Investigating effects of selecting challenging goals

Faiza Tahir, Antonija Mitrović[0000-0003-0936-0806] and Valerie Sotardi

University of Canterbury, Christchurch, New Zealand
faiza.tahir@pg.canterbury.ac.nz

Abstract. Goal setting is a vital component of self-regulated learning. Numerous studies show that selecting challenging goals has strong positive effects on performance. We investigate the effect of support for goal setting in SQL-Tutor. The experimental group had support for selecting challenging goals, while the control group students could select goals freely. The experimental group achieved the same learning outcomes as the control group, but by attempting and solving significantly fewer, but more complex problems. Causal modelling revealed that the experimental group students who selected more challenging goals were superior in problem solving. We also found a significant improvement in self-reported goal setting skills of the experimental group.

Keywords: Self-regulated learning, goal setting, intelligent tutoring system.

1 Introduction

Self-Regulated Learning (SRL) is defined as an "active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation and behavior guided and constrained by their goals and the contextual features in the environment" (Zimmerman, 2011). The goal-setting theory illustrates that setting difficult goals lead to higher performance (Locke & Latham, 1990, 2019). Many studies show the benefits of goal-setting activities (Latham & Yukl, 1975; Locke & Latham, 2002), the power of self-set goals (Locke, 2001), influence of various strategies in goal attainment (Seijts at al., 2005; Masuda, 2015), and the effects of goal commitment (Landers, 2017). Zimmerman (2002) reported that students who set precise and actionable goals often reported higher self-awareness and had higher achievements. As mentioned in a meta-review of achievement (Collins, 2004), meeting a standard or goal is not enough; one should struggle for excellence. The goal-setting theory discussed the greater effects of task-specific over non-task related goals (Latham et al., 2012) and effects of selecting challenging goals (Latham et al., 2017).

Goal setting has been studied in various learning environments (Melis & Siekmann, 2004; Davis et al., 2016; Cicchinelli et al., 2018). In the context of AIED, relevant research connects students' goal-setting behavior with their motivation (Bernacki et al., 2013; Carr et al., 2013; Duffy et al,. 2015). Crystal Island (Rowe et al., 2011) asks students to solve a mystery by accomplishing eleven goals. Their results reveal that students who achieved more goals significantly improved their learning performance. In Meta-Tutor (Harley et al., 2017), four pedagogical agents support SRL via dialogs with the student. The agents determine the student's previous knowledge, and assist the student in selecting goals. Evaluation of Meta-Tutor revealed that students who collaborated more with agents learnt more. This paper discusses the effects of selecting challenging goals on learning in the context of SQL-Tutor (Mitrovic, 2003).

2 Study Design and Procedure

We enhanced SQL-Tutor by adding support for all three phases of the Zimmerman's model (2003), but in this paper we focus on the forethought phase only. SQL-Tutor contains over 300 problems, classified using 38 different problem templates (Mathews, 2006). A problem template covers a set of problems, which require the same problem-solving strategy. The 38 problem templates are grouped into eight high-level goals. The student is required to select a goal at the start of each session, and also after achieving a goal. The system always suggests challenging goals. The student is free to select one of the suggested goals, or any other goal.

We use a simple heuristic strategy to select a challenging goal for the student. At the start, students complete a pre-test, with scores ranging from 0 to 9. The initial goal is determined based on the student's pre-test score, while for the subsequent ones, the system considers both the pre-test score and the student's current level (*slevel*). The student level ranges from 1 to 9, and it is determined dynamically, based on the student's success during problem solving (Mitrovic, 2003). For example, if the student scored 6 or more on the pre-test (i.e. the median score or higher), the challenging goal should be 8. The goal-setting page shows the number of problems per goal, and the number of problems the student has solved. The previously achieved goals are highlighted. If the student with a low pre-test score selects a very challenging goal, the system would suggest an easier goal. To achieve a goal, the student needs to complete at least half of the relevant problems, or solve the five most complex problems.

The SRL instrument used in the study was adopted from (Kizilcec et al., 2017). Out of 24 questions, in this paper we only discuss the goal-setting subscale (4 questions). We also added five self-efficacy questions from the Motivated Strategies for Learning Questionnaire (Pintrich and De Groot, 1990). The survey used a five-point Likert scale, ranging from "Not at all true for me" (1) to "Very true for me" (5).

The participants, volunteers from the second-year database course at the University of Canterbury in 2020, were randomly allocated to the experimental (57) and control group (42). After providing informed consent, the participants completed the pre-test and Survey 1. The experimental group received support during goal setting, while the control group participants selected foals freely. After selecting a goal, students could choose any problem. The study lasted for four weeks. At the end of the study, students completed the post-test of similar structure and complexity as the pre-test, and completed Survey 2 (which was identical to Survey 1).

We hypothesized that the experimental group would achieve higher learning outcomes (H1). We formed a hypothesis for the experimental group: that selecting challenging goals would affect students' learning positively (H2). Finally, we expected that the support for goal setting would improve students' goal-setting skills (H3).

3 Results

We compared the pre/post-test scores of participants who completed both tests (Table 1). There is no significant difference on pre-test scores of the control (59.88%, sd = 28.82) and experimental groups (55.56%, sd = 29.18). The experimental group improved significantly from pre- to post-test (W = 298, p = .03), but the control group students did not (p = .74). Comparing normalized gains revealed no significant difference. These results partially support hypothesis H1. The control group attempted/completed significantly more problems (Table 1). The experimental group completed significantly more complex problems. These findings show that experimental group achieved higher learning gains by completing fewer but more complex problems.

Table 1. Summary of major statistics: mean (sd)

	Control (42)	Experimental (57)	Significance
Attempted Problems	92.98 (61.86)	57.46 (41.33)	U = 783, p = .003
Completed Problems	91.86 (61.33)	56.44 (41.09)	U = 783, p = .003
Problem Complexity	2.92 (0.96)	3.32 (1.08)	U = 1465.5, p =.057
Time (min)	360.19 (335.33)	296.71 (233.22)	p = .58

We divided the experimental group post-hoc into three subgroups (Table 2). Fourteen students always accepted the suggested goals (SG), 18 students worked on the goals in the sequential order (SEQ), while the remaining 25 students used a mixed strategy (Mix). We found no significant differences between the subgroups on the pre-/post-test scores and time, but there were statistically significant differences on the number of attempted goals (H = 8.12, p = .017), achieved goals (H = 10.13, p = .006), the number of attempted/solved problems (H = 13.88, p = .001 and H = 14.41, p = .001 respectively), and problem complexity (H = 12.20, p = .002). The post-hoc analyses revealed no significant differences between the SEQ and Mix groups. The SG subgroup attempted significantly fewer goals in comparison to the SEQ (U = 55, p = .006) and Mix groups (U = 94, p = .016), and achieved significantly fewer goals in comparison to the Mix group (U = 77, p = .003). The SG group also attempted/solved significantly fewer problems in comparison to the SEQ (U = 44, p = .002 in both cases) and Mix groups (U = 74.5, p = .003 and U = 71, p = .002 respectively). However, the average problem complexity of solved problems for the SG group was significantly higher in comparison to the SEQ (U = 40.5, p = .001) and Mix (U = 77.5, p = .004) groups.

Table 2. Summary statistics for the three subgroups: mean (sd)

	SEQ (18)	Mix (25)	SG (14)
Pre-test %	62.97 (27.75)	64.46 (24.01)	61.11 (33.98)
Post-Test %	n=9, 64.21 (31.81)	n=12, 77.78 (28.55)	n=8, 69.45 (21.23)
Time (min)	346.17 (290.49)	283.36 (163.41)	257.0 (263.09)
Attempted goals	6.39 (2.62)	7.04 (1.14)	5.00 (2.18)
Achieved goals	4.72 (2.54)	3.60 (2.43)	1.64 (2.34)
Attempted Problems	78.28 (44.84)	58.96 (38.18)	28.0 (22.34)
Problem Solved	77.50 (44.23)	57.88 (38.02)	26.79 (21.92)
Problem Complexity	2.85 (.74)	3.11 (.86)	4.31 (1.20)

We analyzed the data using the structural equation model (Figure 1). We hypothesized that the pre-test score and the number of attempted problems will have a positive effect on learning. The variable labelled “Accepted goals” shows how many times students accepted the suggested goals. Because not all students completed the post-test, we use a different measure of learning: the highest achieved goal (HAG). All path coefficients are significant at p < .05 except PreTest -> HAG, and the covariance between Accepted Goals and PreTest. There is a significant negative effect of Accepted goals on Attempted problems. These findings suggest that (1) students who accepted system goals tend to achieve higher goals (the confidence interval [.1345, .7074] does not include zero), and (2) students who accepted suggested goals achieved higher goals (the confidence interval [-.5903, -.1133]). Students with lower pre-test scores achieved higher goals when they accepted system suggestion. These findings support H2.

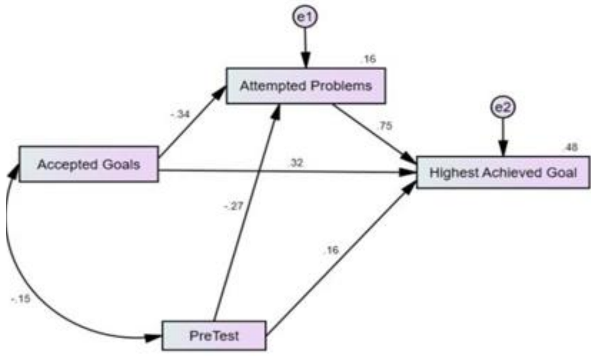

Fig. 1. Multiple mediation model

To test hypothesis H3, we compared the scores from the two surveys. No differences exist at the time of Survey 1 on goal setting and self-efficacy (SE). The goal-setting scores of the experimental group improved significantly (z = -1.93, p = .05), but not in the control group. There is a significant difference (z= -2.97, p < .005) on the goal-setting scores on Survey 2. The SE scores differed both as a function of group and time. At Survey 1, the experimental group had lower SE, but they increased at Survey 2 (z = -1.57, p = .1) whereas the SE scores decreased for the control group (z = -1.86, p = .06). These findings suggest that (a) students who complete the tasks in the absence of the intervention) reported lower SE over time; and, (b) the goal-setting intervention may lead to considerable gains in SE, *especially* for students who started with less confidence. Although it is important to further establish these trends in future research, these findings confirm our Hypothesis 3.

Table 4. Goal setting and self-efficacy scores: mean (sd)

	Goal Setting		**Self-Efficacy**	
	Exper. (21)	**Control (14)**	**Exper. (21)**	**Control (14)**
Survey 1	3.56 (0.63)	3.39 (0.64)	3.38 (0.65)	3.5 (0.66)
Survey 2	3.95 (0.65)	3.28 (0.65)	3.74 (0.65)	2.98 (0.67)

Our findings highlight the effects of setting challenging goals under realistic conditions, in a study that lasted four weeks. The limitations of our study are the small sample size and the low completion rates for Survey 2 and post-test. The results are in line with the goal-setting theory. In future work, we will investigate the effects of the intervention on the monitoring and self-reflection SRL phases.

References

1. Bernacki, M. L., Nokes-Malach, T. J., & Aleven, V. (2013). Fine-grained assessment of motivation over long periods of learning with an intelligent tutoring system: Methodology, advantages, and preliminary results. In *International handbook of metacognition and learning technologies* (pp. 629-644): Springer.
2. Carr, A., Luckin, R., Yuill, N., & Avramides, K. (2013). How mastery and performance goals influence learners' metacognitive help-seeking behaviours when using Ecolab II. In *International handbook of metacognition and learning technologies* (pp. 659-668): Springer.
3. Cicchinelli, A., Veas, E., Pardo, A., Pammer-Schindler, V., Fessl, A., Barreiros, C., & Lindstädt, S. (2018). *Finding traces of self-regulated learning in activity streams.* Proc. 8th Int. Conf. Learning Analytics and Knowledge (pp. 191-200).
4. Davis, D., Chen, G., Jivet, I., Hauff, C., & Houben, G.-J. (2016). Encouraging Metacogniion & Self-Regulation in MOOCs through Increased Learner Feedback. Learning Analytics and Knowledge conference (pp. 17-22).
5. Duffy, M. C., & Azevedo, R. (2015). Motivation matters: Interactions between achievement goals and agent scaffolding for self-regulated learning within an intelligent tutoring system. *Computers in Human Behavior, 52*, 338-348.
6. Harley, J. M., Taub, M., Azevedo, R., & Bouchet, F. (2017). Let's Set Up Some Subgoals: Understanding Human-Pedagogical Agent Collaborations and Their Implications for Learning and Prompt and Feedback Compliance. *IEEE Transactions on Learning Technologies*, 11(1), 54-66.
7. Hayes, A. F. (2017). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. Guilford publications.
8. Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & Education, 104*, 18-33.
9. Landers, R. N., Bauer, K. N., & Callan, R. C. (2017). Gamification of task performance with leaderboards: A goal setting experiment. *Computers in Human Behavior*, 71, 508-515.
10. Latham, G. P., & Piccolo, R. F. (2012). The effect of context-specific versus nonspecific subconscious goals on employee performance. *Human Resource Management, 51*(4), 511-523.
11. Latham, G. P., & Yukl, G. A. (1975). Assigned versus participative goal setting with educated and uneducated woods workers. *Journal of applied psychology, 60*(3), 299.
12. Locke, E. A. (2001). *Self-set goals and self-efficacy as mediators of incentives and personality.* In M. Erez, U. Kleinbeck, & H. Thierry (Eds.), *Work motivation in the context of a globalizing economy* (p. 13–26). Lawrence Erlbaum Associates Publishers.
13. Locke, E. A., & Latham, G. P. (1990). *A theory of goal setting & task performance*: Prentice-Hall, Inc.
14. Locke, E. A., & Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American psychologist, 57*(9), 705.
15. Locke, E. A., & Latham, G. P. (2019). The development of goal setting theory: A half century retrospective. *Motivation Science, 5*(2), 93.
16. Masuda, A. D., Locke, E. A., & Williams, K. J. (2015). The effects of simultaneous learning and performance goals on performance: An inductive exploration. *Journal of Cognitive Psychology, 27*(1), 37-52.
17. Mathews, M. (2006). Investigating the effectiveness of problem templates on learning in intelligent tutoring systems. Honours report, Department of Computer Science, University of Canterbury.

18. Melis, E., & Siekmann, J. (2004). Activemath: An intelligent tutoring system for mathematics. In *Int. Conf. Artificial Intelligence and Soft Computing* (pp. 91-101). Springer, Berlin, Heidelberg.
19. Mitrovic, A. (2003). An intelligent SQL tutor on the web. *Artificial Intelligence in Education, 13*(2-4), 173-197.
20. Pintrich, P. R., De Groot, E. V. (1990) Motivational and self-regulated learning components of classroom academic performance. *Journal of educational psychology, 82*(1), 33.
21. Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In *Handbook of self-regulation* (pp. 451-502): Elsevier.
22. Rowe, J. P., Shores, L. R., Mott, B. W., & Lester, J. C. (2011). Integrating learning, problem solving, and engagement in narrative-centered learning environments. *Artificial Intelligence in Education, 21*(1-2), 115-133.
23. Seijts, G. H., & Latham, G. P. (2005). Learning versus performance goals: When should each be used?. *Academy of Management Perspectives, 19(1), 124-131.*
24. Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory into practice, 41*(2), 64-70.
25. Zimmerman, B.J., & Campillo, M. (2004) *Motivating self-regulated problem solvers.* The psychology of problem solving, 233-262.
26. Zimmerman, B. J., & Schunk, D. H. (2011). *Handbook of self-regulation of learning and performance*: Routledge/Taylor & Francis Group.