

Carelessness and Goal Orientation in a Science Microworld

Arnon HERSHKOVITZ¹, Michael WIXON, Ryan S.J.d. BAKER, Janice GOBERT,
Michael SAO PEDRO

Department of Social Science and Policy Studies, Worcester Polytechnic Institute²

Abstract. In this paper, we study the relationship between goal orientation within a science inquiry learning environment for middle school students and carelessness, i.e., not demonstrating an inquiry skill despite knowing it. Carelessness is measured based on a machine-learned model. We find, surprisingly, that carelessness is higher for students with strong mastery or learning goals, compared to students who lack strong goal orientation.

Keywords: carelessness, goal orientation, educational data mining, science inquiry

Introduction

In recent years, there is increasing evidence that the goals students have during learning play a key role in their learning outcomes. These goals might impact learning by creating different forms of disengagement, but it is yet unclear which forms of disengagement are influenced by students' goals. One such a disengagement behavior is carelessness, i.e., when a student fails in answering a question despite knowing the answer [1]. Both mastery goals (the goal of learning), and performance-approach goals (the goal of demonstrating competence) are positively correlated with persistence and effort and correlated with self-regulated learning (SRL) strategies, hence it seems reasonable to hypothesize that carelessness will be less frequent when students have mastery or performance-approach goals. Within this paper, we operationalize carelessness using an automated detector of contextual slip, i.e., the probability that the student performed incorrectly at a specific time despite knowing the needed skill [2]. The notion of contextual slip matches previous carelessness definitions [e.g., 1], but is easier to apply than previous operational definitions. Our detector uses a log-based machine-learned model, hence can be scaled without being overly time-consuming.

1. Methodology

The learning environment. We study carelessness in demonstrating science inquiry skills (e.g., control for variable strategy). Our phase change activity enables students to

¹ Corresponding author. Arnon Hershkovitz, arnonh@wpi.edu.

² Research was supported by NSF grant DRL-1008649 (to Janice Gobert and Ryan Baker). The authors thank Juelaila Raziuddin, Andy Montalvo, and Adam Nakama, for their support in collecting the data.

use inquiry support tools while engaging in authentic inquiry using “microworlds”, computer simulated worlds in which a student can conduct scientific inquiry. This learning environment detects whether students demonstrate inquiry skills using validated machine-learned models of these behaviors [3].

Participants and Data Set. 148 eighth grade students, aged 12-14 years old, from a public middle school in Central Massachusetts. All students’ fine-grained actions were logged and then analyzed at the “clip” level; a clip is a consecutive set of a student’s actions describing activity in its context.

The data set includes 2114 phase change clips in which the student failed to correctly demonstrate one or more of three inquiry skills: designing controlled experiments using the control for variable strategy (CVS), testing articulated hypotheses, and planning using the table tool. Each clip had a set of 73 features extracted for the machine-learning process, including the numbers of different types of actions that occurred during the clip, the timing of each action, and the probability that the student knew the skill to solve the relevant problem set before their first attempt on action N , $P(L_{n-1})$ (calculated using a Bayesian Knowledge Tracing model of student inquiry skill). In addition, students completed standard questionnaires for the Patterns of Adaptive Learning Scales (PALS) survey [4].

Carelessness Detector. We developed the carelessness detector in RapidMiner 5.0 using REPTree, a regression tree classifier. Carelessness, first predicted at the clip-level, was computed at student-level by taking average values over all of the student clips. The resulting regression tree (a 6-fold cross-validation correlation of $r=0.63$) includes 13 variables, has a size of 35 and a total depth of 13.

Cluster Analysis. Exploratory cluster analysis was conducted to group the students by their PALS measures in order to examine whether certain sub-groups of students which manifest specific characteristic patterns on the PALS survey also differ on carelessness. We used Two-step Cluster Analysis (in SPSS 17.0) with the PALS measures (Z-standardized) and a log-likelihood distance measure. We chose $k=3$ as it led to more interesting separations between aspects of the PALS.

2. Results

Overall, mean carelessness across clips ($N=2114$) was 0.05 ($SD=0.16$). The predicted carelessness across students ($N=130$) had a mean of 0.06 ($SD=0.05$).

Carelessness and PALS Measures. Three of the 8 sub-scales of the PALS survey were significantly correlated with carelessness: a) Carelessness was positively correlated with *academic efficacy* with $r=0.24$, $F(1,121)=7.10$, $p<0.01$; b) Carelessness was negatively correlated with *disruptive behavior* with $r=-0.22$, $F(1,121)=5.96$, $p<0.01$; and c) Carelessness was negatively correlated with *self-presentation of low achievement* with $r=-0.23$, $F(1,121)=6.49$, $p<0.05$.

Carelessness and PALS-based Clusters. In general, cluster analysis suggested that certain patterns of response on the PALS survey might predict carelessness measures. Mean values of the clustering variables are given in Table 1, according to which we named the clusters: 1) *mastery goal orientation*, 2) *performance goal orientation*, and 3) *lack of goal orientation*.

Mean carelessness in cluster 3 was significantly lower from its mean in both cluster 1, with $t(45.94)=2.78$, $p<0.0$, and cluster 2, with $t(76.17)=3.86$, $p<0.01$. For both analyses, the F of Levene’s Test of Equality of Variances was significant at $p<0.05$,

hence equal variances were not assumed. No significant differences were found between clusters 1 and 2, $t(99)=0.12$, $p=0.90$.

Table 1. Centers of the clusters formed by Two-step Cluster Analysis with $k=3$ ($N=121$)

Variable	Mean (std)		
	Cluster 1	Cluster 2	Cluster 3
Mastery goal orientation	4.66 (0.40)	4.38 (0.64)	2.07 (0.87)
Performance-approach goal orientation	1.69 (0.57)	3.20 (1.04)	2.40 (0.82)
Performance-avoid goal orientation	1.86 (0.72)	3.78 (0.67)	3.62 (0.68)
Academic efficacy	4.41 (0.49)	4.22 (0.55)	3.65 (1.06)
Avoiding novelty	1.96 (0.60)	2.58 (1.00)	3.02 (1.21)
Disruptive behavior	1.54 (0.68)	1.61 (0.68)	2.07 (1.01)
Self-presentation of low achievement	1.33 (0.31)	1.59 (0.60)	3.43 (1.00)
Skepticism about the relevant of school for future success	1.57 (0.49)	1.92 (0.82)	2.07 (0.87)
N	35	66	20
Mean Carelessness (SD)	0.06 (0.06)	0.06 (0.05)	0.03 (0.02)

Our results surprisingly suggest that students with strong mastery/performance goal orientation were on average twice as careless as those with no goal orientation. We compared inquiry skills between clusters, as measured by $P(L_{n-1})$ (averaged over time for each student, then over each cluster). There were no significant differences in mean inquiry skills between clusters 1 and 3, $t(53)=0.06$, $p=0.95$; nor between clusters 2 and 3, $t(84)=1.08$, $p=0.29$. Hence, differences in carelessness between clusters are not likely to be due to differences in student inquiry skills.

3. Summary

In summary, the research presented here shows that students characterized by mastery or performance goal orientation have (on average) double the probability of carelessness as compared to students characterized by low scores for these goal orientations. One possible interpretation of the results is that students with higher amounts of mastery or performance goals succeed in learning and correspondingly become more confident (as suggested in [1]), and that this confidence leads to carelessness despite their goal orientation. Further research regarding the ways that goal orientation relates to student behaviors within educational software may have the potential to better elucidate the mechanisms by which goal orientation impacts learning and, in turn, long-term learning outcomes.

References

- [1] Clements, M.A.: Careless errors made by sixth-grade children on written mathematical tasks. *Journal for Research in Mathematics Education*, 13, 136-144 (1982)
- [2] Baker, R.S.J.d., Corbett, A.T., Aleven, V.: More accurate student modeling through contextual estimation of slip and guess probabilities in Bayesian Knowledge Tracing. In *Proceedings of the 9th International Conference on Intelligent Tutoring Systems*, 406-415 (2008)
- [3] Sao Pedro, M.A., Baker, R.S.J.d., Gobert, J.D., Montalvo, O., Nakama, A. (Revise and Resubmit). Using machine-learned detectors of systematic inquiry behavior to predict gains in inquiry skills. *User Modeling and User-Adapted Interaction*.
- [4] Midgley, C., Maehr, M.L., Huda, L.Z., Anderman, E., Anderman, L., Freeman, K.E., Gheen, M., Kaplan, A., Kumar, R., Middleton, M.J., Nelson, J., Roeser, R., and Urdu, T. (2000). *Manual for the Patterns of Adaptive Learning Scale*. Ann Arbor, MI: University of Michigan.