Eliciting Proactive and Reactive Control During Use of an Interactive Learning Environment

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Abstract. The dual mechanisms of control framework describes two modes of goal-directed behavior: proactive control (goal maintenance) and reactive control (goal activation on task demands). Although these mechanisms are relevant to learner behaviors during interaction with intelligent tutoring systems (ITS), their relation to ITSs is under-researched. We propose a manipulation to induce proactive or reactive control during interaction with an online tutoring system. We present two experiments where students solved problems using either proactive or reactive control. Study 1 validates the manipulation by investigating behavioral measures that reflect usage of the intended strategy and assesses whether either mode impacted learning. Study 2 investigates if alternating between control modes during problem solving affects student performance.

Keywords: Cognitive control · problem solving · learning environments

1 Introduction

Cognitive control is the set of processes that enable behavior adjustments based on current goals [2]. It is explored within cognitive science with its roles in functions such as attention, task switching, and goal maintenance [13], self regulation [8]. Previous work has explored these functions at an abstract level in ITSs, through detection of mind wandering [9], divided attention [17], and multi-tasking [11] as well as self-regulatory behaviors such as resisting the urge to game the system [5] and self regulated learning [1]. Detecting these functions to adapt instruction is the main feature of ITSs and it is in interest of AIED community. Although these functions all share the underlying mechanism of cognitive control, cognitive control itself has been explored less in AIED.

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The Dual Mechanisms of Cognitive Control Framework [3] suggests cognitive control has two modes: proactive and reactive control. Proactive control involves anticipating and preparing for future events by biasing attention and actions towards task goals (e.g. a student preparing a strategy for an expected problem in advance). Reactive control involves retrieving goal-relevant information just-in-time when triggered by external stimuli (e.g. a student relies on a keyword in the problem to use a strategy). Even though prior work shows a positive relationship between proactive control and student performance [12,16], proactive control has not been explored in realistic learning settings. In this work, we aim to gain insight into the underlying mechanisms of higher-order functions studied in ITSs and assess if these functions' benefits can be attributed to cognitive control. Our research questions are: (1) How can we induce proactive or reactive modes of cognitive control within an ITS? (2) What is the relationship between cognitive control and learning?

2 Task Design

The relative usage of proactive and reactive control can be determined using the AX Continuous Performance Task (AX-CPT) [3]. Participants are presented with cue-probe pairs of letters and their response time and error rates indicate their bias towards proactive or reactive control. Previous research has successfully shifted this bias through training strategies encouraging the use of one mode over the other [6]. Our task design creates a goal maintenance scenario similar to this manipulation in problem solving. Our task had 9 probability problems in the ASSISTments tutoring system [7]. Problems were divided into 3 to 4 substeps. First, participants were shown the full problem and asked to report their confidence level. Then, they were shown the problem's substeps, which they solve sequentially (see Fig. 1). This design was used in a thinkaloud study where subjects verbalized their thought processes [15] showing success in inducing proactive and reactive control. Here, we do not use the thinkaloud protocol to eliminate confounding factors, and to get more accurate behavioral data.

The initial presentation of the full problem serves to establish a task goal. The substeps of the problem serve to make goal maintenance more challenging. To induce proactive or reactive control, we have participants use an instructed control strategy. The task had two different versions of instructions. In the "proactive" version, in each problem step, participants were instructed: "Think about how this step relates to the goal of the problem,". In the "reactive" version, the instruction was: "Think about how you are solving this step,". The proactive instruction encourages the student to maintain the main problem's goal while solving its substeps and the reactive instructions made the student only focus on the current step and not the overall goal until they need it.

3 Study 1: Inducing Proactive and Reactive Control

We recruited 29 undergraduate students (21 female, 5 male, 3 non-binary; 14 Asian, 13 White/Caucasian, 1 two or more races) between 18 and 22 years old

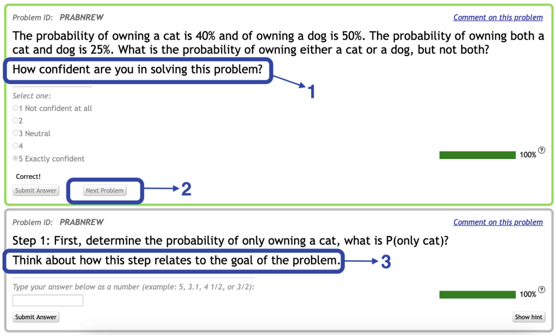

Fig. 1. Screenshot of a sample problem. 1: Participants rate their confidence level. 2: When this button is clicked, the second box with the first problem step unfolds. 3: Prompt to trigger proactive control.

(M = 19.8, SD = 1.13) at a university in the Northeastern US. We recruited participants via email and online bulletin boards. Eligibility criteria included reporting completion of no more than two university-level math courses. Participants first completed a sample problem and a pre-test on ASSISTments. Then, they practiced using proactive or reactive control with another sample problem. They then solved the probability problems using the instructed control strategy, followed by a post-test. Finally they completed a demographic questionnaire.

Data and Measures. One participant's data were excluded as they scored 100% on the pre-test. We also excluded a participant and problem step pair due to a logging error. We had 1035 rows in the final dataset from 28 participants and 37 problem steps. To evaluate participants' compliance with the instructions, we analyzed response times, as previous research showed participants instructed to use proactive control spend more time on problem steps [15]. Studies with AX-CPT report similar results, where response times were significantly different between when proactive and reactive control were used [6]. We measured the time spent on problem steps as the duration between viewing a problem step and the next step. Learning gains were assessed by the difference in the percentages of correctly answered questions between the pre-test and the post-test.

Results. Results of a two-sample t-test show participants in the proactive condition spent significantly more time on the problem steps ($Proactive : M = 21.36, SD = 6.07, Reactive : M = 16.59, SD = 4.53, t(24.05) = 2.36, p < .05$), and marginally more time on the initial step with the full problem ($Proactive : M = 16.50, SD = 6.30, Reactive : M = 12.67, SD = 2.99, t(18.58) = 2.05, p = .05$). In line with the results from [15], the extra time may reflect time spent on proactive strategies. Next, we tested if control strategy affected learning. We first confirmed students' pre-test scores did not differ significantly between the conditions ($Proactive : M = 0.42, SD = 0.20, Reactive : M = 0.52, SD = 0.18$), ($t(25.81) = -0.51, p > 0.5$). Then we used a repeated-measures ANOVA with condition as the between-group variable and the tests (pre and post) as the within-group variable. The significant main effect of test ($F(1, 26) = 51.33, p < .001$) indicated that participants improved from pre to post test. We found no significant interaction between the condition and test ($F(1, 26) = 1.45, p > .05$) indicating no significant difference in learning gain between conditions.

4 Study 2: Shifting from Proactive to Reactive Control

The proactive control manipulation in our task promotes self-explanation by requiring participants to consider the problem steps' relation to the problem goals. Prior work suggests these activities become extraneous to learning once the skill associated with the problem step was acquired [14]. Therefore, in a second study, we investigate if proactive control helps in problem solving when it is used only in the first time that the participant was introduced to a skill.

Adjustments to Task Design. We introduced another condition which we called 'Mixed'. Participants in this condition were given the proactive instructions at first time they see a problem type. In the next occurrences of the same problem type, reactive instructions were given. This condition aims to facilitate skill acquisition while the students' cognitive resources are still available by prompting them to use proactive control at the first occurrence of such skill. In later occurrences, the students will use reactive control to avoid cognitive load proactive control may cause and to speed up solving the problems. Another addition was participants were prompted to indicate their knowledge on each problem step after giving their answer (Fig. 2). This was for ongoing work to study the stages of rule learning.

We recruited 56 undergraduate students (40 female, 14 male, 2 non-binary; 22 Asian, 21 White/Caucasian, 4 African-American, 4 Two or More Races, 3 Hispanic/Latino, 2 did not disclose), ranging from 18 to 27 years old (M = 20.36, SD = 1.41). Participants followed the same procedure as in Study 1.

Data and Measures. Our dataset had 3380 rows consisting of 52 participants (4 participants were excluded as they scored 100% on the pre-test) and 37 problem steps and 28 self-report knowledge prompts. We labeled each row in the dataset with a "step condition" to account for participants' proactive and reactive modes at different steps of a problem. This new column enabled us to compare the time spent between proactive and reactive steps across all participants, including those in the mixed condition who could switch between modes.

Planned Analyses. We build a mixed effects model with time spent on problem steps (excluding the confidence rating and knowledge indication steps, Fig. 2 A and C, as there were no strategic instructions on these steps) as the dependent variable, participant, problem, and problem steps as random factors and step condition as the fixed factor. We found step condition was not effective on time spent as the coefficient of the fixed effect explains time spent on the problem steps decrease by 1.65 s from proactive to reactive steps (Table 1).

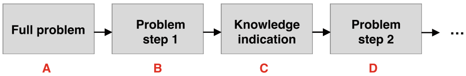

Fig. 2. Sequence of steps in problem solving in Study 2.

To investigate learning, we first confirmed the pre-test scores did not differ significantly ($F(2, 49) = 1.26, p = 0.29$). We conducted a repeated-measures ANOVA with condition as the between-group variable and the tests (pre and post) as the within-group variable. The main effect of test was significant ($F(1, 49) = 116.07, p < .001$) indicating participants improved from pre-test to post-test. The condition and test interaction was not significant ($F(2, 49) = 0.5, p = 0.61$) meaning no significant difference in learning among the conditions.

Table 1. Summary of the planned and post-hoc mixed effects models.

		Planned Analyses			Post-hoc Analyses	
Fixed effects						
(Intercept)	Coefficient	Std. Error	*t* value	Coefficient	Std. Error	*t* value
Step condition (reactive)	28.322	3.687	7.681	19.751	1.926	10.257
	−1.645	1.883	-0.874	−2.716	1.362	−1.993
Random effects						
Groups		Variance	Std. Dev		Variance	Std. Dev
Participant ID		63.52	7.970		15.23	3.902
Problem step: Problem		147.18	12.132		32.35	5.688
Problem		51.49	7.176		10.63	3.261
Residual		372.94	19.312		328.29	18.119

Post-hoc Analyses. We investigated if task design adjustments caused the non-significant result on response time as it contradicts previous results. We first assessed if participants in the mixed condition complied with the instructions. We conducted a paired samples t-test to compare the time spent on problem steps with proactive and reactive instructions. Results showed a significant difference ($t(14) = 9.88, p < 0.001, Proactive : M = 42.91, SD = 10.78, Reactive : M = 26.73, SD = 11.51$). A lack of significant difference in time spent on problem steps between the general proactive and reactive conditions (Table 2) suggests that participants in the proactive condition may not be engaging in the instructed reflection or they may be spending more time on the initial step with the full problem goal they were instructed to maintain. Additionally, they may still engage in reflection during the knowledge indication prompts since those appear before a new problem step. We repeat the mixed effects model including the time spent on the confidence rating and the knowledge indication steps (Fig. 2 A, B, C, D). Results (Table 1) show a stronger effect of step condition as the time spent was decreasing by 2.716 s between proactive and reactive steps. A post-hoc Tukey test shows the difference was significant ($p = 0.04$).

Table 2. Average time spent on the different steps in the experiment in seconds.

Condition	Problem substeps	Confidence rating	Knowledge indication
Proactive	25.7 (22.1)	20.0 (17.7)	7.47 (5.49)
Reactive	26.6 (24.7)	17.3 (12.2)	6.64 (4.65)
Mixed	30.5 (28.3)	16.7 (8.43)	7.70 (5.02)

5 Discussion

Our experiments confirm proactive and reactive control can be induced in a realistic learning setting in line with the prior findings [15]. Even though we obtained mixed results regarding the time spent in study 2, post-hoc analyses showed participants who received the proactive instructions still spent more time when the additional steps in study 2 were considered. These results can indicate the proactive control prompt may encourage other strategies such as reflecting on the solution [10]. We found no significant difference in learning. We argue proactive prompts encourage self-explanations and therefore provide benefits. However, it is possible that the quality of self-explanations was not sufficient for improving learning [4]. Another factor may be the limited problem set we used to ensure consistency with previous work. Participants may have adjusted to the few problem types quickly and therefore there is no visible differences in learning. Another explanation may be the benefits of learner behaviors that involve proactive control could not be isolated to this underlying mechanism, and there may be no direct causal connection between proactive control and learning. Our studies provide preliminary insights into low-level cognitive mechanisms that support higher-level cognitive states studied to understand learner behaviors.

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