Facilitating Students' Learning Through Problem-Solving in a Computer-Based Expert-Supported Learning Environment

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Abstract. Problem-based learning (PBL) has been widely adopted to help students to develop critical thinking, communication, and problem-solving skills as well as improve the construction of knowledge. However, empirical studies indicate that PBL students hardly develop structured knowledge and efficient reasoning strategies because they are not provided with adaptive guidance and support during problem-solving process. To deal with this challenge, a computer-based expert-supported learning environment is designed and developed to facilitate students' learning in a problem-solving context. Experiment results reveal superior performance on problem-solving and knowledge-construction tasks in students learning under the designed environment. Findings of the study provide important implications to instructional designers and educational practitioners on how to facilitate students' problem-solving learning through the design of a computer-based expert-supported environment.

Keywords: Problem-based learning · Problem solving · Knowledge construction · Expert support · Adaptive guidance

1 Introduction

Problem-based learning (PBL) has been widely adopted to help students to develop critical thinking, communication, and problem-solving skills as well as improve the construction of knowledge. From perspective of constructivism, instructional methods such as problem-based learning and inquiry-based learning allow students to acquire subject-matter knowledge and develop problem-solving skills by searching solutions for concrete problems in situated contexts (Albanese and Mitchell 1993).

Compared to conventional teacher-centered, lecture-based teaching method, self-directed problem-driven learning is advocated in PBL. In PBL curricula, students acquire and elaborate domain knowledge by working on realistic problems by themselves. They are more likely active and cooperative participators than passive recipients

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in learning activities. Correspondingly, instead of imparting knowledge directly, teachers are supposed to work as learning facilitators in PBL contexts (Barrows 1996).

However, previous studies indicate that the scarcity of expert support and adaptive guidance to students is a limitation existed in PBL, which may impede students to construct systemic knowledge and develop effective reasoning skills, and finally influence their problem-solving performance and professional competency (Kirschner et al. 2006). Therefore, instructional techniques and domain expertise are necessary to help students develop structured knowledge and proper strategies in PBL environments (Schmidt and Boshuizen 1993).

To meet the challenge, a computer-based, expert-supported learning environment is designed and developed to facilitate students' learning through problem-solving, in which problem-solving and knowledge-construction processes are captured and externalized. Cognitive strategies are integrated into the learning environment to help students to articulate and reflect on their problem-solving and knowledge-construction processes in an explorative learning environment. Model-centered instruction (MCI) model is adopted to enable students to compare their problem-solving process to that of the expert and identify the key points toward domain expertise. Two research questions of this study are specified as follows:

Q-1: How can a computer-based expert-supported learning environment be designed to facilitate students' learning through problem-solving?

Q-2: What are the effects of the designed learning environment on student problem-solving learning?

2 Relevant Studies

To facilitate students' learning through problem-solving, relevant studies on problem-solving learning are integrated into the design of the proposed learning environment.

From perspective of situated and constructivism learning theory, learning could be facilitated problem-solving contexts, when knowledge is learned in a way that it is used to solve realistic problems in authentic contexts (Brown et al. 1989). Situated learning theory provides students an authentic learning situation that integrates knowledge with contextual practice, which maintain the complexity of real world (Young 1995). Thus, students are more likely to develop in-depth understanding of subject-matter knowledge when it is related to the situation in which it is applied.

Despite offering an authentic learning situation that integrates knowledge with contextual practice, cognitive apprenticeship model provides concrete strategies to scaffold students' learning by externalizing their cognitive and intellectual processes in problem-solving contexts. Therefore, it has been widely used as an instructional model in situated learning contexts, such as problem-based learning environments over the last few decades (Clancey 1992). Cognitive apprenticeship presents certain instructional strategies to provide students with coaching and scaffolding in situated environments for exploration, with support of cognitive modeling for articulation and reflection in problem-solving process, to facilitate expertise development in complex problem-solving contexts (Collins et al. 1989, p. 453). The core idea of cognitive apprenticeship model is scaffolding complex cognitive processes by making tacit knowledge underlying problem-solving activities accessible to students (Collins 1991).

Considering the cognitive process and domain expertise underlying problem-solving activities are usually complex and tacit (Bransford et al. 1989, p. 470), the investigations on cognitive tools and techniques to present and explain the complex cognitive process and expert knowledge underlying problem-solving activities becomes especially important (e.g., Doerr 1996; Gravemeijer 1999). Previous research indicates that experts are more likely to capture key elements to problem solutions by the recognition of solution patterns embedded in their mental models (Alexander 2003; Anderson 1993). Model-centered instruction (MCI) introduces mental models as cognitive tools, consisting of chains of actions and associating related knowledge into problem-solving patterns, to help students to explain their actions and represent their intellectual processes in problem-solving contexts (Greca and Moreira 2000). Particularly, expert mental models are provided as learning guidance in students' accomplishment of complex tasks in expert MCI (Alessi 2000, p. 176). In this way, students are expected to recognize problem-solving patterns and identify the domain knowledge underlying problem-solving processes in an expert manner.

3 Methods

Informed by abovementioned learning theories and instructional models, a computer-based, expert-supported learning environment was designed to facilitate students' learning through problem-solving. Glaucoma diagnosis was chosen as the learning topic for this study because medical diagnosis falls under the category of complex problem solving and it is a common content for medical students. An experiment was conducted in a public medical college in southern mainland China to investigate the effectiveness of the designed learning environment on students' problem-solving learning.

Two diagnosticians with decades of experience in glaucoma diagnosis and treatment from two local hospitals were involved in the experiment. They provided expert knowledge and guidance in preparation of learning materials and assessment of learning outcomes. A teacher from the medical college with years of teaching experience helped to arrange learning activities and tests with students.

4 Design of the Learning Environment

A computer-based expert-supported learning environment was designed and devolved to help students solve diagnostic problems in glaucoma diseases. Main functions of the designed learning environment are presented as follows.

4.1 Diagnostic Problem-Solving Contexts

Students learn to solve 5 diagnostic cases in glaucoma diseases in a way that is similar to clinical encounters in the designed learning environment. All the cases used for learning are selected and adapted from real clinical cases and are double confirmed by the diagnosticians.

Once a case is selected from the case database in the system, relevant information of the simulated patient including background information, medical history and chief complaint is presented to the student. According to the initial information, the student may have a preliminary diagnostic plan consisting a series of clinical examination to collect more information. Results of examinations are displayed in terms of laboratory data and images, based on which the student could make clinical judgements and select the next clinical examination (see Fig. 1). The student is permitted to select any examinations from a list as many as he/she want before reaching a diagnostic conclusion.

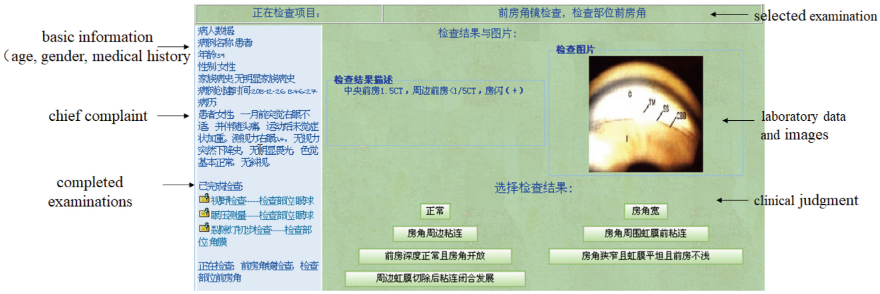

Fig. 1. Diagnostic problem-solving context.

4.2 Modeling of Problem-Solving Process

Students are allowed to diagnose a case as many times as they wanted within the learning program. Each diagnostic process is recorded by the system as diagnostic flowchart in which key points in the process are captured and presented in the designed learning environment. A diagnostic flowchart presents the initial information, clinical examinations, relevant judgments, and a diagnostic conclusion in sequence for each diagnosis (See Fig. 2). The diagnostic flowchart consisting of chains of clinical actions in a sequential order is assumed to reflect reasoning skills and tacit knowledge underlying the problem-solving process (Kinchin et al. 2008).

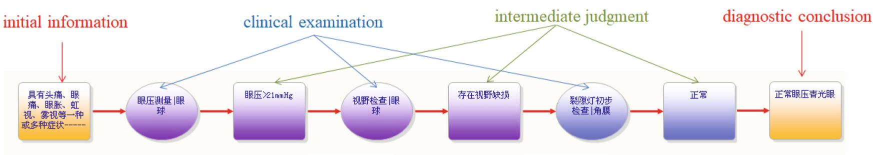

Fig. 2. Modeling of problem-solving process.

In this way, how further information is collected by selecting clinical examinations and making relevant judgment based on incomplete information before reaching a diagnostic conclusion is modeled and demonstrated in a visual format. The model-based problem-solving process reflects the intellectual process students used to understand and approach given problems, and makes it become accessible for students to observe, enact, and practice. Furthermore, changes in students' model-based problem-solving process provide visible evidence on their learning development.

4.3 Expert-Supported Reflection on Problem Solving

For each diagnosis, the diagnostic flow of the expert will be presented in the designed learning environment when the degree of similarity between the student and expert in diagnosing a learning case reached 60% or more (See Fig. 3). Not only the key elements such as clinical examinations and relevant judgements, but also the logic relations are taken into consideration in the calculation of similarity. Moreover, feedback from the system and comments from experts on each problem-solving process can be viewed by the student, indicating the key points and possible errors in diagnosing the case.

Based on the feedback, the student would be able to find how his/her diagnostic process is different from that of the expert. Expert-supported reflection on problem solving helps students to identify the implicit knowledge embedded in problem-solving process and adjust their reasoning strategies in dealing with the next diagnosis.

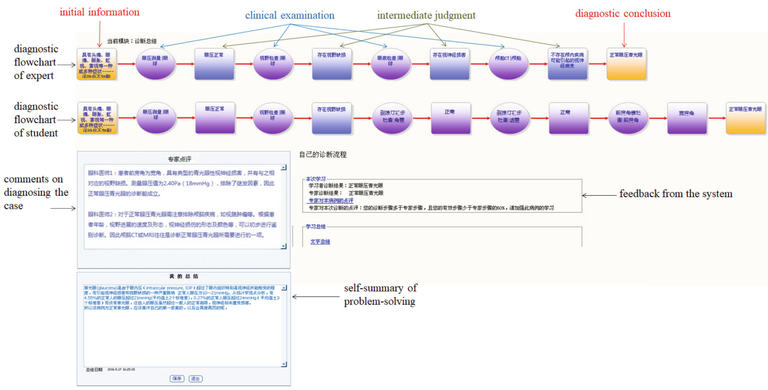

Fig. 3. Expert-supported reflection on problem solving.

4.4 Facilitation of Knowledge Construction

Knowledge structure could be deemed as the internal structure in which relevant ideas or concepts are interrelated that people used to process external information and approach given problems (Patel et al. 1994, p. 188). A well-organized knowledge structure looks like an elaborate, highly-integrated framework in which relevant concepts are highly and meaningfully interconnected to represent in-depth understanding of domain expertise (Feltovich et al. 1993, p. 126). Therefore, students' abilities to construct knowledge are closely related to their performance in problem-solving tasks (Shin et al. 2003).

To help students to frame related concepts and ideas in problem-solving contexts, and make it becomes more retrievable when dealing with similar problems, a graphic tool is provided to students in the designed learning environment. Students would be able to draw a comprehensive mental map to reflect their problem-solving expertise acquired from worked cases (See Fig. 4). The process of drawing a metal map is similar to the construction of relevant domain knowledge, which requires the student to identify the core steps in dealing with the problems and integrate them into a network. In this sense, a mental map that is regarded as the learning product of student in the designed learning environment may reflect the structure of domain knowledge in his/her mental model and predict his/her performance in problem-solving tasks to some extent in future.

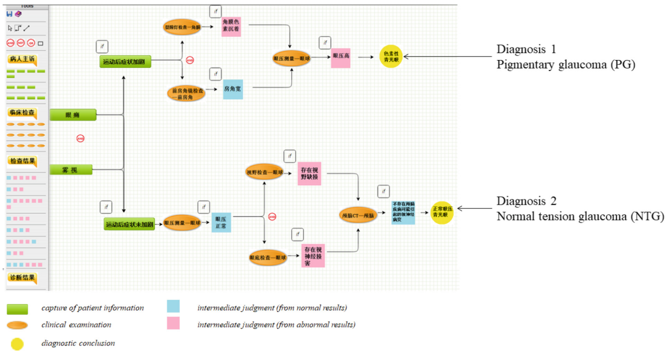

Fig. 4. Facilitation of knowledge construction.

5 Evaluation of the Learning Environment

An experiment was conducted in a public medical college in southern mainland China to investigate the effectiveness of the designed learning environment on students' problem-solving and knowledge-construction performance. 50 senior undergraduate students (fourth-year undergraduate) from two classes participated in the experiment on a voluntary basis. To avoid interaction between participants from the same class during the experiment, they were divided into two groups. 25 students from one class were assigned the experimental group; while 25 students from the other class were assigned to the control group.

At the beginning of the learning program, students were asked to complete a pre-test consisting of (1) a diagnostic problem-solving task as the measure of students' initial problem-solving abilities, and (2) a standardized knowledge test as the measure of students' preliminary level of domain knowledge. Tversky's contrast model (Tversky 1977) was used to evaluate students' performance in diagnostic problem-solving tasks. Based on Tversky's contrast model, key elements (i.e., clinical examinations used to collect further information, intermediate judgments based on examination results, and diagnostic conclusion) as well as scales for each element (i.e., number of valid, redundant and missing items by making comparison to the expert) in diagnostic problem-solving process were identified. Thus, the degree of similarity between the student and the expert in completing a diagnostic task was automatically calculated by the system as the measure of students' performance in the diagnostic problem-solving task.

The learning program lasted for six weeks and no teacher involved except a teacher assistant showing students how to use the learning system and helping them with technical problems during the experiment. Students were suggested to pace themselves and spend three to four hours on learning each case. Students in the experimental group used the designed learning environment to learn to diagnose five cases on glaucoma disease; while students in the control group used another similar system but without expert support and modeling tools to learn to diagnose the same five cases.

At the end of the learning program, students were asked to complete a post-test consisting of (1) a survey questionnaire to collect students' perceptions of cognitive strategies supported by the learning environment, (2) a diagnostic problem-solving task with the same level of difficulty as that in the pre-test as the measure of students' problem-solving abilities after the learning program, (3) drawing of a mental map to represent and connect reasoning process and subject-matter knowledge underlying all five learning cases using a graphic tool provided by the system. The assessment of mental map was essentially the same as that of the performance in diagnostic problem-solving tasks.

6 Results

45 students (25 of experimental group, 20 of control group) completed the entire learning program in the experiment. The level of students' computer skills was reported between good (58%) or intermediate (42%); and most had a strong intention to use computer-assisted learning (82%).

6.1 Problem-Solving Performance

Results of descriptive statistics and independent sample t-test on students' performance on diagnostic problem-solving tasks in pre- and post- tests are given in Tables 1 and 2 respectively. As shown in Table 1, there were no significant differences in scores of diagnostic problem-solving performances between two groups in the pre-test in each scale ($P\_CA = .410$, $P\_IG = .593$, $P\_DC = .697$, $P\_Overall = .433$). The results indicate that students of two groups had equivalent problem-solving abilities before the learning program.

Table 2 shows that students of the experimental group had significantly higher scores of performances in diagnostic problem-solving tasks than did those of the control group in most scales in the post-test ($P\_CA = .002$, Cohen's $d = 1.05$; $P\_IG = .000$, Cohen's $d = 1.25$; $P\_Overall = .009$, Cohen's $d = 0.83$), except the scale of diagnostic conclusion ($DC\_P = .738$). The results indicate that students of the experimental group generally had superior problem-solving abilities than did those of the control group after the learning program. The differences in mean values between the experimental group and the control group was greatest in intermediate judgement based on examination results (0.54 vs. 0.29) among all the scales.

Table 1. Descriptive statistics and independent sample t-test on students' problem-solving performance in diagnostic tasks in pre-test.

Scales		Descriptive statistics				Independent sample t-test	
		EG (n = 25)		CG (n = 20)			
		M	*SD*	*M*	*SD*	*df*	*P*
CA	Number of valid items	1.76	.72	1.45	.76	43	.169
	Number of redundant items	4.32	1.35	3.80	1.96	43	.298
	Number of missing items	1.24	.72	1.65	.88	43	.092
	Similarity to expert	.38	.15	.34	.16	43	.410
IG	Number of valid items	.80	.76	.60	.68	43	.365
	Number of redundant items	5.28	1.54	4.55	2.01	43	.175
	Number of missing items	1.24	.72	1.65	.88	43	.092
	Similarity to expert	.18	.17	.15	.18	43	.593
DC	Number of valid items	.08	.28	.05	.22	43	.697
	Number of redundant items	.92	.28	.95	.22	43	.697
	Number of missing items	N/A	N/A	N/A	N/A	N/A	N/A
	Similarity to expert	.08	.28	.05	.22	43	.697
Overall	.21	.14	.18	.13	43	.433	

EG: Experimental Group CG: Control Group
CA: Clinical examination to collect further information
IG: Intermediate judgment based on examination results
DC: Diagnostic conclusion
**p < .05; **p < .01; ***p < .001.*

Table 2. Descriptive statistics and independent sample t-test on students' problem-solving performance in diagnostic tasks in post-test.

	Scales	Descriptive statistics				Independent sample t-test	
		EG (n = 25)		CG (n = 20)			
		M	*SD*	*M*	*SD*	*df*	*P*
CA	Number of valid items	3.36	.86	2.10	1.12	43	.000**
	Number of redundant items	2.80	1.66	3.10	1.12	43	.493
	Number of missing items	.64	.86	1.90	1.12	43	.000**
	Similarity to expert	.67	.19	.45	.24	43	.002**
IG	Number of valid items	2.60	1.00	1.25	.91	43	.000**
	Number of redundant items	3.72	1.82	4.00	1.08	43	.524
	Number of missing items	.64	.86	1.90	1.12	43	.000**
	Similarity to expert	.54	.20	.29	.21	43	.000**
DC	Number of valid items	.40	.50	.35	.49	43	.738
	Number of redundant items	.60	.50	.65	.49	43	.738
	Number of missing items	N/A	N/A	N/A	N/A	N/A	N/A
	Similarity to expert	.40	.50	.35	.49	43	.738
Overall		.54	.18	.37	.24	43	.009**

EG: Experimental Group CG: Control Group
CA: Clinical examination to collect further information
IG: Intermediate judgment based on examination results
DC: Diagnostic conclusion
**p < .05; **p < .01; ***p < .001.*

6.2 Knowledge-Construction Performance

The results indicate that students of two groups had equivalent problem-solving abilities before the learning program. Results of descriptive statistics and independent sample t-tests on knowledge test in the pre-test are presented in Table 3. As shown, there was no significant difference in the test scores between the experimental group (Mean = .48, SD = .08) and control group (Mean = .47, SD = .08; P = .816) in the pre-test. The results indicate that students of two groups had equivalent level of subject-matter knowledge before the learning program.

Table 3. Descriptive statistics and independent sample t-tests on knowledge test in the pre-test (scores normalized between 0 and 1).

Descriptive statistics				Independent sample t-test	
EG (n = 25)		CG (n = 20)			
M	*SD*	*M*	*SD*	*df*	*P*
.48	.08	.47	.08	41.562	.816

EG: Experimental Group CG: Control Group
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Descriptive statistics and independent sample t-tests results on students' knowledge-construction performance, based on the tasks of drawing a mental map in the post-test are presented in Table 4. As shown, students of experimental group had significantly higher scores on the drawing tasks than did those of control group in the post-test on most scales (P_CA = .000, Cohen's d = 1.39; P_IG = .000, Cohen's d = 1.82; P_Overall = .000, Cohen's d = 1.33), except the scale of diagnostic conclusion (DC_P = .279). The results indicate that students of experimental group had better knowledge-construction performance than did those of control group on the whole after the learning program. The differences in mean values between the experimental group and the control group was greatest in intermediate judgement based on examination results (0.57 vs. 0.35) among all the scales.

Table 4. Descriptive statistics and independent sample t-tests on the drawing task of mental map.

	Scales	Descriptive statistics				Independent sample t-test	
		EG (n = 25)		CG (n = 20)			
		M	*SD*	*M*	*SD*	*df*	*P*
CA	Number of valid items	9.48	2.40	7.35	1.79	43	.002**
	Number of redundant items	4.44	2.42	7.00	2.00	43	.000**
	Number of missing items	6.68	2.43	8.65	1.79	43	.004**
	Similarity to expert	.63	.13	.48	.08	43	.000**

(*continued*)

Table 4. (*continued*)

	Scales	Descriptive statistics				Independent sample t-test	
		EG (n = 25)		CG (n = 20)			
		M	*SD*	*M*	*SD*	*df*	*P*
IG	Number of valid items	8.60	2.45	5.25	1.89	43	.000**
	Number of redundant items	5.44	2.96	9.60	2.37	43	.000**
	Number of missing items	7.52	2.55	9.75	1.80	43	.002**
	Similarity to expert	.57	.14	.35	.10	43	.000**
DC	Number of valid items	3.48	.86	3.20	.62	43	.213
	Number of redundant items	1.52	.82	1.80	.62	43	.213
	Number of missing items	N/A	N/A	N/A	N/A	N/A	N/A
	Similarity to expert	.81	.12	.77	.10	43	.279
Overall		.64	.13	.50	.07	43	.000**

EG: Experimental Group CG: Control Group
CA: Clinical examination to collect further information
IG: Intermediate judgment based on examination results
DC: Diagnostic conclusion
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

7 Implications and Conclusion

This study is an empirical attempt to design a real-life problem-solving learning environment into which cognitive strategies and expert support were integrated. The study has some practical implications for instructional designers and education practitioners in such complex problem-solving domain as medical education.

First, the results of this study revealed that cognitive apprenticeship and model-centered instruction (MCI) could be effective pedagogies to improve students' problem-solving and knowledge-construction performances in problem-based learning (PBL) environments when successfully implemented by virtue of information technology. Modeling of and reflection on of problem-solving process are the key factors in making cognitive process visible. Thus, students could be able to understand how domain knowledge and reasoning strategies are related to reach the solution of a given problem. This aligns with the results of related studies, that computerized models have potentials in scaffolding students' scientific understanding (De Jong et al. 1999; Monaghan and Clement 1999).

Second, cognitive tools such as mental maps could be used to help students to construct functional mental models, in which subject-matter knowledge and reasoning strategies underlying problem-solving processes are excavated and interconnect. In view of this, the design of appropriate tools to externalize mental models is essential to achieve model-centered leaning (MCL) in complex problem-solving domain. This is consistent with previous empirical studies that found that, students are more likely to exhibit superior performance in completing complex tasks when they are able to externalize problem-solving processes and implicit knowledge underlying the tasks by using computer-based cognitive tools (Wang et al. 2013; Wu et al. 2016).

Last, but by no least, expert support plays an important role in students' learning reflection in complex problem-solving context. When provided with expert's diagnostic flowchart in this study, students are more able to identify the difference between themselves and the expert in completion of complex tasks, and may develop expert-like reasoning strategies and knowledge structures. By comparing the features of their mental models with those of experts, students are able to extract problem-solving expertise embedded in complex tasks and ultimately assimilate it into their own knowledge base (Brown et al. 1989; Collins 1991). This confirms the conclusions of previous studies that indicate that novices are more likely to make sense of their learning and construct highly structured domain knowledge when experts' mental models became accessible to them (Grosslight et al. 1991).

In conclusion, this study explores the design and effectiveness of a computer-based expert-supported learning environment to improve students' problem-based learning by scaffolding their reflection on problem-solving and knowledge-construction processes. For this purpose, expert knowledge and problem-solving process are externalized in visual forms and integrated into the designed learning environment, to help students to reflect on and identify the reasoning strategies and subject-matter knowledge underlying problem-solving processes. The results show that the designed learning environment has positive effects on students' problem-solving skills and knowledge-construction performances in terms of clinical examination to collect further information and intermediate judgment based on examination results, with the exception of diagnostic conclusion. One possible explanation for this is that some students made a correct diagnostic conclusion not based on correct reasoning. This might indicate that the designed learning environment is conducive to developing students' reasoning skills rather than problem-solving results. Further studies involve the investigation on long-term effects of the designed learning environment on students' problem-solving learning through a follow-up evaluation study, and the investigation of the designed learning environment in other related domains.

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