When do Students Interrupt Help? Effects of Individual Differences

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Abstract. When do students interrupt help to request different help? To study this question, we analyze a within-subject experiment in the 2003-2004 version of Project LISTEN's Reading Tutor. From 168,983 trials of this experiment, we report patterns in when students choose to interrupt help. To improve model fit for individual data, we adjust our model to account for individual differences. We report small but significant correlations between a student parameter in our model and gender as well as external measures of motivation and academic performance.

1. Introduction

In a companion paper [1], we study when students interrupt help and we report a model to predict the probability that students will interrupt help as shown in Equation 1. This model shows that students interrupt help increasingly often over the first thirty exposures, and then their interruption rate reaches an asymptote. We defer all discussion of the framework of our experiments and participants to that paper. In this paper, we expand our model by adding a student parameter. We show that this student parameter improves model fit. Then we correlate this variable with test scores that measure student attitudes and other affective variables. This paper deals primarily with variables which model personality and character traits; in our conclusion, we suggest directions for future work which might model affective states.

$$P(i) = a * (e^{b * prior\_\exp osures}) + c$$

Equation 1: Base Model

2. Adding a Student Parameter

To account for individual differences, we added a student parameter, *s*, to our model as shown in Equation 2. Conceptually, a student with a high *s* parameter interrupts more often than a student with a low *s* parameter. This student parameter, *s*, alters the asymptote of the graph and is related to a student's interruption rate, a value that should be between zero and one. To insure that values for *s* would be consistent with this idea, we set the initial value for the student parameter *s* at 1, and imposed the limits that *s* must be less than or equal to 1 and greater than -.5. Within this range [-.5, 1], SPSS fit a single student parameter for each student.

$$P(i) = a * (e^{b * prior\_\exp osures}) + c + (\mathrm{s} * (1 - c))$$

Equation 2: Student Parameter Model

3. Comparing Model Fits

Table 1 uses mean squared errors and r^2 to compare the two models with a simple baseline called the overall interruption rate.. The overall interruption rate model simply predicts that 43% of all help will be interrupted, since this is the average interruption rate when all of the data is aggregated together. Table 1 shows that the biggest reductions in mean square error and improvements in r^2 come from applying a base model that takes time into consideration by accounting for the amount of previous help. Adding a student parameter improved the model moderately.

Table 1: Models and Mean Square Errors

Model Name	**Mean Square Error**	r^2
Overall Interruption Rate	.24	-
Base Model (Equation 1)	.19	0.24
Student Parameter Model (Equation 2)	.17	0.30

4. Correlating the Student Parameter against External Measures

The student parameter, *s*, in the model is a variable that may relate to other measures of a student, including process variables and test scores. We considered the following process variables: help request rate, help interruption rate, disengagement (measured as the percentage of questions that students answer hastily [2]), and percentage of time picking stories. We were surprised that we did not find correlations with those affective variables, especially disengagement or help request rate.

For test scores, we considered pre- and post-test scores and gains for the Elementary Reading Attitude Survey (ERAS) [3] and a fluency test. ERAS is a twenty item instrument with ten items each for recreational and academic reading attitudes. The fluency test measures how many words per minute a student reads according to a trained tester; more fluent readers score higher. Small, significant negative correlations exist between the *s* parameter and the ERAS academic and motivational test scores. So, *s* relates to attitudes towards academic and recreational reading. Additionally, a small but marginally significant correlation exists between fluency pre-test and the student parameter *s*, so, *s* may also be related to proficiency. Thus, a more fluent reader is less likely to interrupt. Table 2 displays the correlations.

Table 2: Student Parameter Correlations

Test Name	Pearson Correlation	Signficance
Fluency Pre-Test	-.155	.072
ERAS Recreational Pre-Test	-.267	.002
ERAS Academic Pre-Test	-.283	.001

In order to determine the relationship between *s* and gender, we ran an independent samples T-test and found the mean *s* value for girls (-0.057) differs from the mean *s* value for boys (0.037) at $p<0.001$. Therefore, girls are less likely to interrupt than boys, the difference is significant, and the *s* parameter is related to gender.

4. Future Work and Conclusion

In this paper, we have introduced spoken help interruption as an observable, analyzable outcome variable that is an affective indicator. We refined a mathematical model that predicts help interruption to include a student parameter *s*, and we have shown that *s* is correlated with attitudes towards reading and gender. Attitude and gender are fixed traits, and they influence the asymptote in our model, the portion of the curve that represents more stable behavior. Interesting future work may involve considering those variables which model affective state and determining how they can further improve model fit. Such future work would need to take into account temporal regions of data and would ideally show correlations with other observable behaviors indicative of affective state.

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