	1	1	1	1	1
34	Novice	1	1	0	0	1	0	0	1	0	1	0	0	1	0	1	0	0	0	0	1	1	1
38	Novice	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
4	Novice	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
43	Novice	2	4	0	0	0	0	1	1	1	0	1	1	1	1	1	1	1	0	0	0	1	1
44	Novice	4	1	1	1	1	1	1	1	0	1	1	1	1	0	1	0	0	1	1	1	2	2
49	Novice	4	2	0	0	0	0	1	1	0	1	0	0	1	0	1	0	0	0	0	0	0	1
50	Novice	2	3	0	0	0	0	1	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1
51	Novice	2	2	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	Novice	3	4	1	1	0	0	1	1	1	0	0	1	1	0	1	0	1	0	1	1	1	1
54	Novice	3	3	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
59	Novice	3	2	0	0	0	0	1	1	0	0	0	0	2	0	1	0	1	1	1	1	1	1
61	Novice	1	4	1	2	1	1	1	1	1	0	1	0	1	0	1	0	1	0	0	0	1	1
62	Novice	1	3	0	1	0	0	2	3	2	0	2	2	1	1	2	1	1	1	0	0	2	2

63	Novice	4	4	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	1	1	1	1	1
64	Novice	4	3	1	1	0	0	0	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1
68	Novice	4	1	0	0	0	0	0	1	0	0	0	0	1	1	1	1	0	0	1	0	1	1
69	Novice	2	2	0	1	0	0	1	1	1	1	1	2	1	1	0	0	0	0	1	1	1	1
74	Novice	1	4	1	1	1	1	1	1	0	1	1	0	1	1	1	1	0	0	0	0	0	1
75	Novice	3	3	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1
77	Novice	2	1	0	0	0	0	1	1	1	1	0	1	1	1	1	0	1	0	0	0	1	1
80	Novice	2	2	0	0	0	0	0	1	0	0	0	0	1	1	1	1	1	0	0	0	0	1
84	Novice	1	1	2	2	2	2	2	3	2	1	2	2	1	0	1	0	1	0	0	0	1	1
88	Novice	3	1	1	1	1	2	1	1	1	1	1	1	1	0	1	0	1	0	0	0	1	1
91	Novice	2	1	1	1	1	1	1	2	0	1	0	0	1	0	1	0	0	0	0	0	0	1
92	Novice	4	3	0	0	0	0	1	1	0	0	0	0	1	1	1	1	1	1	0	0	0	0
93	Novice	2	4	0	0	0	0	0	0	0	0	0	0	2	1	1	0	1	0	1	0	1	1
99	Novice	3	3	0	0	0	0	2	2	1	1	1	1	1	0	1	0	1	1	1	1	1	1

Table H. 12: Visited information elements in condition 4

Condition 4 (Low DS + Low CS)																							
UID	expertise	Problem ID	Sequence No	C1	U2	C3	L4	U5	T6	L7	C8	C9	U10	T11	L12	T13	L14	U15	C16	U17	C18	L19	T20
100	Expert	4	4	0	0	0	0	0	1	0	1	0	0	1	0	2	0	0	0	0	0	0	1
12	Expert	2	3	1	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1
1	Expert	4	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
20	Expert	3	3	0	0	0	0	1	1	1	1	0	0	0	0	1	0	0	0	0	0	1	1
22	Expert	3	3	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	0	0	0	0	1
24	Expert	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
2	Expert	4	4	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	2	1
25	Expert	2	4	1	2	1	2	0	3	1	1	1	0	2	0	1	0	0	0	0	0	1	1
26	Expert	1	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	3	2
27	Expert	3	2	1	1	2	1	1	1	1	1	1	2	2	2	1	1	1	2	1	1	1	1
29	Expert	4	4	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
30	Expert	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
31	Expert	1	1	1	2	1	2	2	2	2	2	3	3	2	2	3	1	3	2	1	1	1	1
32	Expert	3	1	2	1	2	2	1	1	3	2	1	1	1	1	2	2	1	1	1	1	1	1
33	Expert	2	2	0	0	0	0	1	1	1	1	1	1	2	1	1	1	0	0	0	0	0	1
3	Expert	4	3	0	0	1	1	1	1	1	1	2	2	2	1	2	3	2	1	1	1	1	1
35	Expert	2	2	0	0	0	0	0	1	1	1	0	0	1	1	1	1	0	0	0	0	1	1
36	Expert	2	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
39	Expert	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

40	Expert	4	1	3	2	1	1	2	2	2	1	1	2	1	1	2	2	1	1	1	1	2	1
42	Expert	1	4	0	0	0	1	1	1	1	0	0	1	1	0	0	0	0	0	1	1	0	1
45	Expert	1	3	0	0	0	0	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1
47	Expert	2	2	0	1	0	1	1	3	1	1	0	1	1	1	1	0	1	1	1	1	1	2
48	Expert	3	2	0	0	0	0	0	1	0	0	0	1	1	0	1	1	1	0	0	0	0	1
52	Expert	3	4	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	1
53	Expert	3	3	1	1	2	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1
55	Expert	1	3	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
57	Expert	3	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
60	Expert	1	4	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1
65	Expert	2	4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
66	Expert	1	2	1	1	1	1	2	1	2	2	0	0	1	1	1	1	1	0	2	2	1	1
67	Expert	4	3	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1
70	Expert	2	3	3	2	0	1	1	1	1	1	0	3	1	3	0	1	0	0	1	2	1	2
71	Expert	3	2	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
72	Expert	1	1	1	1	1	1	2	1	1	1	1	2	1	1	1	1	1	1	2	1	1	1
7	Expert	1	2	0	0	0	0	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0	1
78	Expert	4	2	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	0	1	1
81	Expert	1	3	1	1	1	2	1	0	1	1	1	1	1	1	1	1	1	0	0	0	1	1
83	Expert	2	1	1	0	0	0	1	2	1	1	1	1	1	1	1	1	2	1	1	1	1	1
85	Expert	1	2	0	0	0	0	0	0	1	0	1	1	1	0	0	1	1	0	0	0	1	1
86	Expert	1	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	1	1	1
87	Expert	1	1	1	2	1	1	2	2	1	1	4	2	2	3	1	1	1	1	3	3	4	1
90	Expert	3	1	1	1	0	1	1	1	2	2	3	1	1	1	1	1	1	1	1	1	1	1
94	Expert	4	1	1	0	0	1	1	1	1	1	1	1	1	0	1	0	0	0	1	0	0	1
9	Expert	1	4	0	1	0	1	1	1	0	0	1	1	1	0	1	0	0	0	0	0	0	1
95	Expert	1	4	1	1	1	1	1	2	1	0	1	0	1	1	1	0	0	0	0	1	3	1
96	Expert	3	4	0	1	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1
98	Expert	2	4	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1
111	Novice	4	2	1	1	1	1	1	1	1	1	2	2	1	1	0	0	0	0	1	0	1	1
112	Novice	1	1	0	0	0	0	1	1	1	1	2	1	1	1	0	0	1	0	1	1	1	1
113	Novice	1	1	1	1	1	1	3	3	2	2	0	0	0	0	1	1	2	1	2	3	2	1
114	Novice	2	4	0	0	0	0	1	1	0	0	1	0	1	0	1	0	0	0	1	1	1	1
115	Novice	2	2	0	1	0	1	1	1	1	1	1	0	1	1	1	1	0	0	1	0	0	0
117	Novice	1	1	1	1	1	1	3	1	1	2	1	1	1	1	1	1	1	1	0	0	0	1
118	Novice	2	4	0	1	0	1	1	1	1	1	1	1	1	1	1	2	1	0	1	1	2	1
119	Novice	2	3	2	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1
121	Novice	1	2	1	1	1	1	1	0	2	1	0	0	0	1	1	1	0	0	1	1	1	1
122	Novice	4	1	1	1	1	2	2	2	1	1	1	1	2	2	2	2	1	1	0	0	0	0
124	Novice	4	2	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
125	Novice	2	3	0	0	0	0	1	1	0	1	0	0	0	0	1	0	0	0	1	1	1	1
126	Novice	3	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
13	Novice	4	3	0	0	0	0	2	2	1	0	0	0	1	0	1	0	0	0	1	1	1	1
15	Novice	1	2	2	2	1	1	1	1	1	2	1	1	1	1	1	1	0	0	1	0	0	1

16	Novice	3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	2
17	Novice	4	3	1	2	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
18	Novice	2	4	1	1	1	1	1	1	1	0	1	1	1	0	1	0	0	0	1	1	1	1
21	Novice	3	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	Novice	4	4	0	0	0	1	1	1	1	1	1	2	1	1	1	0	0	0	0	0	0	1
28	Novice	2	2	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
34	Novice	3	3	0	0	0	1	1	1	1	0	0	0	1	1	1	1	0	0	1	2	1	1
38	Novice	1	3	1	1	1	1	1	1	1	1	0	0	1	0	1	1	1	1	0	0	0	1
43	Novice	1	3	0	0	0	0	1	1	1	1	0	0	0	0	1	0	1	0	1	0	1	1
44	Novice	2	2	1	2	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
4	Novice	1	4	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1
49	Novice	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
50	Novice	3	1	1	1	0	0	3	3	1	3	2	1	1	1	1	2	1	1	2	1	0	1
51	Novice	4	1	1	1	1	2	1	1	1	1	0	0	1	1	1	1	3	2	1	1	1	1
5	Novice	4	2	1	1	0	0	3	1	1	2	1	1	1	1	0	1	1	1	1	2	1	2
54	Novice	4	4	1	1	1	1	1	1	1	1	3	2	2	1	1	1	2	1	2	2	1	1
59	Novice	1	3	0	1	0	1	2	1	2	1	1	0	1	1	1	1	0	0	1	1	0	1
61	Novice	4	2	1	2	0	1	1	1	0	0	1	0	1	1	1	0	0	0	1	1	1	1
62	Novice	2	2	1	0	0	0	3	2	1	1	1	2	1	2	1	1	1	1	1	1	2	2
63	Novice	3	3	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
64	Novice	3	4	1	0	0	0	2	1	2	1	0	1	0	1	0	0	1	0	0	0	0	1
68	Novice	1	4	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1
69	Novice	1	4	0	1	0	1	1	1	1	0	2	1	1	1	1	1	1	0	1	1	1	1
74	Novice	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
75	Novice	2	1	1	1	1	1	2	3	2	3	2	2	2	2	2	2	2	1	2	3	1	1
77	Novice	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
80	Novice	3	1	1	1	1	1	0	1	0	1	0	0	0	0	1	0	1	0	1	0	0	1
84	Novice	2	4	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	1
88	Novice	4	3	1	1	1	1	1	1	1	1	0	1	1	1	1	0	0	0	1	1	1	1
91	Novice	3	2	1	0	1	1	0	1	2	1	2	1	2	1	1	1	0	0	1	1	1	1
92	Novice	2	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
93	Novice	1	1	2	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
99	Novice	4	4	0	0	0	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	0