

A novel approach for assisting teachers in analyzing student web-searching behaviors

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Abstract

Although previous research has demonstrated the benefits of applying the Internet facilities to the learning process, problems with this strategy have also been identified. One of the major difficulties is owing to the lack of an online learning environment that can record the learning portfolio of using the Internet facilities in education, such that the teacher can analyze and evaluate the learning performance of students, and hence the teaching strategies can be adjusted accordingly. In this paper, we propose a web-search learning environment, called Meta-Analyzer, which is able to assist the teachers in analyzing student learning behaviors of using search engines for problem solving. Two-hundred and twenty students and 54 teachers contributed to the trial of the system. The results have shown that the novel approach is able to gain a better understanding about students' learning processes and searching strategies in technology-enhanced environments, as well as to assist the teachers to acquire more about the learning status of students, and hence more constructive suggestions can be given accordingly.

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1. Introduction

The rapid progress in information technology can help instructors to teach more efficiently and effectively by employing new strategies with appropriate software tools and environments (Fabos & Young, 1999). Several studies have demonstrated the benefits of applying information technologies to instruction, such as Computer scaffolding (Guzdial et al., 1996), Computer-Supported Collaborative Learning (CSCL, e.g., Harasim,

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1999), Computer-Supported Intentional Learning Environments (CSILE, e.g., Scardamalia, Bereiter, McLean, Swallow, & Woodruff, 1989) and Computer-Integrated Classroom (CiC, e.g., Eshet, Klemes, & Henderson, 2000). Earlier studies of educational tools focused on the development of Computer-Assisted Instruction (CAI) systems. A CAI system can be perceived as a tutorial system, which is a guided system to provide well-constructed information. For example, Burks (1996) presented computer-based tutorials and a virtual classroom to teach circuit analysis; Gang, Jason, and Peter (1996) proposed a tutorial system by using artificial intelligence technology. Some researchers utilized auxiliary software to enhance their tutorial systems (Robert, 1996; William & Marion, 1996), some provided interactive tutorials for manuals with graphical user interface (Sally, 1996) or with rich multimedia formats (Pui & William, 1996). The study of Barrett and Lally (1999) showed the effectiveness of such computer-assisted instruction systems based on empirical evaluation. Davidovic, Warren, and Trichina (2003) also concluded that greater efficiency can be achieved by basing the system development on the theoretical background of cognitive knowledge acquisition.

Recently, the efficiency and popularity of the Internet has received much attention that has motivated efforts towards integrating Web-based learning activities into the curriculum (Chang, 2001; Huang & Lu, 2003; Khan, 1997; Tsai, Liu, Lin, & Yuan, 2001; Tsai & Tsai, 2003). Considerable work has been conducted on the use of Internet as a distance-learning tool (Apkarian & Dawer, 2000), and the use of Web-based simulation tools for education (Sreenivasan, Levine, & Rubloff, 2000). Moreover, some practical usages of Web-based educational systems in industrial training courses have been reported (Poindexter & Heck, 1999). In addition to their obvious use in a distance-learning scenario, those educational tools can also be used to enrich classroom experience through the use of a data projector (Ringwood & Galvin, 2002).

One of the greatest benefits of Web-based learning activities is to allow students to participate in learning as active and self-directed participants (Tsai, 2001). Web-based learning activities often involve information-searching tasks, as Web-based environments are connected with information sites worldwide. The increased access to the Web has raised many issues, including the strategies of information-seeking and use, the skill of processing Web information, the roles of teachers in educating and training, and the development of new environments that facilitate teachers to observe and analyze the information-seeking behaviors of students in Web-based learning environments (Bilal, 2000). Hess (1999) reported that users' cognitive strategies, especially information processing skills, determine a successful search on the Internet. Graff (2005) indicated the differences in web browsing strategies not only between older and younger participants, but also between individuals displaying verbalizer and imager cognitive styles; moreover, Song and Salvendy (2003) emphasized the importance of reusing individual Web browsing experiences. Therefore, it has become an important and challenging issue to observe and analyze the information-searching behaviors of students in Web-based learning environments (Zaphiris, Shneiderman, & Norman, 2002).

In the past decade, several studies (e.g., Bilal, 2000; Poindexter & Heck, 1999; Tsai & Tsai, 2003) have been conducted to analyze the learning behaviors of students in using search engines to collect information for problem solving. Research has indicated that children are more persistent and motivated in seeking information over the Web than in using traditional and online sources (Bilal, 2000). However, it appears to be difficult for Internet novice users to search information effectively and efficiently through the web (Marchionini, 1995). Researchers found that, disorientation is one of the problems that novice explorers tend to have while navigating within a hyperspace (Dias, Gomes, & Correia, 1999); therefore, training novice users, especially children, to use search engines to collect information for problem solving in elementary schools has become an important and challenging issue. Nevertheless, recent studies also indicated that teacher anxiety can often reduce the success of such technological and pedagogical innovations (Chou, 2003; Todman & Day, 2006). The anxiety is owing to the lack of sufficient knowledge to apply those computer systems to their classes, which has become a barrier to conduct information technology-applied instructions (Namlu & Ceyhan, 2003). As most of those online educational tools focus on the student-centered design, necessary supports to assist the teachers in designing learning activities and analyzing student learning performance are often ignored.

Bilal (2000) indicated several limitations in analyzing student learning behaviors of using search engines by an exit interview, including the reliability of the students' affective states gathered from it. Owing to the lack of technical supports, most researchers adopted the qualitative method using an exit interview relied on students' perceptions of and feelings about their experiences with the search engines; therefore, the reli-

ability of the studies may be threatened unless a careful check can be made on the videotapes of traversal activities or the verbalization during traversal, which is known to be time-consuming. Consequently, to allow the researchers and the teachers to make precise quantitative analysis on student learning behaviors, the development of a web-search learning environment, which can record students' problem-solving behaviors of using search engines, is needed. To cope with this problem, in this paper, we propose a web-search analytic environment, called Meta-Analyzer, to assist teachers in observing and analyzing student learning behaviors.

2. Method

To assist the teachers in tracing and analyzing the information-searching behaviors of students, a Web-based learning environment, Meta-Analyzer, has been developed. Moreover, a series of investigations have been conducted to demonstrate the usefulness of the innovative approach.

2.1. System development

Meta-Analyzer is implemented based on the notion of metasearch engine, which is a system that provides unified access to one or more existing search engines. A sophisticated metasearch engine may maintain information about the contents of its underlying search engines to provide better service. When a metasearch engine receives a user query, it can automatically, as well as simultaneously, query appropriate underlying search engines, collect and reorganize the results, and display them to the user in a uniform format (Meng, Yu, & Liu, 2002; Ramanathan, 2001).

Fig. 1 shows the system structure of Meta-Analyzer, which consists of five components: a Search Agent to derive relevant information from various search engines, a Web Content Analyzer to recognize the derived information, a Web Content Reorganizer to reformat the information for display, a Searching Behaviors Recorder to record information-searching portfolio of each user, and a Searching Behaviors Analyzer to assist the teachers in analyzing the student learning behaviors.

To more efficiently conduct the problem solving or search process with Meta-Analyzer, the user accounts are created in advance, so that the students and teachers need not take time for registration in the class; moreover, the identity of each user will be recognized via checking the pre-defined user profile, and hence Meta-Analyze can provide different functions for students and teachers. After logging into Meta-Analyzer, the students will see a list of topics to be investigated, which are pre-defined by the teachers. Once the students select a topic, an information-searching interface for problem solving is displayed.

As shown in Fig. 2, the student interface consists of three operation areas: the question and answer area is located in the left side, the information-searching area is located in the upper-right side, and the web pages

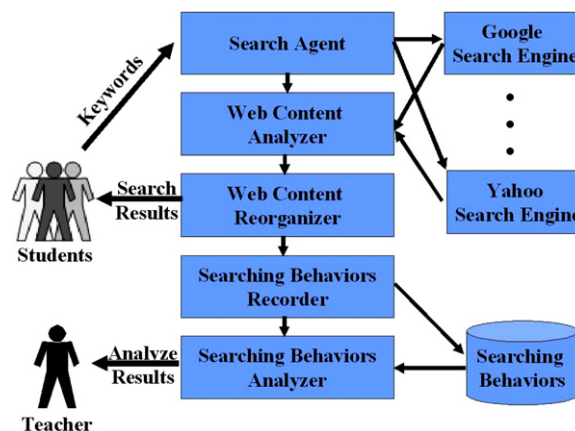


Fig. 1. System structure of Meta-Analyzer.

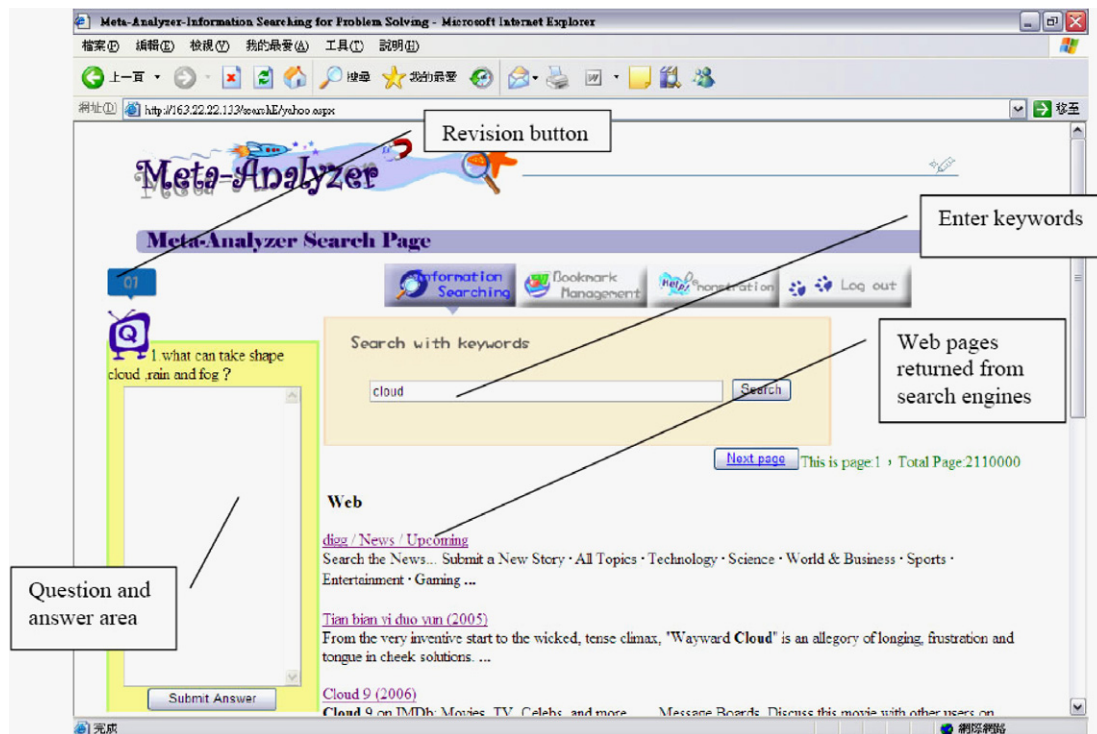


Fig. 2. Example of using Meta-Analyzer to collect information for problem solving.

found by the search engines are given in the lower-right side of the window. To answer the question, the student can input keywords to search information, and then browse the web pages that might be relevant to the topic. The entire user portfolio, including the keywords, the browsed web pages and the user behaviors on the web, will be recorded in the server for further analysis. In addition, a set of control buttons is listed on the top of the window, which provides several useful functions for information-searching, such as bookmark insertion/deletion/browsing and system demonstration.

Fig. 3 demonstrates a web page browsing example. The students can insert the web page to the bookmark list if it is highly relevant to the topic.

Fig. 4 shows the bookmark management interface for individual learners. The bookmark information reflects each learner's judgments of relevance degrees for the web pages to the topic currently investigated, which is very helpful for a school teacher in analyzing the behaviors of students, and hence a certain part of the problem-solving ability of each student can be evaluated by using the bookmark information.

Fig. 5 shows the teacher interface for browsing the information-searching portfolio of individual students. The presented information includes the answer to each question, the web pages that have been visited and the browsing time for each web page, etc. The 'operation' column records the behaviors of each learner, where 1 indicates 'input keywords'; 2, 'browsing web pages'; 3, 'insert web page to bookmark list'; 4, 'remove the web page from the bookmark list'; 5, 'web page selection'; 6, 'revise the submitted answer'. The teacher can trace the actual content of each web page that has been browsed by the student via clicking on the corresponding link.

2.2. Teacher data collection and analysis

Fifty-four teachers from several elementary and junior high schools were invited to use Meta-Analyzer to have some trial experiences. After experiencing some searching tasks with the assistance of Meta-Analyzer, the

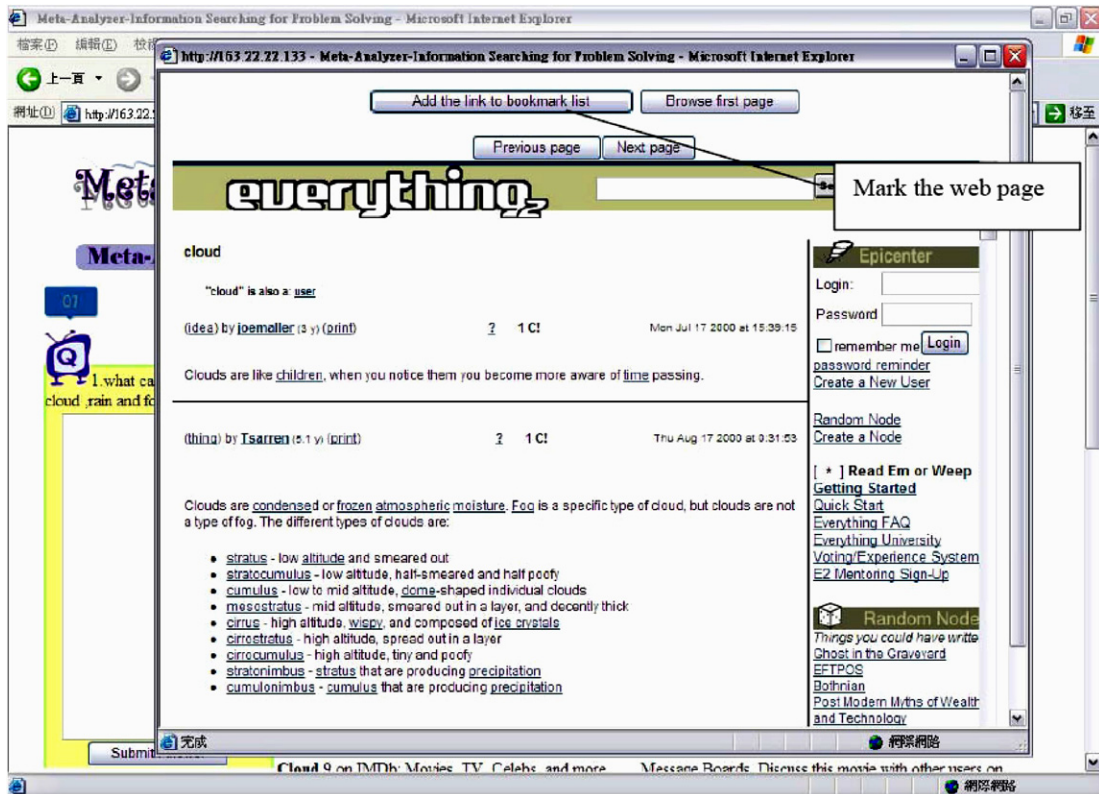


Fig. 3. Example of using Meta-Analyzer to browse the web page for problem solving.

teachers employed Meta-Analyzer to trace and analyze the searching behaviors of all participant teachers as a whole, and then answer a questionnaire to reflect upon the effectiveness and potential applications of Meta-Analyzer.

2.3. Student data collection and analysis

To evaluate the feasibility and the potential application of Meta-Analyzer in tracking the student online search strategies and activities, two-hundred and twenty 4th to 6th elementary school students (including 123 females and 97 males who were capable of using computers and networks) were asked to answer the following four questions with Meta-Analyzer:

- (1) How many nuclear power plants are there in Taiwan? Where are they located?
- (2) What is the scientific principle of using nuclear power?
- (3) What are the advantages and disadvantages of nuclear power?
- (4) Do you agree to develop nuclear power? Why?

These questions were modified from those used by Tsai and Tsai (2003). It should be noted that Questions 1, 2 and 3 are viewed as *knowledge-finding* questions, which were evaluated by the teachers based on the correctness, richness and completeness of the answers; Question 4 could be simply perceived as a *preference* question, which are evaluated based on the clarity of the answer. A knowledge-finding question requires to gather information and provides a summary about relevant knowledge. A preference question is more related to personal opinion. Each student was asked to answer the questions above by using Meta-Analyzer, which would record student online processes thoroughly.

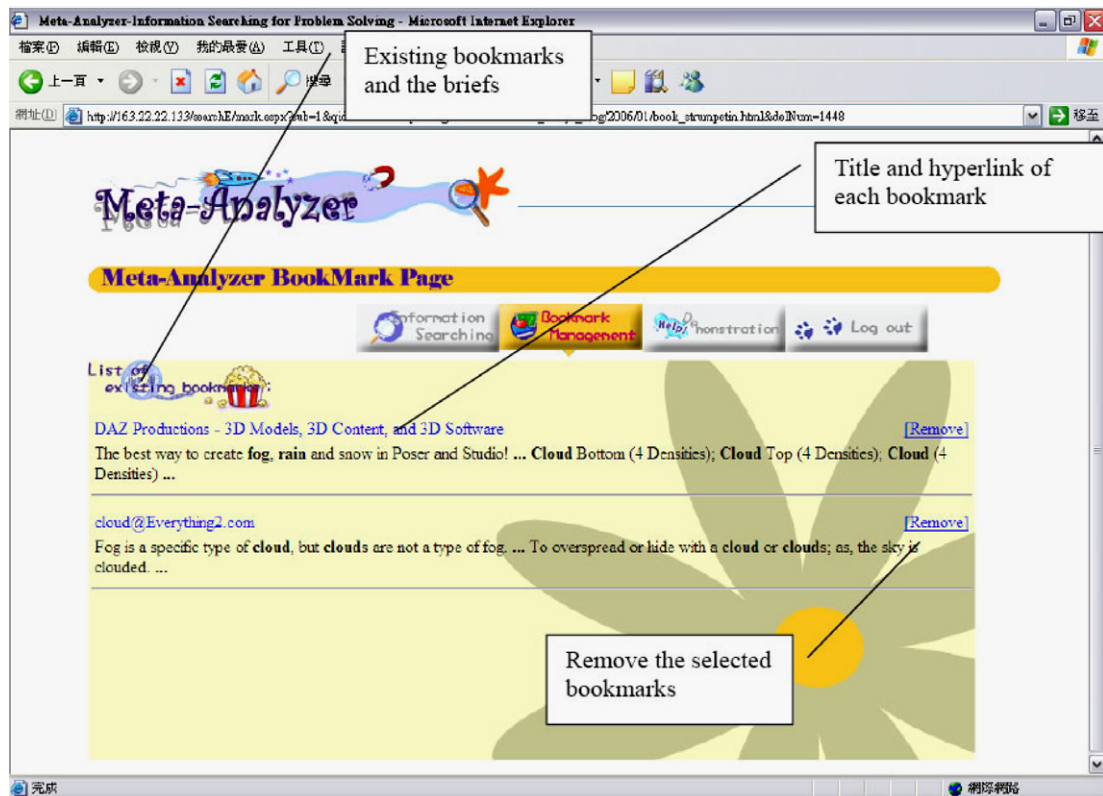


Fig. 4. Bookmark management interface for individual learners.

The online records via Meta-Analyzer were transformed into fourteen quantitative indicators, which are proposed and extended on the basis of the six indicators suggested by Lin and Tsai (2007). These indicators were employed to assist the teachers in tracing and analyzing the web problem solving or searching behaviors of the students in answering each question. In the followings, the quantitative indicators are given and introduced in details:

- (1) *Maximum number of keywords used in a search operation*: This indicator represents the maximum number of keywords used by the student in a search operation for answering the question. For example, if the student attempted to search information three times with keyword sets “energy”, “nuclear energy” and “nuclear energy Taiwan”, respectively, the indicator value is equal to 3.
- (2) *Number of search attempts for answering the question*: This indicator represents the number of attempts for the student to enter keywords to search information for answering the question. For the example given above, the “Number of attempts for answering the question” is equal to 3.
- (3) *Total time for web page selection*: This indicator represents the total amount of time that the student spent on deciding whether to browse the web page from the results returned by the search engine. For example, if the student browsed three web pages for answering the question; before browsing these web pages, it took the student 18 s, 15 s and 10 s, respectively, the indicator value is $18 + 15 + 10 = 43$ s.
- (4) *Number of different browsed and non-adopted pages*: This indicator represents the number of different web pages browsed by the student for answering a question. For example, if the student browsed nine different web pages and adopted three of them for answering the question, the indicator value is 6.
- (5) *Total time for browsing the different non-adopted pages*: This indicator represents the time for the student to browse the non-adopted web pages. For example, if the student browsed nine different web pages and adopted three of them for answering the question, the indicator value is equal to the time spent for browsing these six web pages.

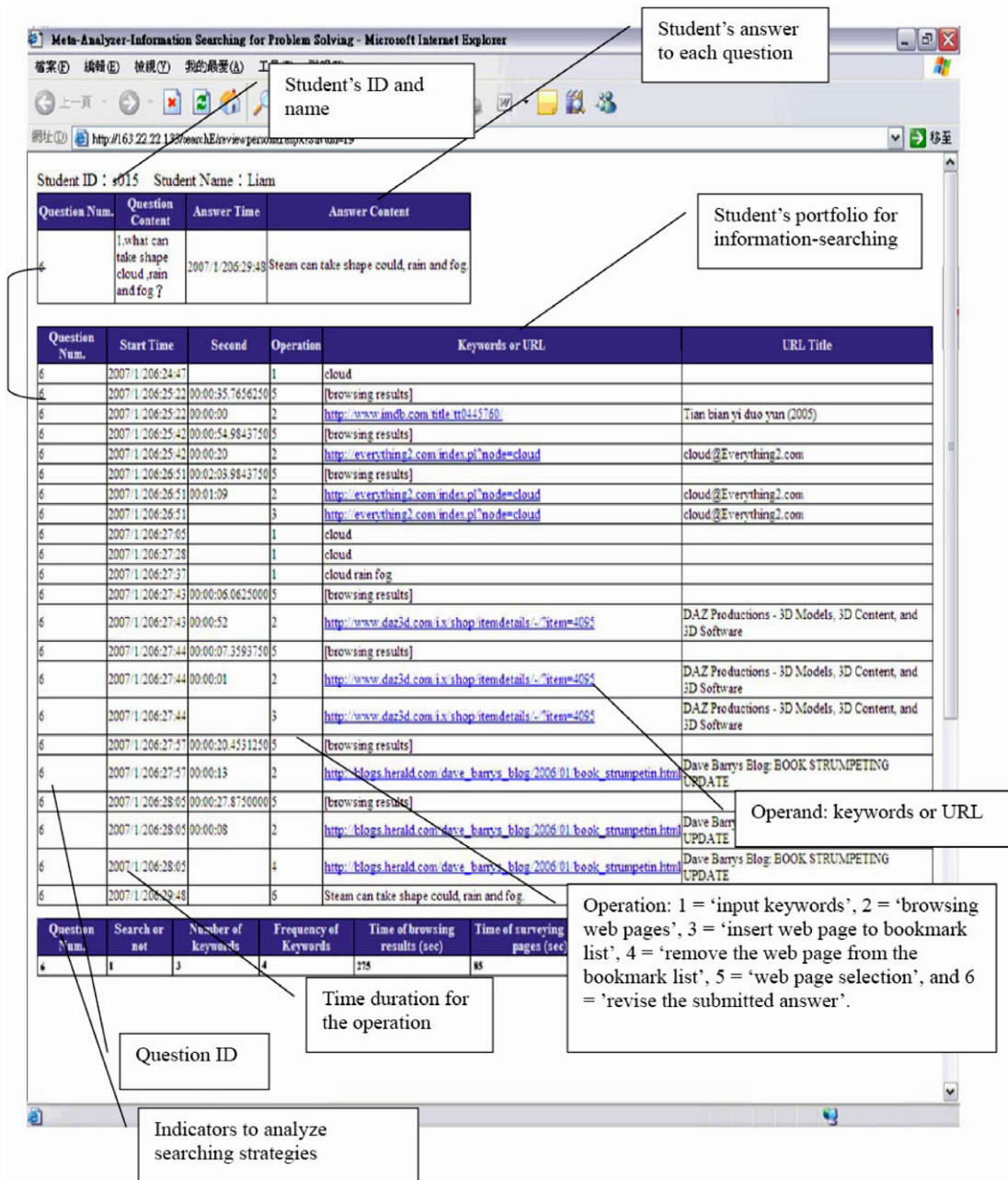


Fig. 5. Teacher interface for browsing information-searching portfolio.

- (6) *Number of different adopted pages*: This indicator represents the number of different web pages whose contents have been adopted by the student for answering the question.
- (7) *Total time for browsing the different adopted pages*: This indicator represents the time for browsing the pages that have been adopted by the student for answering the question.
- (8) *Number of adopted pages with revisits taken into account*: This indicator represents the number of web pages that have been adopted by the student for answering the question, including the revisits of the same pages. For example, if the student adopted four web pages for answering the question and has visited three of them twice, the indicator value is $1 + 2 * 3 = 7$.

- (9) *Total time for browsing the adopted pages with revisits taken into account*: This indicator represents the time for browsing the web pages that have been adopted by the student for answering the question, including the time for revisiting the same pages.
- (10) *Number of browsed and non-adopted pages with revisits taken into account*: This indicator represents the number of web pages that have not been adopted by the student for answering the question, including the added weight of the revisits of the same web pages.
- (11) *Total time for browsing the non-adopted pages with revisits taken into account*: This indicator represents the time for browsing the web pages that have not been adopted by the student for answering the question, including the time for revisiting the same pages.
- (12) *Number of marked and adopted pages*: This indicator represents the amount of web pages that have been marked and have been adopted by the student for answering the question.
- (13) *Number of marked but not adopted pages*: This indicator represents the amount of web pages that have been marked and have not been adopted by the learner for answering the question.
- (14) *Number of revisions made on the answer*: This indicator shows the number of revisions made by the student for improving the quality of the answer to the question. For example, if student revised the answer of question twice after the first submission, the indicator value is equal to 2.

These quantitative indicators are helpful to the teachers in understanding the web-searching behaviors and ability of the students. For example, if the indicator “Number of different adopted pages” is equal to 1, it signifies that the student only referred to one web page for answering the question; that is, the student only copied and pasted data to answer the question without making any comparison for judging the quality of the online information.

To further analyze the relationships among those indicators, the approach of Ford, Miller, and Moss (2001, 2002) was employed. In their approach, factor analysis was applied to analyze the variables to identify clusters of indicators and enable the identification of statistically significant relations between various indicators. By the factor analysis method, researchers can group the indicators into some main searching behaviors for the ease of representation. In the following section, the factor analysis and correlation analysis results on student data will be given to show the relationships among those behaviors.

3. Results and discussion

A series of investigations has been conducted to evaluate the usefulness of Meta-Analyzer. It should be noted that development of Meta-Analyzer aims to record and represent online behaviors, rather than measure the actual quality of the information obtained by the students.

3.1. Teacher data

The first investigation aimed at introducing the functions of Meta-Analyzer to the teachers who were the potential users of the system. Fifty-four teachers from several elementary and junior high schools were invited to experience the use of Meta-Analyzer for online searching, and a questionnaire was used to collect the feedback from the teachers. Table 1 shows the statistical results of the questionnaire, and they also provided some qualitative comments about Meta-Analyzer.

It was found that over 96% of the teachers agreed that Meta-Analyzer could help teachers to acquire more about the learning status of students. Only 2% of the teachers disagreed with this item possibly because they had difficulty in using the system to analyze the learning portfolio of students.

Eighty seven percentage of the teachers agreed that the interface of Meta-Analyzer was easy to use. Some of them suggested adding phonetic symbols, illustration and art designing to engage students, especially for younger students. Again, 2% of the teachers were not good at using the interface of Meta-Analyzer.

Eighty five percentage of the teachers agreed that Meta-Analyzer could help students in paying more attentions to the problem solving or searching process. Those teachers believed that the students would not play computer games or do something irrelevant to the questions under the supervision of Meta-Analyzer.

Table 1
Statistical results of the questionnaire for evaluating Meta-Analyzer

Question	Strongly agree (%)	Agree (%)	Neutral (%)	Disagree (%)	Strongly disagree (%)
Meta-Analyzer is helpful for teachers to realize the learning status of students	59	37	2	2	0
The interface of Meta-Analyzer is easy to operate	39	48	11	0	2
Meta-Analyzer can help students to pay more attentions to the problem-solving process because of the portfolio-recording function	39	46	13	2	0
The use of Meta-Analyzer is helpful for the students to understand the questions	31	63	6	0	0
Meta-Analyzer can enhance the ability of the students for solving problems	41	52	7	0	0
I am willing to use Meta-Analyzer in my class	41	46	13	0	0
I will recommend Meta-Analyzer to other teachers	30	59	11	0	0

Over 93% of the teachers agreed that Meta-Analyzer was able to enhance the problem-solving ability of students. Those teachers believed that by the Meta-Analyzer the difficulties encountered by the students could be detected, and helpful suggestions could be provided by the teachers. Some teachers further suggested showing the problem-solving records (i.e., searching behaviors) to the students so that they could reflect their problem-solving behaviors to achieve better learning performance in the future.

Moreover, 87% of the teachers would like to employ Meta-Analyzer in the future and 89% would recommend to other teachers. Thirteen percentage of the teachers hesitate to use Meta-Analyzer because of the insufficient computer equipments in their school or the lack of computer operation experiences. In sum, we can conclude that Meta-Analyzer is well accepted by most of the teachers.

Finally, the teachers were asked to suggest some courses that are suitable to employ Meta-Analyzer in the student problem-solving process. These elementary and junior high school teachers thought that Social science and Natural science were the most feasible courses for employing Meta-Analyzer, while Math and English were viewed as the least feasible ones (see Fig. 6). The difference is owing to the need of searching information during the problem-solving process. For Math and English courses, usually the students involve more memorization and practices by themselves, while in social science or natural science classes, the students often need to search relevant information for what they have learned.

3.2. Student data

The second investigation aimed at evaluating the effectiveness of Meta-Analyzer by revealing students' online searching behaviors. Two-hundred and twenty 4th to 6th elementary school students were asked to answer the aforementioned four questions with Meta-Analyzer. By responding to the questions, the students

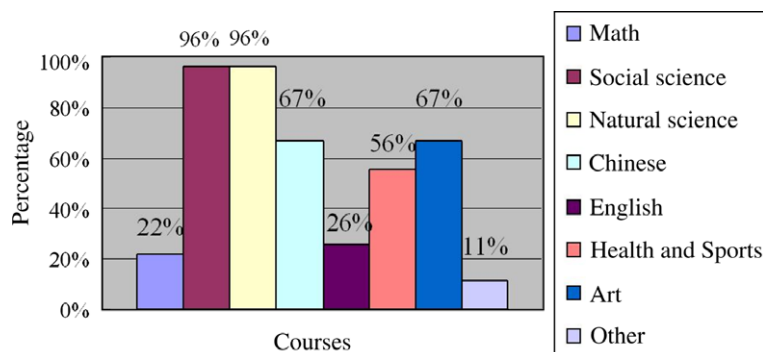


Fig. 6. The statistical results of courses appropriate to apply Meta-Analyzer for teachers.

Table 2
Descriptive statistics of the quantitative indicators with $n = 220$

Quantitative indicators	Mean	SD
I_1 : Maximum number of keywords used in a search operation	0.87 ^a	0.29
I_2 : Number of search attempts for answering the question	1.54	1.08
I_3 : Total time (s) for web page selection	275.12	557.27
I_4 : Number of different browsed and non-adopted pages	1.56	2.53
I_5 : Total time for browsing the different non-adopted pages	119.17	170.97
I_6 : Number of different adopted pages	0.50 ^b	0.57
I_7 : Total time for browsing the different adopted pages	37.55	72.32
I_8 : Number of adopted pages with revisits taken into account	0.54	0.87
I_9 : Total time for browsing the adopted pages with revisits taken into account	36.49	67.33
I_{10} : Number of browsed and non-adopted pages with revisits taken into account	0.56	1.06
I_{11} : Total time for browsing the non-adopted pages with revisits taken into account	21.69	45.29
I_{12} : Number of marked and adopted pages	0.16	0.32
I_{13} : Number of marked but not adopted pages	0.07	0.18
I_{14} : Number of revisions made on the answer	0.06	0.17

^a As part of the students answered the question without using the searching engine, the mean of the indicator I_1 was less than 1.0.

^b As part of the students answered the question without adopting any web content, the mean of the indicator I_6 was less than 1.0.

searched online information by using Meta-Analyzer, which could also record all of their searching behaviors during the problem-solving process. Table 2 shows the descriptive results of fourteen quantitative indicators defined previously by the students.

By using the factor analysis method, the same approach proposed by Ford et al. (2001, 2002), it was possible to investigate the commonalities and differences among these indicators and to identify what these indicators conceptually represent the students' searching behaviors. The indicators in this study included different types of information, such as number of visiting pages, and time of visiting. Therefore, to obtain reasonable results, the values of fourteen quantitative indicators were standardized according to their Z scores while utilizing the factor analysis method. Table 3 presents the results derived from the factor analysis method, revealing three factors among the indicators, called "Information-selecting ability" (factor 1), "answer ability" (factor 2), and "keyword-adopting ability" factor. The eigenvalues of the three factors are greater than

Table 3
Rotated factor loadings and Cronbach's α values for the three factors (subscales) of quantitative indicators with $n = 220$

Items	Factor 1	Factor 2	Factor 3
<i>Factor 1: relevant information-selecting ability $\alpha = 0.89$</i>			
I_{10} : Number of browsed and non-adopted pages with revisits taken into account	0.895		
I_{11} : Total time for browsing the non-adopted pages with revisits taken into account	0.781		
I_4 : Number of different browsed and non-adopted pages	0.743		
I_5 : Total time for browsing the different non-adopted pages	0.711		
I_{13} : Number of marked but not adopted pages	0.689		
I_3 : Total time (s) for web page selection	0.590		
<i>Factor 2: answer ability $\alpha = 0.85$</i>			
I_7 : Total time for browsing the different adopted pages		0.811	
I_6 : Number of different adopted pages		0.784	
I_{12} : Number of marked and adopted pages		0.658	
I_8 : Number of adopted pages with revisits taken into account		0.599	
I_9 : Total time for browsing the adopted pages with revisits taken into account		0.516	
<i>Factor 3: keyword-adopting ability $\alpha = 0.60$</i>			
I_1 : Maximum number of keywords used in a search operation			0.933
I_2 : Number of search attempts for answering the question			0.586
Eigenvalue	6.643	1.251	1.150
% of variance	51.10	9.63	8.85

Overall $\alpha = 0.91$, total variance explained is 69.57%.

Table 4

Inter-correlation matrix of the three factors and task scores with $n = 220$

	Factor 1	Factor 2	Factor 3
Factor 1: relevant information-selecting ability	–		
Factor 2: answer ability	0.64**	–	
Factor 3: keyword-adopting ability	0.45**	0.44**	–
Scores for knowledge-finding questions	0.19**	0.26**	0.21**
Scores for preference question	–0.05	0.05	0.10

** $p < .01$.

1.00 with variance 69.57% explained. An indicator within a factor was retained only when its load is greater than 0.40 on the relevant factor and less than 0.40 on the non-relevant factor. Accordingly, the initial 14 indicators were reduced to 13 indicator items. The internal reliability indexes (alpha coefficients) of the three factors are 0.89, 0.85, and 0.60, respectively; moreover, for the complete item set, the alpha coefficient is 0.91. These coefficients suggested that these factors were sufficiently reliable for representing student searching behaviors.

We further utilized correlation analyses between the three factors and students' search task scores, shown in Table 4. According to Table 4, the three factors about student online searching behaviors were moderately to highly correlated ($r = 0.44$ – 0.64). That is, these online search or problem-solving behaviors were mutually supported. For instance, students' keyword-adopting behaviors were positively related to their information-selecting ability. Moreover, the correlation analysis indicated that the students with higher scores for knowledge-finding questions tended to have significantly higher values for the three factors ($p < .01$). Nevertheless, the students with higher scores for the preference question did not show the tendency of having higher quantitative indicator value for any factor. In other words, students' online search behaviors were not statistically related to their scores on the preference question. Such results are reasonable since the students needed to carefully collect information before they could better answer the knowledge-finding questions; while answering the preference question, the opinions based on personal recognitions may be more important than the data collected from the Web. These results, to a certain extent, also reveal the validity of the quantitative indicators and the three factors utilized by this study.

To investigate the possible differences of quantitative indicators between male and female students, the factors of online searching behaviors of both genders were compared, and no significant difference was found. That is, males and females tended to use similar searching strategies toward the quantitative indicators.

4. Conclusions

Although the study of web-search behaviors is known to be an important issue, previous reports also depict its challenges (Bilal, 2000; Bilal & Kirby, 2002; Tsai & Tsai, 2003). Without any technical assistance, researchers had to use some screen capture software or video camera to record the student online activities. That is, they had to spend a very long time on browsing the web-search portfolio and take notes manually. In this paper, a Web-based environment, Meta-Analyzer, for recording and analyzing the student online search behaviors for solving a problem or completing a learning task is proposed. Meta-Analyzer can be used not only as a research tool, which provides online recording and statistical functions, but also as an instructional tool, helping teachers to acquire a more detailed understanding about each student's online behaviors. Based on the trials and feedback from 54 teachers and 220 students, it was found that the innovative approach can provide researchers and teachers with an effective and efficient way of accomplishing and investigating various educational objectives and research issues.

Past studies have reported the importance of analyzing the search strategies of students on the Web for improving the learning ability related to online activity. For example, categorizing information-searching approaches used by students on the Web is helpful to the teachers in realizing the learning problems of individual students and finding more effective instructional strategies (Drabenstott, 2003; Ford, Miller, & Moss, 2003; Hölscher & Strube, 2000; Tsai, 2004; Tsai & Tsai, 2003). Researchers also reported that students who have advanced online searching and evaluating strategies may develop more accurate and in-depth

understanding of certain topics, which points to the importance of understanding how students use search strategies and to help them develop more sophisticated approaches toward improving Internet-based learning (Hoffman, Wu, Krajcik, & Soloway, 2003).

In additions, Meta-Analyzer facilitates the studies of various research issues concerning the exploration of student online search behaviors, such as the analysis for detecting the navigation processes and strategies used by the students (Bilal, 2000; Tabatabai & Shore, 2005; Tsai & Tsai, 2003), the comparisons of experts and novices' search strategies on the Web (Tabatabai & Shore, 2005), the studies on the interactions among dynamic higher-order thinking, metacognitive operations and the prior knowledge and capacity for students to solve problems with Web-based inquiries (Bilal, 2000, 2001, 2002; Bilal & Kirby, 2002; Rouet, 2003), and the studies on the relationships of different kinds of search strategies and the nature of the tasks to be coped with (Bilal, 2000, 2001, 2002; Hsieh-Yee, 2001; Rouet, 2003). Thus, these studies suggest that investigating students' online searching processes may give researchers greater insights into how different sorts of mental abilities, such as cognition and metacognition, may influence knowledge construction in Web-supported learning environments (Hofer, 2004).

Currently, we are planning to extend Meta-Analyzer to contain more functions and options, such as searching data from Google Scholar, academic databases or journals, which might be useful in analyzing the usage of those digital materials and the online searching behaviors of graduate students and researchers.

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