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An Eye Tracking Study of High- and Low-Performing Students in Solving Interactive and Analytical Problems

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ABSTRACT

Test results from the Program for International Student Assessment (PISA) reveal that Shanghai students performed less well in solving interactive problems (those that require uncovering necessary information) than in solving analytical problems (those having all information disclosed at the outset). Accordingly, this study investigates information-processing strategies in solving these two types of complex problems. High- and low-performing students' eye fixations within certain areas of interest (AOIs) as well as their visits between AOIs were recorded as they solved problems on a computer. High-performing students had long fixation durations for the analytical problem and the problem-solving stage of the interactive problem. With regard to the problem exploration stage of the interactive problem, high-performing students had short fixation durations. These findings demonstrate how students had varying information-processing strategies for different types of problem-solving scenarios at different problem-solving stages. The implications of this study are discussed.

Keywords

Analytical problem solving, Interactive problem solving, Eye tracking, Strategic thinking, Reasoning

Introduction

Problem solving is a critical competence in daily life and work. The development of problem-solving competence has drawn increasing attention, not only from within the domain of educational practice, but also from commentators in society more widely. The term "problem" suggests various qualifiers for its definition and differentiation: these include "well-structured," "ill-structured," "domain-dependent," "domain-independent," "static," "dynamic," "interactive," "analytical," "visual," "creative," and "design" (Knoblich, Ohlsson, & Raney, 2001; Greiff, & Fischer, 2013; Jonassen, 2014; van Meeuwen et al., 2014). While researchers have confirmed the occurrence of certain general competencies across all types of problem solving, distinctive competencies associated with solving certain types of problem have also been identified (Jonassen, 2010). Accordingly, learning to solve only certain types of problem will not guarantee the mastery of competencies necessary to solve others (van Merriënboer, Clark, & De Croock, 2002). Therefore, research on the cognitive processes involved in solving a range of problem types remains important for fostering the development of student problem-solving competencies.

PISA but also our own previous study (Hu, Wu, & Gu, 2017; OECD, 2014) asserted that Shanghai students performed less satisfactorily when solving interactive problems (i.e., those that require uncovering necessary information) compared to performance in solving analytical problems (i.e., those that have all information disclosed at the outset). The possibility that problems in formal school contexts and those in "real-world" contexts are fairly different in terms of structure as well as complexity (Jonassen, 2014) might explain students' different performances in solving analytical, school-like, and interactive complex problems.

Cognitive information processes of problem solving

Mayer and Wittrock (2006) defined the problem-solving process in terms of transformations of a given state into a goal state when no evident method of solution is available. General problem-solving processes may involve various cognitive competencies. These include reasoning, critical thinking, decision making, argumentation, and metacognition (Jonassen, 2014). They also may involve different cognitive activities, such as problem exploration, knowledge representation, problem solution planning, and evaluation (Mayer, 2003). Two typical types of problem have generally been investigated (Fischer et al., 2015; Greiff, Wüstenberg, & Avvisati, 2015; Wirth, & Klieme, 2003) and then have been embedded in international large-scale assessment: one concerns analytical problems, and the other concerns interactive problems (OECD, 2014).

In analytical problem solving, the problem solver needs to structure, represent, and integrate information to construct a problem solution (Simon, 1975). Given the static nature of analytical problems, the problem-solving process is fairly straightforward, with limited opportunity for updating the problem schema, such that mental effort is mainly invested in manipulating operations to change initial states toward some target state. By contrast, in interactive problem solving, the problem situation may change over time, such that changing one variable in a task may lead to manifold changes in other variables (Funke, 2010). A problem solver cannot only rely on the information given at the outset. They must work out a plan to search the space of information, propose and adapt his or her hypotheses, as well as executing the plan to collect information to corroborate or refute the hypotheses and reach a final goal (Greiff & Fischer, 2013). Therefore, a problem solver should keep restructuring or updating the problem representation in order to solve incongruence or to integrate new information: they must adjust problem exploration and reasoning strategies accordingly. Moreover, the problem-solving pathway may vary from one problem solver to another because of the interrelationship between dynamic problem exploration and problem solving (Sprenger & Dougherty, 2012).

Regarding the general information processes during problem solving, several typical strategies have been widely examined. For example, during the problem exploration stage, one strategy has been termed “cue-wise” or “history-cue,” in which people use previously identified cues to drive further problem space exploration (Renkewitz & Jahn, 2012; Sweller, Mawer, & Howe, 1982). Another strategy is termed “trial-and-error,” in which random attempts are made to select the operant. While during the problem-solving process, one strategy has been called “schema-driven,” in which individuals conduct forward reasoning on the basis of the constructed knowledge schema (Gick, 1986). A further strategy has been called “means-end,” in which attempts are made to reduce the difference between the current state and the goal state.

The assertion of Fischer et al. (2015) that analytical problem-solving and interactive problem-solving address a common core of problem-solving competence cannot explain the reason why Chinese students perform better in the former type of problem than they do in the latter (Hu et al., 2017; OECD, 2014). Certain studies have confirmed that solving interactive and analytical problems requires different competencies in terms of both knowledge acquisition and knowledge application. For example, Greiff and Fischer (2013) argued that problem exploration as well as representation each require strategic knowledge on capturing critical information, constructing well-organized problem schema, and generating, as well as testing, hypotheses. Wirth and Klieme (2003) asserted that interactive problem solving includes aspects of self-regulated learning, as well as processes of feedback management.

Eye tracking in problem solving

Eye-tracking technology offers an attractive and powerful tool to reveal the cognitive processes of student learning (Lai et al., 2013). Many studies use eye-tracking techniques for focusing on different learning domains, such as multimedia learning (van Gog & Scheiter, 2010), conceptual learning (Ariasi & Mason, 2011), language learning (Whitford & Titone, 2012), and category learning (Rehder & Hoffman, 2005). Given that a complex problem-solving process requires the integration of different competencies, multimodal data (such as the log data of learning behavior (Worsley & Blikstein, 2015)), eye movements, learning outcomes, and self-report, can all provide distinct analytic perspectives for deepening our understanding of this field. For example, visual attention during problem-solving, as measured by eye movements, can be used to reveal the critical aspects of the process that traditional measures, such as solution time and accuracy or behavior-level keystrokes, cannot address (Grant & Spivey, 2003; Lee & Anderson, 2001; Tsai, Hou, Lai, Liu, & Yang, 2012; van Meeuwen et al., 2014; Yeh, Tsai, Hsu, & Lin, 2014).

For the recording of eye movements, two basic measures are used: first eye fixation, which is a relatively stable state of eye position and, second, saccades, which are the rapid eye movements between eye fixations (Rehder, Colner, & Hoffman, 2009). Based on these two measures, eye-tracking indices of three forms can be used for analysis. Counts are also possible, both spatial and temporal, such as number of fixations, fixation positions, and saccade durations (Radach & Kennedy, 2004). In addition, researchers may be interested in identifying the information that learners gaze at, typically called ‘the area of interest’ (AOI), but also the gazing duration, and the gazing sequence. In this way, eye-tracking indices can provide rich information in relation to the different AOIs and transitions among different AOIs. However, how to interpret measurements effectively in various learning contexts is a vital issue when applying the eye-tracking method in educational research (Lai et al., 2013). For example, mental effort investment can be directly measured using temporal scales (such as fixation duration) (Saß, Schütte, & Lindner, 2017); count measures of fixation can be used to reveal the importance of visual materials (Balslev et al., 2012); and different patterns of saccadic eye movement may be taken to imply different information-processing strategies (van Meeuwen et al., 2014). Lai et al. (2013) has reported that previous studies employed temporal indicators most frequently, followed by spatial and count indicators.

By examining major themes in eye-tracking studies, Lai et al. (2013) argued that considerable effort should be focused on the process of reasoning. For example, Renkewitz and Jahn (2012) investigated memory retrieval during decision making and identified different gaze patterns associated with different underlying memory retrieval strategies. Thibaut and French (2016) explored search strategies reflected in different looking patterns pertaining to the analogy problem. However, most tasks in these studies lasted for only seconds and so cannot be considered complex problems. In other words, a body of knowledge on information processing strategies in complex problem-solving performances has not yet been realized.

Research hypotheses

The general assumption underlying our study is that information-processing strategies during problem solving will be reflected in eye movement patterns. Moreover, that eye movements will be aligned with different problem-solving performances and relate to efficiencies. Specifically, we propose the following research questions:
Research question 1: How does eye movement differ between high- and low-performing students in solving analytical and interactive problems?

Research question 2: What different information-processing strategies can be inferred from the eye movements of high- and low-performing students during the solving of analytical and interactive problems?

Methods

Participants

Twenty-eight undergraduate students from the first year (n = 12), the second year (n = 10) and the third year (n = 6) of a university in Shanghai voluntarily took part in this study. There were no restrictions relating to the discipline and prior knowledge of the participants. The only requirement was that all participants should have normal eye sight or wear glasses, because the computer screen would be placed approximately 80 cm from the eyes of the participants to collect eye movement data. Ten participants (35.7%) were male. Their average age was 20.7 years with age ranging from 19 to 21. Every participant received a small souvenir for their participation.

The reason for selecting undergraduates instead of K-12 students is twofold. First, given that finding K-12 students to participate in the study in our laboratory was difficult, we recruited undergraduate students from our own university on the basis of convenience sampling. Second, our purpose was to investigate information-processing strategies between high- and low-performing students in solving two types of problems, rather than to identify the problem-solving features of Chinese K-12 students. Therefore, as we stress in the Discussion section, although this study may elucidate possible explanations of Chinese students' performance in PISA tests, the present findings may not be generalized to other levels of students.

Materials

We adopted two PISA test problems and built a computer-based problem-solving environment for their presentation. One was a rule induction problem, called 'birthday party', which belongs to the analytical problem category. This problem required students to arrange seven different animals using drag and drop methods around a table to meet all conditions in a given list. A total of nine conditions were present in the study. For example, one condition was that the tiger sits neither next to the elephant nor next to the mouse. The score of this problem task ranges from zero to seven depending on how many animals were correctly arranged.

The other problem was a multi-variable system problem, which is a type of interactive problem. In this problem, a computer-simulated forest system was presented, which included three manipulation variables (inputs) to affect three quantities (outputs): temperature, precipitation, and population of species. The problem involved two stages, i.e., problem exploration and problem solving. The rationale of this two-stage interactive problem was for students to explore the problem situation as well as to understand the underlying system (system representation) and then to apply obtained knowledge (represented system) to solve a new problem situation.

In the first stage, the students were asked to figure out the relations between input variables and output variables through adjusting the input values by clicking a button to simulate the system to the next time step, as well as by reading the line charts of output values ranging from the very beginning until the present. The students then draw lines between inputs and outputs to represent the relations of this multivariable system. Given that this multi-variable system contains four relations between inputs and outputs, the score for this problem task ranges from zero to four, with each correct relation getting one point.

In the second stage, the correct relationships underlying this multi-variable system were provided along with current and target output values, regardless of whether students identify the relations correctly in the first stage. The students were asked to determine the most efficient way to manipulate input variables to reach the output targets. In other words, the fewer simulation steps, the better. The total score is four, with each of three output goals being reached getting one point and with the completion of the task within 7 steps getting one point.

Research procedure and apparatus

The study took place in our laboratory, where the participants conducted the experiment one at a time. All participants completed the tasks in three steps. First, the test procedure was described, including the use of the problem-solving environment and the eye tracking system. Second, the participants were seated at an approximate distance of 80 cm in front of a 17-inch screen with a 1280 x 1024 pixel resolution. They submitted to eye-tracking calibration and then addressed the demonstration problem in this computer-based problem-solving context. Third, they were required to solve one analytical problem and one interactive problem. The whole experiment lasted approximately 30 minutes. Data were collected using the Tobii T120 eye tracker (120 Hz sampling rate) manufactured by Tobii Technology (Stockholm, Sweden). This eye tracker is not intrusive. A large "track box" provides the user with the freedom of head movement and considerable comfort. Eye movement data during problem solving were screen-captured and analyzed with Tobii-Studio (3.1.6) software.

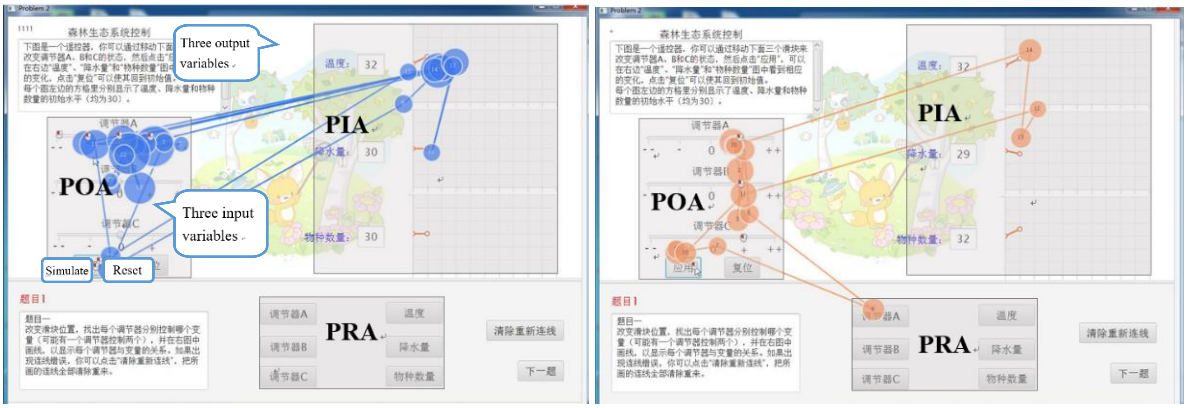
Data collection and analysis

Problem-solving performance data were collected automatically by the system in a log file, which included the scores of problem-solving solutions and the test duration for solving each problem. For the analysis of eye movement patterns, the AOI was defined first. One rectangle area called the problem information area (PIA) and one called the problem operation area (POA) were selected in the three problem tasks (i.e., analytical problem, the problem exploration stage of the interactive problem, and the problem-solving stage of the interactive problem). The POA in analytical and interactive problems is the area where problem solvers select operations to solve the problem. On the other hand, PIA in the analytical as well as the interactive problem is the area where all the information on the problem is presented at the outset and where simulated dynamic information is also presented. In addition, one rectangular area called the problem representation area (PRA) was selected in interactive problems, where problem solvers were required to represent their understanding of the interactive problem and also apply this problem representation to solve a new problem situation. Figures 1 to 3 depict the defined AOIs.

(a) (b)

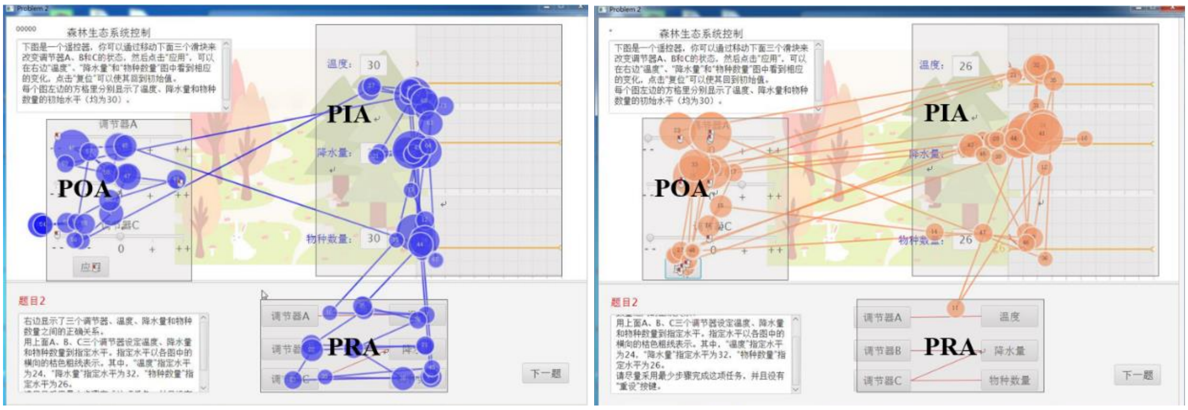
Figure 1. Eye movement in analytical problems—(a) eye fixations and saccades of a high-performing student, (b) eye fixations and saccades of a low-performing student. *Notes.* PIA stands for problem information area; POA stands for problem operation area.

Eye movement indicators generated from the Tobii studio included fixation duration, fixation count, visit duration, and visit count on all target AOIs. Fixation in this study was identified as a gaze point that lasted for at least 60 ms, which is the minimum time for a stimulus to travel from the retina to the region of the brain that processes the information (Chien et al., 2015; Rayner, 1998). Fixation duration was calculated as the average length of fixations in a look zone. Fixation count was the number of fixations at a certain area on the screen. Visit time refers to the period from entering a specific AOI until moving out of this area and is calculated as the durations between the first and the last consecutive fixations in the AOI.



(a) (b)

Figure 2. Eye movements in the problem exploring stage of interactive problems—(a) eye fixations and saccades of a high-performing student, (b) eye fixations and saccades of a low-performing student. *Notes.* POA stands for problem operation area; PIA stands for problem information area; PRA stands for problem representation area.



(a) (b)

Figure 3. Eye movements in the problem-solving stage of the interactive problem—(a) eye fixations and saccades of a high-performing student, (b) eye fixations and saccades of a low-performing student. *Notes.* POA stands for problem operation area; PIA stands for problem information area; PRA stands for problem representation area.

We used the mean test performance in each problem-solving test as a threshold to divide the participants into the low- and high-performing groups, assuming that performance for all participants may not be consistent across all three problem tasks. We conducted the Chi-squared test of group division in each problem task and confirmed that group divisions in all three problem tasks differed from one another: $(1, N = 28) = 5.038$, $p = .051$ for tasks 1 and 2; $(1, N = 28) = 2.798$, $p = .125$ for tasks 1 and 3; $(1, N = 28) = 1.152$, $p = .433$ for tasks 2 and 3.

First, descriptive statistics and independent sample *t*-tests were conducted to examine the difference of eye movement patterns between the high- and the low-performing groups on analytical and interactive problem-solving processes. Second, purposeful sampling was used to select two students for case study, considering the typicality of the case. One student from the high-performing group and one from the low-performing group were selected to analyze their eye movement sequences qualitatively.

Results

Comparison of eye movement difference between the high- and low-performing groups

Analytical problem solving

To test the eye movement difference between the two groups in the analytical problem context, independent sample t-tests were conducted (see Table 1). Regarding PIA, the students in the high-performing group had significantly longer fixation durations compared with the students in the low-performing group. Significantly fewer fixation counts are found for the high-performing group than for the low-performing group. Regarding the completion time of solving the analytical problems, significantly shorter test durations were found for the high-performing group than for the low-performing group.

Table 1. Eye movement differences between the high- and low-performing groups in analytical problem solving

AOI	Indicator	Low (N = 11)		High (N = 17)		t-test		
		M	SD	M	SD	MD	t	p
Problem information area (PIA)	Fixation duration(s)	.26	.11	.45	.14	.18	3.80	$.00^{**}$
	Fixation count	163.69	60.47	74.60	44.33	−89.09	−4.49	$.00^{**}$
	Visit time(s)	2.56	.95	2.80	1.16	.24	.59	.56
	Visit count	40.39	21.55	26.27	11.06	−14.12	−2.13	$.04^{*}$
Problem operation area (POA)	Fixation duration(s)	.44	.16	.43	.11	−.01	−.12	.91
	Fixation count	193.85	198.91	230.00	207.05	36.15	.47	.64
	Visit time(s)	2.26	.75	2.07	.66	−.19	−.70	.49
	Visit count	38.46	30.03	35.67	24.00	−2.79	−.27	.79
	Test duration(s)	237.10	83.80	137.03	75.10	−100.07	−3.33	$.00^{**}$

Note. $^{*}p < .05$; $^{**}p < .01$.

Problem exploring stage of interactive problems

To test the eye movement difference between these two groups in the problem-exploring stage in the interactive problem, we conducted independent sample *t*-tests (see Table 2). Regarding POA, significantly shorter fixation durations were found for the high-performing group than for the low-performing group and significantly fewer visit counts for the high-performing group than for the low-performing group. Regarding PIA, significantly shorter fixation durations were found for the high-performing group than for the low-performing group and significantly fewer visit counts for the high-performing group than for the low-performing group. Regarding the completion time of the problem exploration stage of the interactive problem solving, a significantly shorter test duration was found for the high-performing group than for the low-performing group.

Table 2. Eye movement differences between the high- and low-performing groups in the problem exploration stage of interactive problem solving

AOI	Indicator	Low (N = 13)		High (N = 15)		t-test		
		M	SD	M	SD	MD	t	p
Problem operation Area (POA)	Fixation duration(s)	.62	.21	.32	.07	−.30	−4.87	$.00^{**}$
	Fixation count	36.85	21.47	38.80	20.58	1.95	.25	.81
	Visit time(s)	1.51	.64	2.03	1.36	.52	1.25	.22
	Visit count	17.54	6.63	7.47	2.64	−10.07	−5.14	$.00^{**}$
Problem information area (PIA)	Fixation duration(s)	.58	.22	.33	.13	−.24	−3.64	$.00^{**}$
	Fixation count	56.77	36.37	38.73	25.47	−18.04	−1.54	.14
	Visit time(s)	1.77	.47	1.74	.58	−0.03	−1.60	.87
	Visit count	14.31	4.29	8.27	3.08	−6.04	−4.32	$.00^{**}$
Problem representation area (PRA)	Fixation duration(s)	.41	.14	.40	.11	−.01	−.23	.82
	Fixation count	3.08	1.71	2.60	1.64	−.48	−.75	.46
	Visit time(s)	.23	.26	.14	.18	−.09	−1.04	.31
	Visit count	4.69	3.99	5.20	5.41	.51	.28	.78
	Test duration(s)	89.15	32.88	51.09	22.15	−38.06	−3.63	$.00^{**}$

Note. $^{*}p < .05$; $^{**}p < .01$.

Problem-solving stage of interactive problems

To test the eye movement difference between these two groups in the problem-solving stage of the interactive problem, we conducted independent sample *t*-tests (see Table 3). Regarding POA, significantly longer fixation durations were found for the high-performing group than for the low-performing group and significantly fewer visit counts for the high-performing group than for the low-performing group. Regarding PIA, significantly longer fixation durations were found for the high-performing group than for the low-performing group and fewer visit counts for the high-performing group than for the low-performing group. Regarding PRA, significantly longer fixation durations were found for the high-performing group than for the low-performing group. Regarding the completion time of the problem-solving stage of interactive problem solving, a significantly shorter test duration was found for the high-performing group than for the low-performing group.

Table 3. Eye movement differences between the high- and low-performing groups in the problem-solving stage of interactive problem solving

AOI	Indicator	Low (N = 10)		High (N = 18)		*t*-test		
		M	*SD*	*M*	*SD*	*MD*	*t*	*p*
Problem operation Area (POA)	Fixation duration(s)	.27	.14	.53	.25	.25	2.89	.01*
	Fixation count	74.00	49.69	61.72	26.61	−12.28	−.86	.40
	Visit time(s)	1.07	.35	1.11	.36	.04	.29	.77
	Visit count	37.20	14.45	21.22	6.25	−15.98	−3.33	.01*
Problem information area (PIA)	Fixation duration(s)	.29	.12	.52	.20	.23	3.40	.00**
	Fixation count	84.60	50.52	68.61	22.71	−15.99	−.95	.36
	Visit time(s)	1.25	.40	1.41	.56	.16	.79	.44
	Visit count	27.60	9.26	16.83	5.07	−10.77	−4.00	.00**
Problem representation area (PRA)	Fixation duration(s)	.13	.15	.30	.14	.17	2.99	.01*
	Fixation count	6.00	5.72	5.78	6.48	−.22	−.09	.93
	Visit time(s)	.45	.14	.31	.26	−1.39	−1.55	.13
	Visit count	.90	1.10	1.28	1.36	.38	.75	.46
	Test duration(s)	130.54	67.97	69.41	22.34	−61.13	−2.76	.02*

Note. $^{*}p < .05$; $^{**}p < .01$.

Case analysis of eye movement patterns

The complete eye movement record in solving one problem lasted several minutes and contained a significant number of circles (fixations) and lines (saccades) that make the figures difficult to read. Therefore, this preliminary study presented eye movement within a small time window (around ten seconds) to illustrate the information-processing strategies during the problem-solving stage reflected from the eye movement patterns.

Analytical problem-solving strategies

Analytical problem solving requires planning and execution processes, in which rule search strategy and reasoning are needed. When examining the fine-grained fixation transitions of problem solving, we can see clearly how two strategies were conducted by a high-performing student and a low-performing student, respectively. For example, after the application of the first three rules, the current problem state was four animals, including monkey, horse, dog, and tiger, settled on the table. A high-performing student (see Figure 1(a)) gazed at rule four, which said that the elephant sits next to either the turtle or the pig (includes none of those four animals), and then saccade to the next one until he or she gazed at rule six (includes a cue about tiger that is already on the table). Subsequently, the application of rule six reduced the options of choice and moved the problem state a step close toward the target. By contrast, a low-performing student (see Figure1(b)) visited the problem-solving area after gazing at each rule, not noticing that the application of certain rules (e.g., rule 4 and rule 5), in fact, caused additional alternatives and expanded the problem space.

Searching strategies in the problem exploration stage of interactive problems

In the problem exploration stage of a multivariable system, the control of variables strategy (CVS) is an ideal strategy and is generally defined as a learning goal for a novice problem solver to grasp (Greiff, Wüstenberg, & Avvisati, 2015; Lazonder, 2014). The CVS refers to varying one thing at a time to identify the relations between multi-inputs and multi-outputs. The interactive behavior of a CVS adopter (see Figure 2(a)) shows the manipulation of one variable at a time (i.e., fixation transition between POA and PIA after gazing at one input variable), which cannot be found in the behavior of a non-CVS adopter (i.e., fixation transition within POA among different input variables before transiting back and forth between POA and PIA) (see Figure 2(b)).

Reasoning strategies in the problem-solving stage of interactive problems

In the problem-solving stage of interactive problems, the purpose is to manipulate three inputs and simulate the system to reach three target output values in the fewest steps. Two typical strategies, i.e., schema-driven and means-end, are commonly mentioned in the problem-solving domain (Patel, Groen, & Frederiksen, 1986; van Meeuwen et al., 2014). As described by van Meeuwen et al. (2014), the use of means-end analysis would be manifested by frequently focusing on the goal to reason backward, which is an effort-demanding strategy, whereas the use of schema-driven strategies would be manifested by frequently focusing on the elements that are affected by the problem-solving steps to reason forward, which is a highly efficient strategy. Figure 3(a) illustrates that a high-performing student gazed at PRA and PIA before transiting fixation within POA among different input variables (to work out a solution and conduct a schema-driven strategy) and with little back and forth between POA and PIA. While a low-performing student (see Figure 3(b)) had frequent fixation transitions between POA and PIA (to conduct a means-end approach) with a few fixations on PRA.

Discussion

Analytical problem-solving

In analytical problem solving, two strategies were identified in relation to different performances. High-performing students adopted a heuristic search strategy to narrow the problem space efficiently. They searched from the rule list to identify the rule that contained the critical information relating to the current problem state. However, low-performing students adopted trial-and-error approaches to apply the rules in the original sequence as presented in the problem statement.

The aforementioned descriptions of the two strategies cannot be easily identified from the behavior during problem solving. However, according to the eye movement indicators of different AOIs, we find distinctive eye movement patterns in line with these two strategies. Therefore, compared to low performing students, high-performing students have longer fixations and fewer visit counts in PIA, which, in turn, causes shorter test durations. In analytical problem-solving, the cue-wise strategy of relevant rule selection costs extra time in gazing at PIA that the trial-and-error strategy needs, whereas the latter strategy leads to frequent back and forth between PIA and POA due to the expansion of the problem space. Therefore, we can infer from these critical indicators, including fixation durations and visit counts, whether or not the problem solver adopted a superior strategy. Goldberg and Kotval (1999) also argued that a few fixation counts indicate highly efficient search.

Consistent with Renkewitz and Jahn’s study (2012), the case analysis of eye movement patterns further verified that the fixation duration of cue-wise strategy adopters’ on rules—including specific cues in the current solution state—reflected the rule selection order by this strategy. On the other hand, trial-and-error strategy adopters had similar fixation durations on all rules. The quantitative analysis of eye-tracking indicators and the qualitative case analysis of eye movement patterns corroborate the argument that information reduction abilities can be demonstrated by long fixation duration and a few visit counts (van Meeuwen et al., 2014).

Strategic planning and reasoning in interactive problem-solving

In interactive problem solving for a multi-variable system problem, two consecutive stages were addressed: problem exploration and problem solving. Different information-processing strategies in these two stages were confirmed and were in line with previous studies (Saß, Schütte, & Lindner, 2017). For the first stage, the present study identified information-processing strategies that reflect the adoption and non-adoption of CVS, which is further confirmed by two distinctive eye movement patterns (Greiff et al., 2015). As for eye movement patterns, CVS adopters showed shorter fixation durations in POA and PIA compared with non-CVS adopters. Moreover, low-performing non-CVS adopters shifted their fixation back and forth among different AOIs frequently (i.e., additional visit counts), thereby suggesting that in the knowledge representation phase these students failed to build up the correct mental model that would be required to constantly re-evaluate their mental model with incoming information to solve incongruence.

For the second stage, we found two types of reasoning strategy. The first type is schema-driven forward reasoning that leads to highly efficient and effective performances (Patel, Arocha, & Zhang, 2005; van Meeuwen et al., 2014; Wills, Lavric, Croft, & Hodgson, 2007). The second type is means-end backward reasoning that is an effort-demanding strategy. Students adopting this strategy search the problem space continuously to reduce the difference between the current state and the goal state (Simon, 1975). Our findings corroborated that low-performing students had high visit counts and short fixation durations, which suggests that their attention was focused on frequent adjustment of input variables and the comparison of the current output values as well as the target values that a means-end strategy would exhibit. By contrast, high-performing students tend to retrieve and apply their previously constructed problem schema to solve current problems with long fixation durations in PRA, POA, and PIA. The short visit counts in PIA and POA also suggest the well-planned reasoning strategy of high-performing students. Further case analysis of two typical examples triangulates the quantitative findings of different strategy adoptions. These findings are consistent with Cook et al. (2008), which indicates that students with high prior knowledge had longer fixation durations on critical information compared with those with low prior knowledge.

Comparison of information-processing strategies between analytical and interactive problem solving processes

By comparing the eye movement dynamics between analytical and interactive problem solving processes, we found similar fixation duration patterns in analytical problems and the problem-solving stage of interactive problems. Our findings add new knowledge to the work of van Meeuwen et al. (2014), by suggesting that not only the efficient scan path of relevant information but also the capability of retrieving a problem schema, as identified during problem exploration, can be predicated by long fixation durations within a certain AOI.

Contrary to analytical problem solving, high-performing students in the problem exploration stage of interactive problem solving showed short fixation durations, which may suggest that restructuring dynamic information during an interactive problem-solving process is the end result of active memory search processes that differ from cognitive processes underlying the analytical problem-solving process (Fleck, 2008). Analytical problem solving requires cue-wise rule induction, (i.e., long fixation durations within the problem information area), whereas interactive problem solving requires CVS strategies for problem exploration (few visit counts) followed by knowledge-schema-driven problem solving (long fixation duration within a problem representation area). Therefore, this study adds empirical findings to Chen et al. (2014) and further argues that different problem-solving performances can be predicted by different eye movement indicators according to different problem types.

Conclusion and limitations

The findings of this exploratory study verify the following. (1) In analytical problem solving, high-performing students had longer fixation durations as well as fewer fixation counts and visit counts in PIA compared with low-performing students, while the high- as well as low-performing groups evidently adopt the cue-wise strategy and the trial-and-error strategy, respectively. (2) In the problem exploration stage of interactive problems, high-performing students had short fixation durations and a few fixation counts in PIA and POA, and the high-performing group evidently adopts the CVS strategy. (3) In the problem-solving stage of interactive problems, high-performing students had long fixation durations in PIA, POA, and PRA as well as a few visit counts in PIA and POA, and the high- as well as low-performing groups evidently adopt the schema-driven strategy and the means-end strategy, respectively.

The study also validates the notion that different problem tasks may require different visual attention and mental effort allocations in different parts of a problem. For example, in analytical problem solving, PIA is more important compared with POA for critical information selection; in the problem exploration stage of interactive problems, considerable attention should be given to the relation between PIA and POA; while in the problem-solving stage of interactive problems, all three areas—including PRA, PIA, and POA—should draw considerable attention and in the correct sequence to reduce fixation transitions among different areas.

To foster the deep learning of students during problem solving, we need initially to extract observable and critical indicators (Knoblich, Ohlsson, & Raney, 2011; van Meeuwen et al., 2014). Only then can we possibly provide visual cues as guidance or through personal feedback during problem-solving activities (Jarodzka et al., 2012). This study proves that, through examining fixation duration, fixation count, and visit count, we can tell why students show different levels of performance in different problem tasks, which is, in turn, a result of adopting different information processing strategies.

This study opened a new window for the future analysis of complex problem-solving competencies on the basis of eye movement data. Previous studies have corroborated that commonly used problem-solving analytic approaches, such as think-aloud and performance analyses, may involve certain side effects, including inaccurate data, missing data, and misleading data (such as arise from the issue of gaming the system (Baker et al., 2008)). Eye movement data, which are real-time, rich, and unobtrusive as well as involving eye-mind coordination, can provide fine-grained analysis to build a deep understanding of problem solving and to triangulate with evidence obtained from traditional ways of problem-solving assessment. In short, the results verify that an eye-tracking approach yields valuable insights on information processing strategies during problem solving. We found distinctive patterns of eye movements in solving analytical problems, as well as in exploring and solving interactive problems.

This study chose undergraduate students for the problem-solving test using PISA test problems that are appropriate for K-12 students. Although the purpose of this study was to investigate different information processing strategies adopted by high- and low-performing students to solve the two types of problems, the mismatch between student levels and problem complexity can be considered a limitation. So the findings of this study may apply to the same level of students but may not be generalized to other levels of students directly. The small sample size is another limit to the generalizability of the findings of this study. A further limitation is that only two samples were selected in each problem scenario to analyze fixation transition manually. In future studies, we must consider using sequential pattern recognition technology to analyze a large sample of fixation transitions automatically. A fourth limitation is concerned with the presence of only two problems in this study, one for the analytical problem and one for the interactive problem. Possibly, different types of analytical and interactive problems may be aligned with different information processing strategies. Therefore, whether these findings of eye movement patterns can be generalized to other interactive and analytical problem-solving processes remains an open question. Lastly, future studies need to consider cognitive load and further differentiate the cause of eye movement dynamics between the mental effort of knowledge retrieval and strategic thinking (Amadieu et al., 2015) because problem solving requires information-processing strategies and memory capacities.

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