

Modelling engagement in Technology-mediated Peer-Instruction

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ABSTRACT TO DO

CCS CONCEPTS

• **Applied computing** → **Computer-assisted instruction**; • **Computing methodologies** → **Natural language processing**.

KEYWORDS

Peer Instruction, Text Mining

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1 INTRODUCTION

Technology-mediated peer instruction platforms [4][1] prompt students to not only answer multiple-choice items, but also provide explanations that justify their reasoning. Students are then prompted to revise their answer choice by reading some of the explanations written by their peers, for another answer choice. This modality is a specific case of *learnersourcing*[5], wherein students generate content as part of their own learning process, that is ultimately used to help their peers learn as well.

At this *review step*, students are also presented with peer-written explanations for the same answer choice. The student now has three options:

- (1) Change their answer choice, by indicating which of their peer's explanations was most convincing
- (2) keep their answer choice, but *change explanations* by choosing one that is for the same answer as their own
- (3) choose "I stick to my own", indicating that their own explanation is best from amongst those that are shown.

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In many teaching contexts, teachers do not have the time to review, and provide feedback, to every student explanation for every question item. The feedback students receive is primarily based on the correctness of their first and second answer, not the explanations they write and choose. Moreover, activities from online learning environments are often used for formative assessment, and carry little weight in terms of course credit. Framed as a low-stakes test, this can lead to low student motivation [6]. A version of the expectancy-value model [2], which describes factors that influence the effort students will direct towards a task, include "how important they perceive the test to be", and the "affective reaction to how mentally taxing the task appears to be" [7].

This may explain, in part, the tendency for students to simply "stick to their own", as shown in figure 1. Of the students who choose the correct answer choice on the first step, more than half choose their own as "most convincing" over the explanations that are shown on the *review step* (39% vs 35%). Of those who begin with incorrect answer, and maintain their incorrect answer on the review step, we find approximately the same relative ratios (9% vs 8%). The last third of these students demonstrate some form of *learning* as well, as they transition to the correct answer after reading their peer's explanations.

These numbers suggest that when a student chooses a peer's explanation as more convincing than their own, for the same answer choice, this "vote" that has been cast, can be interpreted as a proxy for learner *engagement*.

In this work, we suggest that if we can accurately model when students *change* explanations, we may have proxy for student *engagement*.

2 RELATED WORK

2.1 Engagement

2.2 Modelling Argument Persuasiveness

3 METHODOLOGY

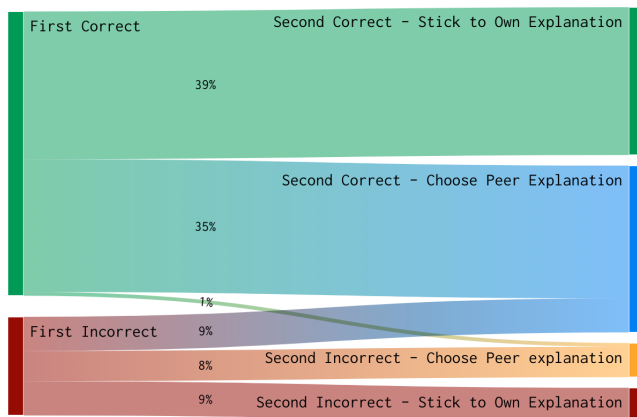
3.1 Engagement

$$Engagement_{student} = P(ChosenExplanation \neq OwnExplanation) \quad (1)$$

3.2 Features

3.2.1 Surface Features.

- (1) Word count of explanation that the student wrote



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Figure 1: Sankey Diagram depicting transitions in peer-instruction platform. On the left, responses are separated by whether the student chose the correct answer at the first step, or not. For each of these two scenarios, there are three possible transitions towards the right: a) keep the same answer choice, and choose their own explanation, b) keep the same answer choice, and choose a peer’s explanation, or c) choose a different answer choice (by choosing a peer’s explanation for the other answer choice option presented) TO DO: make diagram for different disciplines

- (2) Word counts of explanations that were shown on the review step
- (3) Number of explanations shown that were much shorter, or much longer than than the student’s own explanation
- (4) First answer correct

3.2.2 *Convincingness Features.* Two measures of *convincingness* are explored in this work:

- (1) **Win Rate:** a heuristic measure [3]
- (2) **Bradley-Terry**

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TO DO

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